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# Aligning Tree Locations from VHR Images with LiDAR Data Using Deep Learning Models

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## PREFACE

Deep learning is like an endless journey, where each step brings new discoveries and wonders, much like life itself, where learning and joy are intertwined in every moment.

When we look at the changes in human life over the past 200 years, we see how science and technology have pushed the boundaries of what was once possible, and today's world is nothing like the world of the past. I am happy to have witnessed these changes over the last 40 years, seeing how life is evolving in ways that were once unimaginable.

This thesis was initiated by Arbonaut OY. I am deeply grateful to its CEO, Tuomo Kauranne, for granting me this opportunity and providing financial support for my research. I sincerely hope that the outcomes of this work prove to be meaningful and impactful.

I am profoundly thankful to my supervisor, Dr. Amir Dirin, for his invaluable guidance, insightful feedback, and steadfast encouragement throughout the course of this research. Your expertise and dedication have been crucial in shaping this work, and your support has made this journey more fulfilling.

To my dearest family, I owe my deepest gratitude for their unwavering love and support in all my endeavors—through both successes and challenges. A very special acknowledgment goes to my best friend and life partner, Dr. Narges Ghorbani. Your advice, patience, and constant encouragement have been the foundation of my strength throughout this journey. "It is thanks to you that I was able to see this through to the end. Without your support and your words, I would have faltered long ago. Thank you for everything."

Finally, my heartfelt thanks to my little son, Ryan, who fills our lives with endless love, laughter, and joy. You are my constant source of inspiration and happiness.

Lappeenranta, Finland, 01.03.2025

Hamed

## Abstract

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Deep learning, particularly computer vision algorithms, has gained significant attention in remote sensing for solving various object detection problems. The development of efficient object recognition techniques has been a longstanding challenge, leading to the proposal of numerous unique methods over time to address this issue.

In this master thesis Computer vision algorithms were used to align VHR images with their corresponding Lidar canopy height images, in the area near Lappeenranta in Finland. The models had been designed to predict the positions of trees, tree boles (top of trees) and canopy height, with a primary focus on accurately identifying real tree locations, accounting for tilt effects in satellite imagery caused by the satellite's viewing angle during image capture.

To achieve this, convolutional neural networks (CNNs) were combined with transformer architectures, leveraging pre-trained models to extract weights from large-scale datasets, thereby enhancing performance and reducing training time. Through rigorous experimentation, the best-performing model — the DeepLabV3 architecture with the ADOPT optimizer, attention mechanisms — achieved:

- Canopy height estimation: Lowest Validation Regression Loss (RMSE) of 3.065 meters, indicating accurate continuous canopy height predictions.

- Tree cover classification: Highest validation accuracy of 89.735%, with Class 0 Accuracy of 85.344% and Class 1 Accuracy of 91.353%, demonstrating balanced and reliable tree cover mapping.
- Tree centroid classification: Centroid classification accuracy of 77.285%, confirming the model's ability to identify tree canopy centers with reasonable precision.

These results highlight the feasibility of using deep learning approaches for forest structure analysis, with CNN-based architectures outperforming transformer-based models for fine-grained spatial prediction tasks.

**Keywords:** tree location, artificial intelligence, computer vision, Computer vision, deep learning, pre-trained models, Remote Sensing, convolutional neural networks

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## List of Abbreviations

VHR	Very High-Resolution
LiDAR	Light Detection and Ranging
CNNs	Convolutional Neural Networks
AI	Artificial Intelligence
GIS	Geographic Information System
ALS	Airborne Laser Scanning
RGB	Red, Green, Blue
NIR	Near-Infrared
AI	Artificial Intelligence
ML	Machine Learning
DL	Deep Learning
KNN	K-Nearest Neighbors
CNNs	Convolutional Neural Networks
CV	Computer Vision
IPCC	International Panel on Climate Change
GEDI	Global Ecosystem Dynamics Investigation
CHM	Canopy Height Model
NDVI	Normalized Difference Vegetation Index
EVI	Enhanced Vegetation Index
DTM	Digital Terrain Model
DSM	Digital Surface Model
ReLU	Rectified Linear Unit
GELU	Gaussian Error Linear Unit
ViT	Vision Transformers
Adam	Adaptive Moment Estimation
ADOPT	Adaptive Optimization
BCE	Binary Cross-Entropy
HPC	high-performance computing
RMSE	Root Mean Square Error
CBAM	Convolutional Block Attention Module

SE	Squeeze-and-Excitation
SAM	Spatial Attention Module

## 1 Introduction

The application of deep learning in remote sensing has transformed forestry management by automating tasks such as tree location identification and canopy height estimation. This master's thesis investigates the potential of computer vision techniques, particularly Convolutional Neural Networks (CNNs) (Kattenborn et al., 2021) and Transformers, to analyze remote sensing data and improve forest monitoring processes.

Remote sensing plays a fundamental role in environmental monitoring, offering critical insights into the rapid changes affecting forests. Forestry change is accelerating due to deforestation driven by agriculture, urbanization, and unsustainable logging, compounded by climate change impacts such as rising temperatures and increased wildfires (Prochazka et al., 2023). Illegal activities, population growth, and the spread of pests and diseases further exacerbate forest loss, threatening biodiversity, disrupting ecosystems, and intensifying climate change (Hussain et al., 2022; van Lierop et al., 2015). As technology advances and sensor resolutions improve, managing the vast influx of data has become increasingly challenging. This underscores the need for accurate, robust, and efficient image processing techniques—a gap that deep learning is well-positioned to address.

Deep learning, a subset of machine learning, has gained significant recognition for its exceptional performance across a wide range of tasks. Utilizing neural networks, deep learning algorithms can process complex information with remarkable accuracy, making them invaluable for analyzing and interpreting remote sensing data in environmental applications.

Light Detection and Ranging (LiDAR) has become a cornerstone technology for high-precision 3D mapping and terrain analysis. Despite its unparalleled accuracy, its high cost and infrequent data collection limit its continuous application and scalability. To address these limitations, very high-resolution

(VHR) satellite imagery offers a promising alternative. By leveraging deep learning models trained on existing LiDAR datasets, it becomes possible to predict LiDAR-like data from satellite imagery, effectively bridging the temporal gaps between LiDAR acquisitions. This approach not only enhances the availability of 3D mapping data but also makes large-scale and continuous environmental monitoring more feasible and cost-effective.

The central question of this study is:

How accurately can deep learning models, such as CNNs and Transformers, translate LiDAR data from VHR satellite imagery?

This inquiry aimed to evaluate the potential of advanced deep learning architectures to generate reliable, LiDAR-like 3D mapping data from satellite imagery, bridging temporal and financial constraints associated with direct LiDAR acquisitions.

This study is conducted in collaboration with Arbonaut Oy, a leading Finnish company specializing in remote sensing and Geographic Information System (GIS) solutions for sustainable forest management. The research focuses on a special area near the city of Lappeenranta, covering approximately 35 km<sup>2</sup>, aiming to develop and evaluate a deep learning model that integrates LiDAR and satellite data for forest inventory and natural resource management.

Arbonaut has established itself as a pioneer in applying advanced technologies like LiDAR and satellite imagery to forestry, offering a comprehensive suite of services designed to enhance forest monitoring, inventory, and resource planning. The company conducts airborne laser scanning (ALS) forest inventory projects, leveraging LiDAR's high precision to capture detailed 3D data of forest canopies and terrain. This data is critical for applications such as forest stand delineation, semiautomatic species-specific inventories, and timber volume estimation. By combining LiDAR data with high-resolution satellite imagery, Arbonaut ensures a comprehensive approach to forest management, enabling cost-effective monitoring over large and inaccessible areas.

In addition to its data acquisition capabilities, Arbonaut integrates GIS tools like ArcGIS to support forest road construction, sustainable resource management, and advanced mapping. The company also develops proprietary software, such as the ArboLiDAR forest inventory technology, which has been continually refined to meet the needs of commercial timberland owners and managers. Mobile field terminals further complement these solutions by enabling efficient data collection and real-time decision-making in the field.

Arbonaut's commitment to innovation extends to its collaborations with research institutions and government bodies. Its services are used by some of the world's largest forestry companies and national agencies responsible for forest resource management. Recent advancements, including the integration of deep learning models, enable the company to extract even greater value from LiDAR and satellite imagery, addressing critical challenges such as cost, temporal resolution, and scalability in forest monitoring. This thesis focuses on automating tree cover mapping, bole tree identification, and canopy height estimation using multispectral VHR imagery and LiDAR datasets.

This thesis has been organized into ten sections:

- 1- Introduction: The opening chapter provides the context for the study, explaining the purpose and scope of the research on automating forestry monitoring using deep learning. It outlines the study's aims and central research question.
- 2- Research Methodology and Research Questions: A detailed description of the research approach follows, covering the problem statement, key research questions, and study limitations. The methodology is designed to ensure the reliability and accuracy of the findings.
- 3- Background / Literature Review: This chapter examines existing research related to forestry monitoring and deep learning, identifying gaps and establishing the technical foundation for the proposed solution.

- 4- Design: The system's design is presented here, with a focus on dataset preparation, model architecture, and algorithm selection. The rationale behind each design choice is clearly explained.
- 5- Implementation: The transition from design to a working system is described in this section, highlighting the tools, frameworks, and techniques used to build and train the deep learning model.
- 6- Testing and Analysis: A comprehensive overview of the testing procedures and performance evaluation is provided, along with an analysis of the model's accuracy, efficiency, and reliability.
- 7- Discussion: The significance of the research findings is discussed, with attention to the challenges encountered and the broader implications of automating forestry monitoring.
- 8- Conclusion: This final chapter summarizes the main contributions of the research, reflects on the achievement of its objectives, and offers a concluding assessment of the developed system.
- 9- Future Work: To conclude, suggestions are made for potential improvements and extensions that could enhance the model's accuracy and applicability, offering directions for future research and development.
- 10- Summary: This section offers a concise overview of the entire thesis, summarizing the key findings, contributions, and conclusions of the research.

## 2 Research Methodology and Research Questions

This section introduces the problem state, research questions and the methods used in this study.

### 2.1 Problem statement

Aerial remote sensing systems, such as Airborne Laser Scanning (ALS) have been extensively used for vegetation monitoring and forest management, relying on diverse data sources and processing methods to extract information such as tree cover mapping, canopy structure, and tree bole identification. Among these technologies, LiDAR has emerged as a cornerstone for high-precision 3D mapping and terrain analysis, offering unparalleled accuracy and versatility. LiDAR's ability to penetrate vegetation and capture detailed elevation data has made it indispensable across various sectors, including urban planning, forestry, disaster management, and archaeological surveying. However, despite its remarkable capabilities, LiDAR faces significant challenges that hinder its widespread application and scalability.

A primary limitation of LiDAR is its high cost and operational complexity. LiDAR surveys require specialized equipment mounted on aircraft, drones, or terrestrial vehicles, resulting in operational expenses that can reach tens of thousands of dollars per project (*Defining the True Cost behind Implementing Lidar Systems into Your Bus – Candrone*, n.d.). This financial barrier limits the frequency of data collection, with surveys often conducted annually or even less frequently. Consequently, temporal gaps emerge between acquisitions, restricting the ability to monitor dynamic changes in rapidly evolving environments (Mitchell et al., 2018), such as urban expansion, deforestation, or coastal erosion.

To overcome the limitations of LiDAR, VHR satellite imagery offers a promising alternative. VHR imagery, captured at resolutions as fine as 30 cm, provides frequent and widespread coverage at a fraction of the cost of LiDAR surveys (Cubaynes et al., 2024). However, VHR imagery alone cannot replicate the 3D

capabilities of LiDAR, as it primarily produces 2D surface-level data. By leveraging deep learning models trained on existing LiDAR datasets, it is possible to approximate elevation models and infer 3D structures from VHR images, thereby filling the temporal gaps between LiDAR acquisitions (L. Wang & Zhang, 2024).

This hybrid approach offers several advantages. VHR imagery is captured regularly, with some satellites revisiting the same location on a daily or weekly basis, ensuring continuous monitoring of surface changes (*VHR Satellite Imagery Made Easy!* - DHI, n.d.). Deep learning models, once trained, can process this imagery to generate near-real-time desired models, reducing the reliance on costly LiDAR updates. This approach not only enhances the temporal resolution of topographic data but also maximizes the value of existing LiDAR datasets, extending their usability over time.

Thus, the integration of VHR imagery and deep learning represents a cost-effective and scalable solution to mitigate the limitations of LiDAR, ensuring more frequent and comprehensive environmental and infrastructural monitoring.

### **“Addressing the Temporal and Cost Limitations of LiDAR through VHR Imagery and Deep Learning”**

## 2.2 Research questions

The following research questions are designed to guide the investigation and assess the feasibility of using deep learning for tree cover mapping, canopy height estimation, and tree bole identification.

1. How accurately can deep learning models, such as Convolutional Neural Networks (CNNs) and Transformers, map tree covers and identify individual tree boles from multispectral and VHR imagery?
2. How effective are deep learning models in estimating canopy height from VHR satellite imagery and multispectral data?

3. Can LiDAR-derived canopy height model be used to train deep learning algorithms to infer canopy height from 2D imagery?

These questions reflect the core objectives of the thesis, focusing on automating forest monitoring processes, reducing reliance on costly data collection methods, and enhancing the accuracy of forest structure analysis.

## 2.3 Research Methodology

The methodology adopted for this study is the Case Study Methodology, which is particularly suited for in-depth exploration and analysis of specific problems within a real-world context (Ratnasari & Sudradjat, 2023). This approach provides a structured framework to investigate the feasibility of integrating deep learning models with VHR satellite imagery and LiDAR data to address the limitations of traditional methods in forest monitoring.

### 2.3.1 Overview of Case Study Methodology

A case study is a research approach that examines a particular subject, system, or phenomenon in detail to generate insights that can be generalized or applied to similar contexts. In this thesis, the case study methodology focuses on a selected forest region where LiDAR data and VHR imagery are available, enabling the evaluation of deep learning techniques for the three research objectives.

The primary goal is to investigate how effectively these methods can achieve tree cover mapping, canopy height estimation, and tree bole identification, providing practical and scalable solutions for forest management.

### 2.3.2 Why Case Study Methodology?

- **Real-World Context:** The methodology allows an in-depth exploration of how the proposed techniques perform in actual forest environments, considering the complexities of diverse forest types and canopy densities.

- **Flexibility:** Case studies facilitate iterative experimentation with deep learning models, providing room for refining techniques based on initial findings.
- **Scalability Insights:** By analyzing one case in detail, this approach can identify challenges and opportunities for scaling the solution to other regions.

By employing the case study methodology, this research aims to provide practical, evidence-based recommendations for improving forest monitoring through the integration of advanced remote sensing technologies and deep learning techniques.

## 2.4 Limitations

Detecting, mapping, and classifying trees, as well as predicting tree height from very high-resolution (VHR) imagery, is a complex and challenging task. While this study presents a novel approach to generating tree inventory data, several critical limitations have been identified. These challenges highlight the need for further refinement and research to enhance the accuracy, scalability, and applicability of such methods in future studies.

1. **Limited Image Variation Testing:** Due to the vast scope of computer vision and image processing (da Silva et al., 2023; Papa et al., 2023), testing all possible variations of imagery is impractical within the constraints of this study. Image processing and model training are time-intensive, limiting the number of variations that can be explored. To mitigate this, the study focuses on selecting the most relevant and impactful image variations to ensure meaningful results within the available time.
2. **Computational Constraints and Model Optimization:** Deep learning models often improve with increased computational power, longer training times, and extensive hyperparameter optimization (Simon et al., 2023). However, this research is limited by the available computational resources

and the project's time frame. Consequently, only the most promising model architectures and configurations were tested, prioritizing efficiency and feasibility over exhaustive exploration.

3. **Dataset Limitations and Labeling Challenges:** The dataset used for this study is limited in size, partly due to the complex nature of the research topic and the time-intensive process of labeling data. Manual annotation introduces the potential for human error and inconsistencies, even with quality control measures in place. These inconsistencies can negatively impact model performance and introduce biases into the results (Farooq, 2023).
4. **Temporal Discrepancy Between VHR Imagery and LiDAR Data:** A significant limitation of this study is the temporal gap between the datasets. The VHR imagery used was captured in 2023, while the LiDAR data dates back to 2020-2021. This time difference can introduce noise and inconsistencies, particularly in dynamic forest environments where tree growth, deforestation, and other disturbances occur. Such temporal discrepancies may affect the accuracy of model predictions (M. J. Q. Zhang & Choi, 2023), as newer vegetation changes are not reflected in the older LiDAR data.

### 3 Background / Literature Review

This chapter provides essential background information on remote sensing, deep learning, and its various models that can be applied to this thesis, along with a literature review of the thesis topic.

#### 3.1 Remote Sensing for Environmental Monitoring

Remote sensing has revolutionized environmental monitoring by providing comprehensive, large-scale data for forest analysis and management (Kanga, 2023). Equipped with advanced imaging sensors, satellites, drones, and airplanes capture detailed views of Earth's surface, facilitating the study of vegetation patterns, urban expansion, and deforestation (Matyukira & Mhangara, 2024). Currently, with approximately 1,000 operational satellites dedicated to environmental monitoring, remote sensing data plays a pivotal role in biodiversity conservation, climate research, and forest management (*Earth Observation Satellite Launches 2024 | Pixalytics Ltd, n.d.*).

Remote sensing involves the collection and use of geo-referenced data gathered remotely, typically by aircraft or satellite. This data has broad applications in forestry, including assessing forest size and diversity, calculating urban green volume, and monitoring changes over time. The ability to collect data across multiple electromagnetic spectrums, such as visible, infrared, and radar, further enhances its effectiveness in analyzing vegetation and landscape features (Zahra et al., 2024). Integrating aerial and satellite imagery with ground-based measurements strengthens models for predicting environmental changes and monitoring forest growth. Two of the most used forms of remote sensing data in forestry are satellite imagery and LiDAR. These data sources provide complementary insights, making multi-model approaches highly effective for challenging forestry problems (Dubayah & Drake, 2000; X. Li et al., 2019).

### 3.1.1 VHR Imagery

VHR imagery, with sub-meter resolution, allows precise visualization of individual trees, aiding in species classification and forest mapping (Pu & Landry, 2020). This high-resolution data is essential for urban forestry studies and biodiversity analysis (X. Zhu & Helmer, 2018).

VHR imagery typically includes several spectral bands, which are crucial for different analytical purposes. These bands generally consist of the Red, Green, Blue (RGB) bands, which capture visible light and create true-color imagery that mimics human vision. These RGB bands are particularly useful for urban mapping, land use classification, and infrastructure analysis. In addition to the visible bands, VHR imagery often includes the Near-Infrared (NIR) band, which extends beyond the visible spectrum. The NIR band is highly sensitive to vegetation health, water features, and soil moisture, making it invaluable for advanced vegetation analysis and environmental monitoring. By using NIR data, VHR imagery enables the calculation of vegetation indices like NDVI. These capabilities make VHR imagery, particularly with its RGBN bands, a critical tool in urban planning, precision agriculture, and ecosystem monitoring (Eugenio & Marcello, 2019).

However, challenges such as cloud cover, seasonal variations, and shadows can affect the accuracy of the data collected (X. Zhu & Helmer, 2018). Additionally, tilted objects, such as trees or buildings, can create distortions in the imagery, leading to inaccuracies in spatial measurements and classification, further complicating the interpretation of VHR data (K. Liu et al., 2021).

### 3.1.2 LiDAR

LiDAR complements remote sensing imagery by generating high-resolution 3D representations of landscapes. This technology uses light waves to calculate distances, producing a nominally unordered set of points (XYZ space) representing surfaces where light is reflected. LiDAR is highly effective for precise

canopy height estimation and tree structure mapping (*What Is Lidar? | OpenTopography*, n.d.). Given the raw nature of LiDAR data, it is often rasterized to create image-like formats. Commonly derived rasters include:

- Digital Terrain Model (DTM): Measures the absolute height of the ground.
- Digital Surface Model (DSM): Measures the absolute height of the tallest object.
- Canopy Height Model (CHM): Represents the height of the tallest object relative to the ground, calculated as the difference between DSM and DTM.

Among these, CHM is most widely used in forestry applications, such as biomass evaluation and tree detection. The integration of LiDAR data with multi-spectral and hyper-spectral imagery is particularly effective for tackling complex forestry challenges. These multi-model approaches combine the strengths of each data type, such as LiDAR's detailed structural data and imagery's spectral information, to enhance the accuracy of models used for forest management and environmental monitoring. By uniting these technologies, researchers can better monitor forest dynamics, assess biodiversity, and predict environmental changes, making remote sensing an indispensable tool for sustainable forest management and conservation efforts (Verbeeck & Van Orshoven, 2012).

### 3.2 Machine Learning for Remote Sensing Data

Artificial Intelligence (AI) is significantly enhancing remote sensing by enabling the automation of complex tasks such as environmental monitoring, land-use classification, and disaster management. Remote sensing involves collecting and analyzing data about the Earth's surface using satellite or aerial imagery. With the increasing volume of high-resolution spatial and temporal data, traditional methods of analysis are often inadequate. AI, through techniques like Machine Learning (ML) and Deep Learning (DL), offers powerful tools to extract insights from this data efficiently and accurately. For instance, AI-driven models can detect deforestation, monitor urban growth, and predict climate-related

phenomena by analyzing satellite images with minimal human intervention (Christin et al., 2019; X. X. Zhu et al., 2017).

### 3.2.1 ML in Remote Sensing

ML, a subset of AI, has been pivotal in remote sensing applications by enabling systems to learn patterns from data and make predictions. ML algorithms, such as Decision Trees and K-Nearest Neighbors (KNN), have traditionally been employed for tasks like land-cover classification and vegetation analysis. However, these methods often rely on handcrafted features, which can limit their ability to capture complex spatial and spectral patterns in remote sensing data (Ball et al., 2017; Xie et al., 2019).

### 3.2.2 DL: Advancing Remote Sensing Analysis

DL, a specialized branch of ML, has significantly advanced remote sensing by automating feature extraction and enabling the analysis of raw data with minimal preprocessing (Corbane et al., 2021; X. Wang & Wang, 2020). DL models, particularly Convolutional Neural Networks (CNNs), excel at handling high-dimensional and structured data, such as multispectral and hyperspectral images. CNNs automatically learn hierarchical features from raw satellite images, making them ideal for tasks such as object detection, change detection, and segmentation. For example, CNNs can identify land-use changes or detect specific features like roads and water bodies without the need for extensive manual intervention (Alzubaidi et al., 2021; X. X. Zhu et al., 2017).

### 3.2.3 Computer Vision in Remote Sensing

Computer Vision (CV) is a key field within AI that focuses on enabling machines to interpret and understand visual information from the world, similar to how humans process and analyze images. In the context of remote sensing, computer vision techniques are essential for analyzing visual data from satellite imagery, aerial photography, and other imaging systems. CV aims to extract meaningful

insights, such as detecting patterns, recognizing objects, and analyzing spatial or spectral features in large datasets (LeCun et al., 1998; Lowe, 2004). These techniques are integral to the success of AI in remote sensing, as they automate complex tasks and significantly reduce the need for manual processing (Ahmad et al., 2021).

Several important applications of computer vision play a critical role in enhancing the effectiveness of remote sensing technologies, as they enable the automated extraction and analysis of crucial information from large datasets. These tasks include object detection, image segmentation, feature extraction, and change detection, which help in monitoring land use, detecting environmental changes, and classifying land cover in satellite or aerial imagery (Ahmad et al., 2021).

1. **Object Detection:** This refers to identifying specific objects or regions of interest (e.g., roads, buildings, water bodies) in satellite or aerial imagery. In remote sensing, this is crucial for tasks like land-use classification, urban planning, and environmental monitoring (B. Wang et al., 2023).
2. **Image Segmentation:** Segmentation involves dividing an image into multiple regions or segments to simplify its analysis. In remote sensing, segmentation can help distinguish different types of land cover or identify particular features like roads or fields (Talha et al., 2023).
3. **Feature Extraction:** In CV, feature extraction identifies critical characteristics (e.g., edges, textures, shapes) in images to aid in understanding the visual content. In remote sensing, this could mean analyzing the textures of forests or the shapes of urban areas to classify land cover types (Chairet et al., 2019).
4. **Change Detection:** CV algorithms can also identify differences between images taken at different times, which is important for monitoring dynamic environmental changes such as deforestation, urban expansion, or natural disasters (Dong et al., 2024).
5. By automating these tasks, Computer Vision enhances the ability to monitor and analyze vast regions of Earth's surface efficiently and accurately.

### 3.2.4 CNNs in Remote Sensing

The integration of CV techniques with CNNs has revolutionized remote sensing, delivering unparalleled precision and efficiency. CV tasks such as object detection, image segmentation, feature extraction, and change detection provide the foundation for analyzing and interpreting satellite and aerial imagery. When paired with CNNs, these techniques become even more effective, as CNNs specialize in identifying localized spatial patterns, such as edges, textures, and shapes, that are essential for understanding structured visual data.

This synergy has enabled numerous applications, including accurate land-use classification, detailed urban and natural environment mapping, and efficient monitoring of environmental changes. CNNs are also widely used in forestry, where they automate tasks like log identification and assess environmental damage using aerial imagery (Pi et al., 2020). The precision of CNNs in capturing fine-grained details makes them indispensable for a variety of remote sensing tasks (Q. Xie et al., 2024).

### 3.2.5 Transformers: A New Era in Remote Sensing

Transformers, originally developed for natural language processing, are redefining remote sensing with their ability to capture global dependencies through self-attention mechanisms (Aleissae et al., 2023). Building on the localized strengths of CNNs, transformers introduce a groundbreaking capability for analyzing entire images holistically (Pereira & Hussain, 2024).

Vision Transformers (ViTs), for example, divide satellite images into smaller patches and analyze the relationships between these patches, offering a comprehensive understanding of spatial and spectral data. Their global context awareness makes them particularly effective for tasks such as scene classification, land-use mapping, and anomaly detection, where understanding broader spatial relationships is critical (Bolcek et al., 2025).

By combining the localized precision of CNNs with the global context awareness of transformers, remote sensing technologies are entering a new era in remote sensing that delivers unprecedented accuracy and efficiency. CNNs excel at extracting fine-grained details from images, while transformers provide a broader understanding of spatial and spectral relationships. Together, they enable advanced applications such as detailed scene classification, precise land-use mapping, and comprehensive anomaly detection. This powerful combination is transforming the capabilities of environmental monitoring, urban transformation analysis, and other large-scale remote sensing tasks (Bolcek et al., 2025).

### 3.2.6 Transfer Learning

Transfer learning has emerged as a powerful technique in deep learning to overcome the challenges of training models from scratch, particularly when datasets are limited or computational resources are constrained. This approach leverages pretrained models trained on large-scale datasets and adapts them to target tasks, thereby improving efficiency, reducing overfitting, and enhancing generalization (Naushad et al., 2021; M. Xie et al., 2015).

In the context of land cover classification, the significant diversity in remote sensing data—arising from variations in sensors, geographic regions, and resolutions—makes transfer learning especially valuable. Instead of starting from random initialization, models can inherit generalized features from pretrained architectures and then fine-tune them for specific tasks. This reduces the need for extensive labeled data and computational effort (Naushad et al., 2021).

At its core, transfer learning is a methodology that allows knowledge gained from training a model on one type of data to be applied to another, similar data type, without requiring the model to be trained entirely from scratch. This is especially valuable when data labeling is expensive or time-consuming. Unlike traditional machine learning, which assumes the training and testing data come from the same domain, task, and distribution, transfer learning is designed to handle scenarios where these conditions differ (Pan & Yang, 2010). This flexibility makes

it an indispensable tool in deep learning, particularly in domains where computational resources are a bottleneck.

One of the most effective techniques in transfer learning is fine-tuning, where a pretrained model is further trained on a target task with its weights adjusted to better fit the specific domain. Fine-tuning involves selectively updating certain layers of the pretrained model while keeping others fixed, depending on the similarity between the source and target tasks (Y. M. Li et al., 2021).

Fine-tuning not only enhances the adaptability of pretrained models but also ensures efficient utilization of computational resources by focusing training efforts on domain-specific features. In remote sensing applications, fine-tuning has proven particularly beneficial for addressing challenges such as sensor variability, resolution differences, and limited labeled data (Ma et al., 2024).

These combined models leverage transfer learning to fine-tune pretrained weights from large-scale datasets (such as ImageNet) and adapt them for specific remote sensing image segmentation tasks. By inheriting generalized features from the pretrained models, they are better equipped to handle the variations in remote sensing data, such as sensor differences, resolution variations, and geographic diversity. Fine-tuning these hybrid models allows them to effectively adapt to the challenges of remote sensing segmentation, improving accuracy and reducing the need for extensive labeled data.

Transfer learning plays a crucial role in enhancing segmentation tasks, especially when using advanced hybrid architectures that integrate the strengths of U-Net (Weng & Zhu, 2015), DeepLabv3 (Chen et al., 2017), and Swin Transformer (Z. Liu et al., 2021). These models are designed for high-resolution segmentation tasks such as land cover classification. By combining these architectures, by leveraging their complementary strengths:

U-Net provides a robust and well-established framework for semantic segmentation with its encoder-decoder structure and skip connections that help retain spatial details.

DeepLabV3, known for its ability to capture multi-scale contextual information using techniques like Atrous Spatial Pyramid Pooling (ASPP) (Espinosa-Curilem et al., 2024) . Integrating DeepLabV3 with U-Net enhances the model's ability to extract both fine-grained details and broader contextual features.

Swin Transformer, when combined with U-Net, leverages self-attention mechanisms to model long-range dependencies efficiently. This is particularly beneficial for dense prediction tasks, where capturing global spatial relationships is critical (Khoshkhahtinat et al., 2023; Z. Zhao et al., 2023).

By integrating these architectures, hybrid models can achieve superior segmentation accuracy, effectively addressing challenges such as sensor variability, resolution differences, and limited labeled data. The synergy of convolutional and transformer-based methods enables more precise land cover classification, making these models highly suitable for large-scale remote sensing applications.

### 3.2.7 Model Performance Enhancement Methods

Various techniques can be implemented to improve model performance, and the following sections will elaborate on each method.

- Attention Mechanisms

Attention mechanisms in deep learning represent a fundamental shift in how models process visual information, taking inspiration from human visual cognition to selectively focus on relevant features(Viet et al., 2023). The evolution of attention mechanisms has been remarkable, starting from early spatial attention approaches Recurrent Attention Model(Bang et al., 2024) and progressing to more sophisticated channel-based and self-attention methods.

Channel attention mechanisms, exemplified by the highly influential Squeeze-and-Excitation Networks, have demonstrated significant improvements in model performance by explicitly modeling relationships between feature channels(Yuan

et al., 2021). These approaches work by adaptively recalibrating channel-wise feature responses, allowing models to emphasize informative features while suppressing less useful ones(Q. Wang et al., 2019).

The introduction of self-attention mechanisms, particularly through transformers, has revolutionized how models capture contextual relationships in visual data(Sharma & Verma, 2023). Self-attention allows models to consider the relationships between all elements of an input simultaneously, enabling the capture of both local and long-range dependencies(Ramachandran et al., 2019). This capability has proven especially valuable in complex visual tasks where understanding the relationships between different parts of an image is crucial(Fu et al., 2018) Modern attention approaches often combine multiple types of attention mechanisms, integrating both spatial and channel attention to provide a more comprehensive understanding of visual content(Hemis et al., 2024). This multi-faceted approach to attention has shown particular effectiveness in improving model robustness and reducing noise in feature processing(Viet et al., 2023).

To improve the learning and representation of tree canopy structures, we incorporate various attention modules that enhance feature selection, spatial dependencies, and long-range contextual relationships. The implemented model integrates:

- Squeeze-and-Excitation (SE) Block

SE Blocks emphasize channel-wise dependencies by adaptively reweighting feature maps.

The primary function of SE blocks is to perform channel-wise recalibration, effectively increasing the network's attention to informative features while suppressing less relevant channel information (X. Li et al., 2023). This selective emphasis allows the network to learn which channels carry the most meaningful information during the training process, thereby improving its overall feature extraction capabilities

(Su et al., 2023), Therefore, this mechanism allows the model to learn which spectral bands carry the most meaningful information for canopy height estimation.

The module operates by first "squeezing" spatial information through global average pooling to create channel-wise descriptors, followed by an "excitation" operation that uses fully connected layers to generate channel-specific weights (Su et al., 2023). The success of SE blocks has led to their widespread adoption and influenced the development of more sophisticated attention mechanisms, such as Convolutional Block Attention Module (CBAM), which builds upon SE's channel attention concept by adding spatial attention capabilities (Su et al., 2023).

- CBAM

CBAM represents a significant advancement in attention mechanisms by integrating both channel and spatial attention into a single, lightweight module that can be easily incorporated into existing CNN architectures (Raimundo et al., 2023; Tian et al., 2021). Channel attention helps identify the most relevant spectral information (e.g., Red, Green, Blue, and Near-Infrared bands) and spatial attention highlights important regions, such as tree crowns, by assigning higher importance to pixels contributing to canopy height prediction.

The module continuously adjusts attention weights for features that have the greatest impact on the target task, while suppressing less important features (Z. Song & Yao, 2022). The effectiveness of CBAM stems from its ability to enhance feature representation by combining the strengths of both attention types - channel attention identifies which features are most meaningful, while spatial attention highlights where these features are most relevant in the spatial domain (Tian et al., 2021). This comprehensive approach to attention has made CBAM a valuable tool for improving CNN performance across various computer vision tasks (Raimundo et al., 2023).

- Spatial Attention Module (SAM)

The SAM operates as a complementary mechanism to channel attention, focusing specifically on identifying where important features are located within the spatial dimensions of feature maps (Jin et al., 2023; B. Zhang et al., 2024) (e.g., tree crowns, gaps in the forest, and individual tree tops). By generating weight masks for each spatial position, SAM enables the network to enhance regions of interest while suppressing irrelevant background areas (Jin et al., 2023).

The processing pipeline of SAM begins after the Channel Attention Module has refined the feature channels. It takes the channel-refined features and applies both global average pooling and global maximum pooling operations along the channel dimension to create two distinct feature maps (Z. Wang et al., 2023). These pooled features capture different aspects of spatial information, with average pooling providing global context and maximum pooling highlighting the most prominent spatial features (Mia et al., 2023).

The effectiveness of SAM lies in its ability to help the network learn the relative importance of different pixel locations within the same channel in an adaptive manner (Mia et al., 2023). This spatial awareness is particularly valuable for tasks that require precise localization, such as identifying specific regions of interest or distinguishing between target features and background elements (Dang et al., 2022).

By working in sequence with the Channel Attention Module, SAM completes CBAM's dual-attention approach, enabling the network to not only identify what features are important (through channel attention) but also precisely where these features are located in the spatial domain (Mia et al., 2023; B. Zhang et al., 2024).

- Non-Local Block

The Non-Local Block emerged as a fundamental advancement in attention mechanisms by introducing self-attention to computer vision tasks, enabling networks to capture long-range dependencies across entire images (X. Wang et al., 2017). Unlike traditional convolutional operations that process local

neighborhoods, Non-Local Blocks compute responses by considering weighted relationships between all positions in the feature space, allowing for truly global context modeling (Cao et al., 2019). Therefore, Non-Local Block computes self-attention between different spatial locations, ensuring that information about tree structures is shared effectively across the image and by using query, key, and value matrices, the module learns global context, which is particularly useful for detecting tree top points and understanding complex canopy patterns.

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- Regularization techniques

Here are the key regularization techniques used in modern deep learning:

- **Dropout:** A fundamental technique that randomly deactivates neurons during training, forcing the network to learn redundant representations and preventing co-adaptation of features (Srivastava et al., 2014). This method has proven particularly effective in large neural networks, significantly reducing overfitting while improving performance across various tasks including vision, speech recognition, and document classification (Q. Li & Ke, 2024).
- **Batch Normalization:** Normalizes layer inputs to maintain zero mean and unit variance, which stabilizes training and enables the use of higher learning rates (Ioffe & Szegedy, 2015). It adds a small amount of noise during training, preventing over-dependence on specific examples and enhancing generalization (Hammam et al., 2024).
- **Weight Decay (L2 Regularization):** Penalizes large weight values by adding a term to the loss function based on the squared magnitude of weights. This encourages simpler models that are less likely to overfit (Hammam et al., 2024). Recent research has shown that weight

decay is particularly effective for addressing long-tailed recognition problems(Alshammari et al., 2022).

- Activation functions Tuning

The Rectified Linear Unit (ReLU) and Gaussian Error Linear Unit (GELU) are fundamental non-linear activation functions used in neural networks. ReLU, introduced first, simply outputs the input value if it's positive and zero if it's negative, creating a sharp transition at zero(Dheda & Cheng, 2020). GELU, developed later, can be viewed as a smoother version that multiplies inputs by a probability derived from Gaussian cumulative distribution, effectively determining how likely an input would be sampled in a Gaussian distribution(Hasan et al., 2023). This probabilistic approach makes GELU's behavior more nuanced than ReLU's binary decision of completely passing or blocking signals. While ReLU gained popularity for solving the vanishing gradient problem in deep neural networks, GELU emerged as part of the trend toward more sophisticated activation functions that maintain good gradient flow while adding beneficial statistical properties(Shaik & Kishore, 2024).

At their core, ReLU and GELU use different mechanisms to control information flow in neural networks. ReLU employs a simple binary gating mechanism that multiplies inputs by either 0 (for negative values) or 1 (for positive values), creating a sharp threshold at zero(Huang, 2024)(Sivari et al., 2023). In contrast, GELU uses the Gaussian cumulative distribution function as its gating mechanism, allowing it to multiply inputs by any value between 0 and 1 based on the input's magnitude(Huang, 2024)

- Optimizer Tuning

Adam (Adaptive Moment Estimation) represents a significant advancement in optimization algorithms for deep learning, combining the best aspects of several previous approaches(Shi et al., 2024). A key feature of Adam is its incorporation of momentum, which accelerates convergence through running averages of past gradients, while simultaneously utilizing adaptive learning rates inspired by

RMSProp(Shi et al., 2024). This combination of features has made Adam particularly effective at managing sparse gradients and varying learning rates across different parameters(Kumar et al., 2023), leading to its widespread adoption as the default optimization choice in many deep learning applications(Makinde, 2024).

However, Adam's theoretical foundations have been challenged by several critical limitations that affect its convergence guarantees(M. Liu et al., 2020). ADOPT (Adaptive Optimization) represents a significant advancement in addressing the theoretical limitations of Adam while maintaining practical effectiveness. The algorithm achieves the optimal convergence rate of  $O(1/\sqrt{T})$  with any choice of  $\beta_2$  parameter, eliminating the need for problem-dependent parameter tuning. The key innovation of ADOPT lies in two crucial modifications to Adam's architecture. First, it removes the current gradient from the second moment estimate, which helps prevent the algorithm from being misled by temporary gradient fluctuations. Second, it alters the sequence of operations by changing the order of the momentum update and the normalization by the second moment estimate.

What sets ADOPT apart from previous solutions is that it achieves these theoretical guarantees without relying on the impractical assumption of uniformly bounded gradient noise that other approaches require. This makes ADOPT more applicable to real-world deep learning scenarios.

Empirical validation through extensive experiments has shown that ADOPT outperforms both Adam and its variants across a diverse range of applications, including image classification, generative modeling, natural language processing, and deep reinforcement learning(Taniguchi et al., 2024).

- Loss Function Tuning

Loss functions are fundamental mathematical constructs in machine learning that quantify how well a model's predictions align with actual observed data(Lyu et al., 2023). The selection of an appropriate loss function is crucial as it significantly

influences both the behavior and performance of the model during training(Bukowski et al., 2024). The value computed by the loss function represents the sum of errors made for each sample in training or validation sets, providing a continuous signal that guides the optimization process toward better parameter values(Lay-Ekuakille et al., 2021). For models that combine multiple objectives, such as those handling both regression and classification tasks, weighting coefficients of each task like  $\alpha$ ,  $\beta$ , etc are used to balance the relative importance of each loss component(Eivazi et al., 2023).

In regression problems, two fundamental approaches are commonly used: the squared loss function (L2 loss) and the absolute loss function (L1 loss). The L2 loss applies a quadratic penalty that grows exponentially with the error size, making it particularly sensitive to large deviations. In contrast, the L1 loss increases linearly with error magnitude, offering a more moderate penalty approach(H. Wang, 2021).

However, each of these basic loss functions has limitations. While L1 loss can be more forgiving of large errors, it presents a mathematical challenge due to the absence of a derivative at zero, which can affect optimization. This led to the development of SmoothL1Loss, which cleverly combines both approaches by using a squared function near zero for smoothness while maintaining L1's linear behavior for larger errors(H. Wang, 2021).

In machine learning classification tasks, the choice of loss function plays a crucial role in model training and performance. One significant challenge that often arises is class imbalance, where certain classes have substantially fewer samples compared to others, which can severely impact the model's ability to learn and predict minority classes effectively(Nguyen-The et al., 2021).

The Binary Cross-Entropy (BCE) loss function serves as a fundamental component in classification tasks, offering several advantages such as computational simplicity, differentiability, and providing probabilistic interpretations of model outputs. BCE is specifically designed to generate high

loss values for incorrect predictions and low loss values for correct ones, thereby guiding the model toward optimal prediction behavior (Terven et al., 2023; P. Zhao et al., 2024).

However, when dealing with imbalanced datasets, BCE's equal treatment of all samples becomes problematic. This limitation led to the development of Focal Loss, a modified version of cross-entropy loss that specifically addresses class imbalance issues by adjusting the weight of samples during training (Terven et al., 2023). The Focal Loss achieved notable success in object detection tasks by addressing the extreme foreground-background class imbalance, demonstrating its effectiveness in handling imbalanced datasets (Lin et al., 2017).

The hybrid approach of combining BCE and Focal Loss offers several distinct advantages that address the limitations of using either loss function alone (G. Song et al., 2021). By fusing these loss functions with adjustable weights, the hybrid approach provides greater flexibility in controlling how the model treats different types of samples during training (G. Song et al., 2021).

A key benefit of this hybrid approach is its ability to maintain the basic classification capabilities of BCE while incorporating the class-balancing properties of Focal Loss. This combination is particularly effective in scenarios with imbalanced datasets, where it helps prevent the model from being overwhelmed by majority classes while still maintaining good performance on easier examples (Kashyap et al., 2024). In practice, hybrid loss functions have shown particular utility in specialized domains such as image segmentation, where preserving both spatial and label-wise information is crucial (Ewaidat et al., 2024).

The flexibility of hybrid loss functions comes from their tunable parameters - not only can the relative weights between BCE and Focal Loss be adjusted, but the focal loss parameters themselves ( $\gamma$  and  $\alpha$ ) can be fine-tuned to achieve optimal performance for specific use cases (G. Song et al., 2021). This adaptability makes

hybrid loss functions particularly valuable in real-world applications where dataset characteristics may vary significantly.

- Gradient Clipping

Deep neural networks face two fundamental training challenges that were first identified in the 1990s: vanishing gradients and exploding gradients (Bengio et al., 1994; Fairbank & Samothrakis, 2020; Hochreiter & Schmidhuber, 1997).

Gradient clipping operates by imposing constraints on gradient values during the neural network training process to prevent them from becoming excessively large (Varshney et al., 2023; G. Zhang & Liu, 2024). This technique can be implemented in two main ways: value-based clipping and norm-based clipping. Value-based clipping simply enforces minimum and maximum limits on individual gradient values. Norm-based clipping, which is more commonly used, scales the entire gradient vector when its magnitude exceeds a specified threshold (Varshney et al., 2023).

- Early Stopping and Learning Rate Adjustments

Early stopping has emerged as a widely-used regularization technique for preventing overfitting in deep neural networks through careful monitoring of model performance during training (Mahsereci et al., 2017; Vardasbi et al., 2022). The implementation typically involves splitting the dataset into training and validation sets, where the validation set serves as an unbiased proxy for assessing generalization performance (Vardasbi et al., 2022).

The core mechanism involves continuously tracking the model's performance on the validation set throughout the training process. When the validation performance begins to degrade or fails to improve for a specified number of epochs, training is terminated (Veldanda et al., 2022). This approach is particularly effective for overparameterized deep networks, where the risk of overfitting is higher (Veldanda et al., 2022).

A key implementation consideration is the "patience" parameter, which determines how many epochs of non-improvement to allow before stopping. Higher patience values generally permit longer training times but risk overfitting, while lower values might lead to premature stopping(Hussein & Shareef, 2024). The technique works by saving and updating the best model weights throughout training, ensuring that the final model represents the optimal point in the training trajectory(Tan et al., 2023).

Early stopping offers significant practical benefits beyond just preventing overfitting. It enhances computational efficiency by avoiding unnecessary training iterations and helps maintain a balance between fitting the training data and ensuring good generalization to unseen data. The dynamic nature of this approach allows it to adapt to each model's unique learning behavior rather than relying on predetermined training durations(Ramdass et al., 2024).

Learning rate is one of the most critical hyperparameters in deep neural network training, directly controlling how much model parameters are adjusted during each update(Basodi et al., 2020). The fundamental challenge lies in the tradeoff between training speed and optimization quality. Higher learning rates allow models to train faster but may lead to suboptimal solutions, while lower learning rates can achieve better solutions but require significantly more training time(Basodi et al., 2020; H. Li et al., 2023).

This tradeoff creates practical challenges during model training. When the learning rate is too high, the model may exhibit unstable behavior, either diverging completely or oscillating around the optimal point without settling. Conversely, an overly low learning rate can cause the model to become trapped in local minima or progress so slowly that training becomes impractical(Kim, 2024). Real-world experience has shown that when model training stagnates, reducing the learning rate by a factor of 2-10 can often help the model escape local minima and resume effective optimization(He et al., 2018; H. Li et al., 2023).

### 3.3 Literature review

Remote sensing is essential for repeated canopy height estimation, facilitating forest growth assessment, disturbance detection, illegal logging identification and ecosystem services (T. Zhang et al., 2023). Advances in remote sensing and machine learning have significantly improved the precision of these forestry applications.

Tree cover mapping has been revolutionized by the integration of multispectral imagery, LiDAR data, and advanced machine learning models. Cook-Patton et al. (2020) created a global map of carbon accumulation, highlighting discrepancies between predicted values and International Panel on Climate Change (IPCC) default estimates (Cook-Patton et al., 2020). Similarly, Cuni-Sanchez et al. (2021) found that carbon stocks in African tropical forests were two-thirds higher than IPCC estimates, reinforcing the need for accurate CHMs (Cuni-Sanchez et al., 2021).

To reduce uncertainties in biomass modeling, forest height measurements are vital, as tree height directly correlates with carbon sequestration rates (Harris et al., 2021). NASA's Global Ecosystem Dynamics Investigation (GEDI) and ICESat-2 missions have significantly advanced canopy height estimation. GEDI measures vegetation height at 25 m resolution (Dubayah et al., 2021), while ICESat-2 collects canopy height data over 13x100 m footprints (Markus et al., 2017). For instance, Qi et al. (2019) utilized GEDI data to refine height measurements from TanDEM-X InSAR at sites in the United States and Costa Rica (Qi et al., 2019). On a larger scale, Sothe et al. (2022) combined data from ICESat-2, GEDI, Sentinel-1, Sentinel-2, and PALSAR-2 with a random forest algorithm to produce a forest canopy height map of Canada at 250 m spatial resolution, achieving a mean error of 4.2 m. Globally (Sothe et al., 2022), Potapov et al. (2021) used GEDI height data alongside Landsat imagery and a tree ensemble model to create a 30 m resolution canopy height map with a mean error of 9.1 m (Potapov et al., 2021). More recently, Travers-Smith et al. (2024) applied satellite LiDAR from ICESat-2, Landsat data, and a random forest model to map

the canopy height of forest-tundra ecosystems in Canada's northern regions (Potapov et al., 2021; Travers-Smith et al., 2024).

Regional models have demonstrated even higher precision. For example, Liu et al. developed a canopy height map with 3 m resolution using Planet imagery (S. Liu et al., 2023), while Wagner et al. produced sub-meter CHMs using aerial imagery and LiDAR data (Wagner et al., 2024). These detailed models are particularly useful for estimating biomass and monitoring deforestation locally.

ML approaches, particularly CNNs, have enhanced tree detection and canopy height estimation. Lang et al. applied CNNs to Sentinel-2 imagery, creating a 10 m canopy height map (Lang et al., 2023). Additionally, U-Net models have been trained on aerial LiDAR data to produce accurate tree height maps (S. Liu et al., 2023).

Emerging research highlights that DL methods can outperform traditional machine learning models in canopy height prediction by learning complex patterns directly from raw data (Fayad et al., 2024). These models offer greater flexibility in network design and loss function optimization, enabling more accurate predictions of outliers, such as very tall trees (Fayad et al., 2024). For example, Lang et al. (2023) developed a probabilistic DL model that combined sparse GEDI data with dense Sentinel-2 imagery to generate global 10 m resolution canopy height maps with an RMSE of 7.9 m (Lang et al., 2023). Fayad et al. (2024) also applied a vision transformer model with advanced loss formulation to map Ghana's canopy height, improving the sensitivity to taller trees (Fayad et al., 2024). Liu et al. (2023) employed 3-m Planet imagery, airborne LiDAR, and U-Net CNNs to predict tree height and cover in Europe, reporting an average RMSE of 5.4 m. At a regional scale (J. Liu et al., 2023), Tolan et al. (2024) used a self-supervised DINOv2 model to produce canopy height maps at 0.59 m resolution for California and São Paulo (Tolan et al., 2024), significantly surpassing the spatial resolution achieved in earlier studies (Lang et al., 2023; Potapov et al., 2021). However, their method required high-end resources, such as airborne LiDAR, Maxar imagery, and multiple GPUs, making it less accessible

to smaller research teams. In contrast, Wagner et al. (2024) used USDA-NAIP imagery and airborne LiDAR to train a regression U-Net CNN model, achieving sub-meter resolution canopy height maps for California with an RMSE 1.6 times lower than that of Tolan et al. (2024)(Wagner et al., 2024).

In addition to CNNs, vision transformers have gained prominence in modeling canopy structure. Xu et al. used Swin transformers for high-resolution land cover classification, demonstrating superior edge detection and segmentation performance compared to CNNs(Xu et al., 2021). Martin Brandt et al. (2021) used a method based on U-Net to perform tree detection over large-scale regions in West Africa's Sahel and Sahara areas, estimating the number of trees in that region(Brandt et al., 2020). Guo et al. (2024) utilized the Deeplabv3 network and incorporated semi-supervised learning to generate urban tree canopy maps across Brazil on a national scale(Guo et al., 2023).

Transformers are particularly effective for dense prediction tasks and tree segmentation, as they capture long-range dependencies and spatial relationships. Gibril et al. (2023) used vision transformers to segment date palm trees from drone imagery, achieving high accuracy across varying resolutions(Gibril et al., 2023).

Automated tree delineation from remote sensing data increasingly leverages multispectral imagery and LiDAR point clouds. Larsen et al. and Kaartinen et al. conducted comparative studies on tree crown detection algorithms, emphasizing the strengths of LiDAR data(Kaartinen et al., 2012; Larsen et al., 2011). Fayad et al. applied a U-Net CNN teacher model through knowledge distillation to derive a 10-m CHM of Ghana, integrating data from Sentinel-1, Sentinel-2, and aerial LiDAR(Fayad et al., 2024). Recent studies consistently show that integrating high-resolution LiDAR with DL techniques enhances canopy height estimation accuracy(J. Liu et al., 2023; Tolan et al., 2024; Wagner et al., 2024). These methods eliminate the need for manual feature engineering, allowing the models to automatically learn relevant features from raw data(Fayad et al., 2024).

Overall, the integration of remote sensing technologies and advanced machine learning models has significantly improved forest monitoring and management, paving the way for more accurate assessments. This body of work highlights the evolving capabilities of remote sensing and machine learning in forestry applications.

## 4 Design

The research design was carefully developed to structure the study into distinct, logical phases, ensuring an organized workflow. It outlines the methodologies employed, detailing the use of models and datasets to meet the research objectives effectively. To enhance the reliability and validity of the findings, robust measures were implemented, minimizing potential biases and improving the credibility of the results (Roberts & Priest, 2006). Figure 1 provides an overview of the research design, which emphasizes a systematic approach to achieving the study's goals. The design integrates key phases, including objects defining, data acquisition, preprocessing, models selection and training, and evaluation.

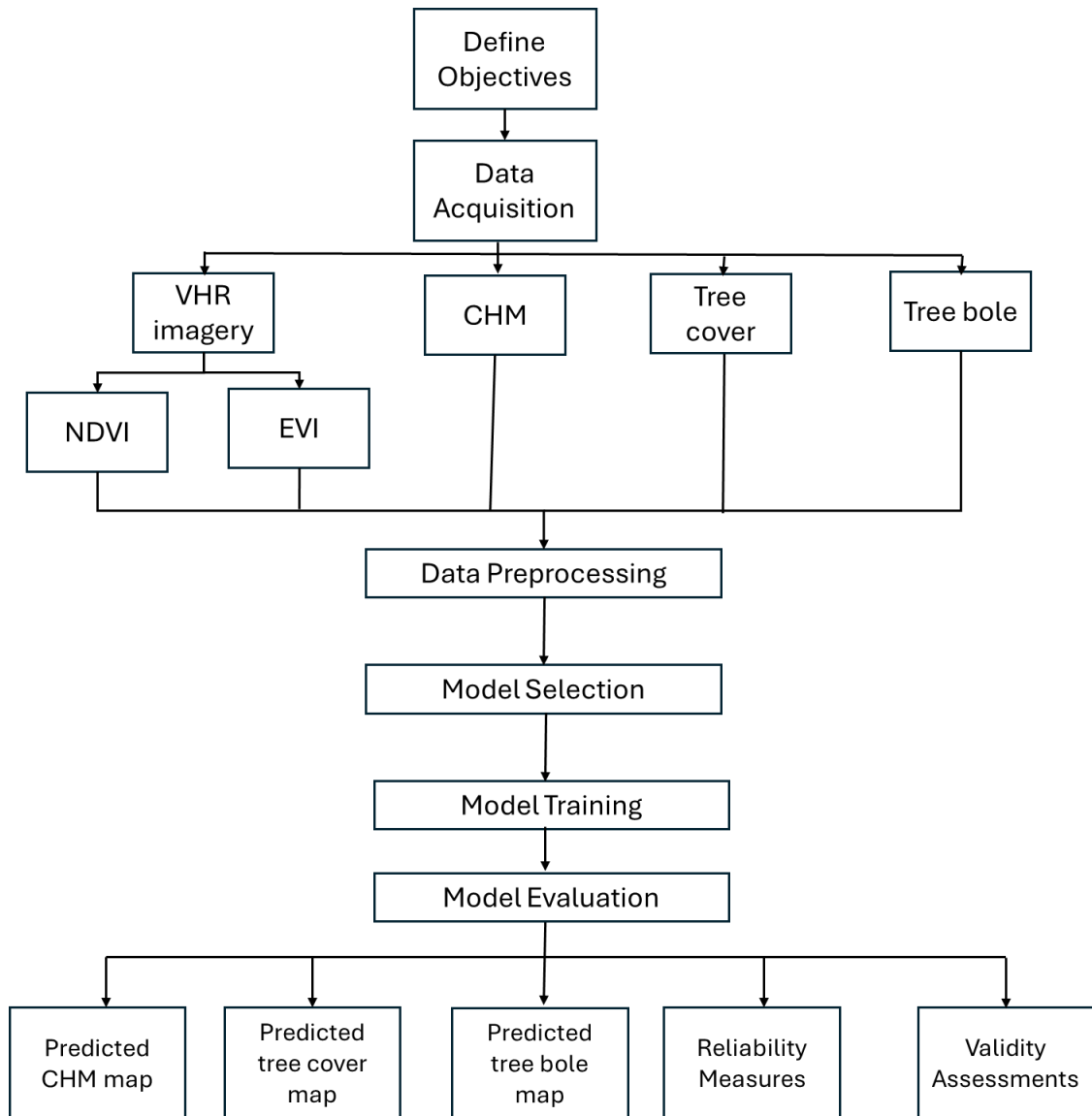


Figure 1: Research Design

#### 4.1 Define Objectives

The study's primary objectives are to apply AI-bases analysis on:

- Tree cover mapping
- Canopy height estimation
- Tree bole identification

To achieve these objectives, a structured workflow was designed, integrating various data sources and processing techniques.

## 4.2 Data Acquisition

The research relies on multiple data sources to enhance accuracy and robustness. These include:

- VHR Imagery: Used for vegetation analysis, with indices such as:
- CHM: Provides height information for tree canopy estimation.
- Tree Cover Data: Used to identify and classify vegetation cover.
- Tree Bole Data: Helps in detecting tree trunks and structures.

## 4.3 Data Preprocessing

Once data is acquired, preprocessing steps are applied to ensure consistency and remove noise. This phase includes:

- Data cleaning and normalization
- Feature extraction from imagery
  - **NDVI** – Measures vegetation health.
  - **EVI** – Improves sensitivity in high biomass regions.
- Spatial alignment of datasets
- Patching large image to smaller images
- Splitting data into training, evaluation and test datasets

#### 4.4 Model Selection and Training

Appropriate machine learning and deep learning models are selected based on the research goals. The models are trained using the processed datasets to:

- Predict tree cover distribution
- Estimate canopy height
- Identify tree boles

#### 4.5 Model Evaluation

The trained models are evaluated for accuracy and reliability using various performance metrics. The evaluation phase includes:

- **Predicted CHM Map** – Validates canopy height estimations.
- **Predicted Tree Cover Map** – Assesses vegetation classification accuracy.
- **Predicted Tree Bole Map** – Measures the accuracy of tree bole identification.
- **Reliability Measures** – Ensures model robustness.
- **Validity Assessments** – Confirms the credibility of results.

This structured research design ensures a systematic and reliable approach to achieving the study's objectives, integrating advanced remote sensing techniques with AI-driven models.

## 5 Implementation

The implementation phase of this study focuses on applying research design to process data, train models, and generate outputs. This chapter details the practical execution of each stage, from data acquisition to model training and evaluation. The workflow follows the structured approach outlined in the research design (Figure 1) to ensure consistency and reproducibility.

### 5.1 Computing Platforms and Tools

To efficiently implement and train deep learning models, high-performance computing (HPC) platforms and cloud-based resources were utilized to ensure optimal computational efficiency and scalability. The primary platforms used for model development and training were Puhti ([www.puhti.csc.fi/public/](http://www.puhti.csc.fi/public/)) and Google Colab with A100 GPU. Additionally, I leveraged Python and PyTorch as the core programming and deep learning frameworks.

### 5.2 Programming Language and Frameworks

The model implementation was conducted using Python, utilizing the following key libraries and frameworks:

- 1) PyTorch – for deep learning model development, training, and GPU-accelerated computations.
- 2) NumPy – for handling and manipulating numerical data arrays, and performing mathematical operations on image data.
- 3) Rasterio – for reading and processing raster datasets such as satellite imagery.
- 4) Matplotlib – for visualizing the data and results of the model, including plotting training/validation curves and sample images.
- 5) Torchvision – for pre-trained models, transformations, and handling image datasets.

- 6) Scikit-learn – for model evaluation, including splitting datasets and calculating metrics like F1-score and class weights.
- 7) TQDM – for displaying progress bars during model training to monitor progress in real-time.
- 8) OpenCV – for image preprocessing tasks such as resizing, normalization, and augmentation.

These libraries combined enabled the implementation of an efficient and effective solution for the given task.

The integration of these libraries enabled the development of an efficient and effective solution for the task at hand. The computational power of Puhti and the flexibility of Google Colab provided a balanced approach throughout the development process. While Puhti was utilized for large-scale training and computationally intensive tasks, Google Colab offered a convenient platform for experimentation and model testing. This strategic use of both platforms ensured a streamlined workflow, optimizing performance at different stages of the model's development and enhancing overall efficiency in training and deployment. Click or tap here to enter text. Click or tap here to enter text. Click or tap here to enter text. Click or tap here to enter text. Click or tap here to enter text. Click or tap here to enter text. Click or tap here to enter text. Click or tap here to enter text.

### 5.3 Data Acquisition

The study area, a 35 km<sup>2</sup> forested region near the city of Lappeenranta, Finland, was selected due to the availability of relevant data. The primary datasets include:

- Multispectral VHR imagery with RGBN bands (Red, Green, Blue, and Near-Infrared).
- LiDAR-derived canopy height models.
- Tree centroid maps.

- Binary tree coverage maps.

## 5.4 Preprocessing

The preprocessing phase is presented in to ensure the accuracy of the resulting models.

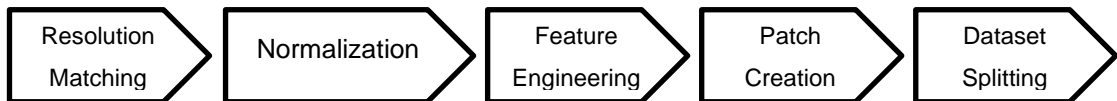


Figure 2: The preprocessing phase of model training

The preprocessing phase is essential to standardize data, enhance feature extraction, and ensure compatibility with machine learning models. By resampling, normalizing, and engineering features, the data becomes more structured and reliable for accurate analysis and model performance.

- **Resolution Matching:** Resampling VHR imagery and canopy height models to ensure consistent spatial resolution. The raster data will be resampled to match the VHR imagery resolution of 0.5 meters, enabling accurate pixel-by-pixel comparisons and integration in subsequent analyses.
  - **Normalizing VHR imagery Bands:** Since VHR imagery includes four bands (Red, Green, Blue, and Near-Infrared), each band will be divided by  $2^{15} = 32768$  for a more manageable analysis.
- 9) **Feature engineering:** Vegetation indices such as the **Normalized Difference Vegetation Index (NDVI)** and **Enhanced Vegetation Index (EVI)** will be derived through feature engineering to improve analysis based on remote sensing principles. The formulas for these indices are:  
**NDVI** is calculated as:

$$\text{NDVI} = \frac{(B4 + B1)}{(B4 - B1 + 1e - 10)}$$

where:

- B4 is the Near-Infrared (NIR) band,
- B1 is the Red band.

**EVI** is calculated as:

$$EVI = G \times \frac{(B4 - B1)}{(B4 + C1 \times B1 - C2 \times B3 + L + 1e - 10)}$$

where:

- B4 is the NIR band,
- B1 is the Red band,
- B3 is the Blue band,
- G is the gain factor (typically 2.5),
- C1 and C2 are coefficients (typically 6 and 7.5),
- L is the canopy background adjustment (typically 1).

These indices help to improve the model's accuracy during training and evaluation.

- **Patch Creation:** Due to the large size of raster images, they will be divided into smaller patches (224\*224 pixels) compatible with pre-trained models.
- **Dataset Splitting:** The data will be split into training, validation and testing subsets to ensure comprehensive performance assessment. The test dataset will comprise 70% of the total data, while the remaining 30% will be used for training and evaluation. Of this remaining 30%, 80% (24% of the total data) will be allocated for training, and 20% (6% of the total data) will be used for evaluation.

## 5.5 Model Development

The model development focuses on utilizing a combination of CNNs and Transformer architectures to analyze remote sensing data for forest structure assessment. Several architectures have been proposed and tested for the study.

It is recommended to employ different pre-trained architectures such as Swin Transformer [Click or tap here to enter text.](#), DeepLabv3 [Click or tap here to enter text.](#) and U-Net [Click or tap here to enter text.](#) with pre-trained deeplabv3\_resnet101 [Click or tap here to enter text.](#) for improved performance and transfer learning.

The integrated models are trained to:

- 1) Predict tree covers,
- 2) Estimate canopy height,
- 3) Identify and segment tree boles and crowns

The models are designed to learn how to predict LiDAR data from VHR imagery by translating the structural information observed in the 2D VHR images into the 3D features typically provided by LiDAR data. This unified approach harnesses the complementary strengths of CNNs for feature extraction and Transformers for capturing spatial relationships and context across the datasets, ultimately allowing the model to infer 3D forest structure from 2D imagery.

The following outlines the design and implementation of two deep learning models developed for multi tasks, combining a regression and two classifications. The models are based on two state-of-the-art architectures: DeepLabV3 with a U-Net decoder and Swin Transformer with a U-Net decoder. Each model's architecture and implementation details are presented below. These hybrid (CNNs and transformers) approaches leverage both the detailed spatial information from CNNs and the global context modeling capabilities of transformers. [Click or tap here to enter text.](#)

- UNetDeepLabV3 model:

The UNetDeepLabV3 model combines the DeepLabV3 encoder—a powerful CNN designed for semantic segmentation—with a U-Net-style decoder. This hybrid architecture builds on the strengths of DeepLabV3 while incorporating a decoder module for more refined segmentation results.

The encoder is based on DeepLabV3 with a ResNet-101 backbone, pre-trained on ImageNet. The initial convolution layer has been modified to support a custom number of input channels, making it adaptable for multi-channel images. Feature maps are extracted at four different stages of the ResNet-101 backbone, with channel dimensions of [256, 512, 1024, 2048].

To further enhance feature learning, self-attention mechanisms such as SAM, CBAM, SE, and Non-Local blocks are integrated. These mechanisms help the model capture both local and global dependencies more effectively, leading to improved segmentation performance. Figure 3 presents the overall structure of the model, illustrating how the DeepLabV3 encoder and U-Net-style decoder work together to achieve accurate segmentation.

```
class UNetDeepLabV3(nn.Module):
    def __init__(self, n_classes_reg=1, n_classes_class=1, in_channels=3):
        super(UNetDeepLabV3, self).__init__()
        self.encoder = segmentation.DeepLabV3_ResNet101(weights=segmentation.DeepLabV3_ResNet101_Weights.DEFAULT)

        # Modify the first convolution layer for custom input channels
        self._modify_first_conv_layer(in_channels)

        encoder_channels = [256, 512, 1024, 2048]
        self.up_conv3 = self.upconv_block(encoder_channels[2], encoder_channels[2])
        self.dec_conv3 = self.conv_block(encoder_channels[2] + encoder_channels[2], encoder_channels[2])
        #self.se3 = SEBlock(encoder_channels[2])
        self.se3 = SAM(encoder_channels[2])

        self.up_conv2 = self.upconv_block(encoder_channels[2], encoder_channels[1])
        self.dec_conv2 = self.conv_block(encoder_channels[1] + encoder_channels[1], encoder_channels[1])
        #self.se2 = SEBlock(encoder_channels[1])
        self.se2 = CBAM_SE_Block(encoder_channels[1])

        self.up_conv1 = self.upconv_block(encoder_channels[1], encoder_channels[0])
        self.dec_conv1 = self.conv_block(encoder_channels[0] + encoder_channels[0], encoder_channels[0])
        #self.se1 = CBAM_SE_Block(encoder_channels[0])
        self.se1 = CBAM_SE_NonLocal_Block(encoder_channels[0])

        self.up_conv0 = self.upconv_block(encoder_channels[0], encoder_channels[0] // 2)
        self.dec_conv0 = self.conv_block(encoder_channels[0] // 2, encoder_channels[0] // 2)

        # Output layers for regression and classification
        self.out_reg = nn.Conv2d(encoder_channels[0] // 2, n_classes_reg, kernel_size=1)
        self.out_class1 = nn.Conv2d(encoder_channels[0] // 2, n_classes_class, kernel_size=1)
        self.out_class2 = nn.Conv2d(encoder_channels[0] // 2, n_classes_class, kernel_size=1)
```

Figure 3: UNetDeepLabV3 model

- UNetSwinTransformer Model:

The UNetSwinTransformer model combines a Swin Transformer encoder with a U-Net-style decoder, creating a powerful architecture for dense prediction tasks. The Swin Transformer efficiently captures long-range dependencies using windowed self-attention while maintaining computational efficiency. It extracts hierarchical feature maps, which are then processed by the decoder to reconstruct high-resolution outputs.

Encoder: The encoder uses a Swin Transformer (base variant, patch size 4, window size 7) to extract multi-resolution feature maps through hierarchical self-

attention. It is initialized with a ResNet-101 backbone pre-trained on ImageNet. Similar to the DeepLabV3 model, a custom convolution function modifies the patch embedding layer to support multi-channel input images. The extracted feature maps have channel dimensions of [128, 256, 512, 1024].

Decoder: The decoder mirrors the encoder's structure but uses patch expanding layers instead of patch merging. These layers progressively upsample feature maps to restore spatial resolution. Skip connections link corresponding encoder and decoder levels, preserving fine spatial details. To further enhance feature learning, self-attention mechanisms such as SAM, CBAM, SE, and Non-Local blocks are integrated, improving both local and global feature representation. Figure 4 presents the model structure, illustrating how the Swin Transformer encoder and U-Net decoder work together for accurate segmentation.

```

class UNetSwinAttention(nn.Module):
    def __init__(self, n_classes_reg=1, n_classes_tree=1, n_classes_centroid=1, in_channels=3):
        super(UNetSwinAttention, self).__init__()

        # Load Swin Transformer encoder from timm
        self.encoder = timm.create_model('swin_base_patch4_window224', pretrained=True, features_only=True)

        # Modify first convolution layer for custom input channels
        self._modify_first_conv_layer(in_channels)

        encoder_channels = [128, 256, 512, 1024]

        # Shared decoder for regression and tree classification
        self.up_conv3 = self.upconv_block(encoder_channels[3], encoder_channels[2])
        self.dec_conv3 = self.conv_block(encoder_channels[2] + encoder_channels[2], encoder_channels[2])
        self.se3 = SAM(encoder_channels[2])

        self.up_conv2 = self.upconv_block(encoder_channels[2], encoder_channels[1])
        self.dec_conv2 = self.conv_block(encoder_channels[1] + encoder_channels[1], encoder_channels[1])
        self.se2 = CBAM_SE_Block(encoder_channels[1])

        self.up_conv1 = self.upconv_block(encoder_channels[1], encoder_channels[0])
        self.dec_conv1 = self.conv_block(encoder_channels[0] + encoder_channels[0], encoder_channels[0])
        self.se1 = CBAM_SE_NonLocal_block(encoder_channels[0])

        self.up_conv0 = self.upconv_block(encoder_channels[0], encoder_channels[0] // 2)
        self.dec_conv0 = self.conv_block(encoder_channels[0] // 2, encoder_channels[0] // 2)

        # Separate decoder for Centroid classification
        self.up_conv_centroid = self.upconv_block(encoder_channels[1], encoder_channels[0])
        self.dec_conv_centroid = self.conv_block(encoder_channels[0] + encoder_channels[0], encoder_channels[0])

        self.up_conv_centroid_final = self.upconv_block(encoder_channels[0], encoder_channels[0] // 2)
        self.dec_conv_centroid_final = self.conv_block(encoder_channels[0] // 2, encoder_channels[0] // 2)

        # Output layers
        self.out_reg = nn.Conv2d(encoder_channels[0] // 2, n_classes_reg, kernel_size=1)
        self.out_class_tree = nn.Conv2d(encoder_channels[0] // 2, n_classes_tree, kernel_size=1)
        self.out_class_centroid = nn.Conv2d(encoder_channels[0] // 2, n_classes_centroid, kernel_size=1)

```

Figure 4: UNetSwinTransformer Model

## 5.6 Model Performance Enhancement Methods

To improve model performance, various techniques will be applied and the following sections will describe each method.

- Data Augmentation

During training in some scenario, we sample random tiles of size 224×224 pixels with data augmentation: random scaling from 0.5 to 2, and rotations 0, 90°, 180°, or 270°.

- Attention Mechanisms

Various attention mechanisms are integrated and tested to enhance feature selection, spatial dependencies, and long-range contextual understanding across different tasks. These include SE blocks for channel-wise refinement, CBAM for combined channel and spatial attention, SAM for spatial focus, and Non-Local Blocks for capturing global dependencies. Each mechanism is evaluated based on its impact on segmentation accuracy, object localization, and overall model performance in canopy structure representation and related tasks.

- Click or tap here to enter text. Click or tap here to enter text. Click or tap here to enter text. Click or tap here to enter text. Regularization techniques

The model is tested with and without regularization techniques such as Dropout, Batch Normalization, and Weight Decay (L2 Regularization). Dropout helps prevent overfitting by randomly deactivating neurons, while Batch Normalization stabilizes training and improves generalization. Weight Decay, set to 1e-4 in the model, penalizes large weight values to encourage simpler models and reduce overfitting.

- Activation functions Tuning

The model is evaluated using two activation functions: ReLU and GELU.

- Optimizer Tuning

Both Adam (Adaptive Moment Estimation) and ADOPT optimization are applied to evaluate the model's performance.

- Loss Function Tuning

Loss functions play a critical role in machine learning models, as they guide the optimization process and determine how well the model's predictions match the actual data. In this model, the BCE loss function is initially used for classification tasks, while a combination of BCE and Focal Loss is used to address class imbalance in the dataset. Figure 5 and Figure 6 present the Focal Loss and Hybrid Loss functions, which are defined in the model. The hybrid approach combines the strengths of BCE and Focal Loss, allowing the model to maintain classification accuracy while handling imbalanced datasets more effectively. Finally, the hybrid loss function is applied to the final model, as it showed the best performance in the testing phase.

```

class FocalLoss(nn.Module):
    def __init__(self, alpha=0.25, gamma=2.0, reduction='mean'):
        """
        Focal Loss for addressing class imbalance.
        Args:
            alpha (float): Weighting factor for the rare class.
            gamma (float): Focusing parameter to reduce the loss contribution from easy examples.
            reduction (str): Reduction method to apply to the output ('mean', 'sum', 'none').
        """
        super(FocalLoss, self).__init__()
        self.alpha = alpha
        self.gamma = gamma
        self.reduction = reduction

    def forward(self, inputs, targets):
        """
        Forward pass for Focal Loss.
        Args:
            inputs (torch.Tensor): Predicted logits with shape [batch_size, 1, H, W].
            targets (torch.Tensor): Ground truth binary labels with shape [batch_size, 1, H, W].
        Returns:
            torch.Tensor: Computed Focal Loss.
        """
        # Apply sigmoid to get probabilities
        probs = torch.sigmoid(inputs)
        BCE_loss = F.binary_cross_entropy_with_logits(inputs, targets, reduction='none')
        pt = torch.exp(-BCE_loss) # pt is the probability of the true class
        focal_loss = self.alpha * (1 - pt) ** self.gamma * BCE_loss

        if self.reduction == 'mean':
            return focal_loss.mean()
        elif self.reduction == 'sum':
            return focal_loss.sum()
        else:
            return focal_loss

```

Figure 5: Focal Loss Function

```

def compute_class_weights(class_targets, device):
    # Flatten targets to compute class weights
    flattened_targets = class_targets.view(-1).cpu().long().numpy() # Convert to numpy array of integers
    classes = np.unique(flattened_targets)
    if len(classes) < 2:
        # Avoid errors if only one class is present
        return torch.tensor([1.0]).to(device)
    weights = class_weight.compute_class_weight(class_weight='balanced', classes=classes, y=flattened_targets)
    # pos_weight is the weight for the positive class (assumed to be class '1')
    pos_weight = torch.tensor([weights[1] / weights[0]]).to(device)
    return pos_weight

import torch.nn as nn

class HybridLoss(nn.Module):
    def __init__(self, alpha=0.8, gamma=2, pos_weight=None):
        super(HybridLoss, self).__init__()
        self.bce_loss = nn.BCEWithLogitsLoss(pos_weight=pos_weight)
        self.focal_loss = FocalLoss(gamma=gamma) # Make sure to define or import FocalLoss
        self.alpha = alpha

    def forward(self, inputs, targets):
        bce = self.bce_loss(inputs, targets)
        focal = self.focal_loss(inputs, targets)
        return self.alpha * bce + (1 - self.alpha) * focal

```

Figure 6: Hybrid Loss Function

Finally, hybrid loss functions will be used for classification tasks, as it showed better results in the testing phase. Figure 7 presents the loss function for each task in the model, defined separately based on the fact that both classification tasks (tree mapping and bole tree classification) are imbalanced, while the canopy height task is treated as a regression task.

```

model = UNetDeepLabV3(n_classes_reg=n_classes_reg, n_classes_class=n_classes_class, in_channels=in_channels)
#model = UNetSwinAttention(n_classes_reg=n_classes_reg, n_classes_tree=n_classes_class, in_channels=in_channels)

#fine_tune_model(model, layers_to_unfreeze=2)

# Compute class weights based on training data
pos_weight = compute_class_weights(torch.tensor(train_classes), device)
pos_weight1 = compute_class_weights(torch.tensor(train_centroids), device)

#classification_criterion = FocalLoss(alpha=0.8, gamma=2.0, reduction='mean')

classification_criterion = HybridLoss(alpha=0.8, gamma=2, pos_weight=pos_weight).to(device)
centroid_criterion = HybridLoss(alpha=0.8, gamma=2, pos_weight=pos_weight1).to(device)
#regression_criterion = nn.MSELoss()
#Regression loss
regression_criterion = SmoothL1Loss()

```

Figure 7: Loss function of each task of the models

- Gradient Clipping

To address issues like vanishing and exploding gradients, Gradient Clipping is defined in the model. Figure 8 illustrates how Gradient Clipping is defined in the model.

```
scaler.scale(loss).backward()

# Unscale gradients before clipping
scaler.unscale_(optimizer)

# Clip gradients (max_norm is the threshold)
torch.nn.utils.clip_grad_norm_(model.parameters(), max_norm=1.0)

# Update parameters
scaler.step(optimizer)
scaler.update()
```

Figure 8: Using Gradient Clipping in Training

- Early Stopping and Learning Rate Adjustments

In this study, the initial learning rate is set to  $lr = 0.001$ , and the patience for early stopping is set to 30 epochs. To further optimize learning rate adjustments, the ReduceLROnPlateau scheduler is employed:

- Purpose: Adjusts the learning rate when validation loss stops improving.
- Patience = 3: Reduces the learning rate after three consecutive epochs of no improvement.
- Factor = 0.5: Reduces the learning rate by half when triggered.

This adaptive learning rate strategy ensures that the model continues to improve while preventing unnecessary fluctuations in optimization.

Figure 9 illustrates the Early Stopping and Learning Rate Adjustments parameters, as well as the weight for the loss function for each task.

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```
num_epochs = 100
patience = 30
lr_scheduler = ReduceLROnPlateau(optimizer, mode='min', patience=lr_decay_patience, factor=0.5)
lr_decay_patience = 3
alpha1 = 0.1 # Weight for regression loss
beta1 = 2.0 # Weight for classification loss
gamma1 = 2.0 # Weight for centroid loss
initial_lr = 0.001 # Set this to the desired initial learning rate
```

Figure 9: Early Stopping and Learning Rate Adjustments

## 5.7 Model Saving Methodology

To ensure optimal model performance and reproducibility, a robust method for saving the best-trained model was implemented. This process is designed to monitor model performance during training and store the model that achieves the highest predictive accuracy, particularly with regard to the F1 score, while ensuring that the accuracy of each class in the binary classification of tree cover mapping (most important task) remains above 80%. This section outlines the strategy employed to achieve this objective.

- Evaluation Metrics for Model Selection

The selection of the best model was based on multiple evaluation metrics to ensure both global and per-class performance. Specifically, the following criteria were applied:

- **F1 Score:** The harmonic means of precision and recall, providing a balanced evaluation of the model's classification performance, particularly suitable for imbalanced classes.

- **Per-Class Accuracy:** The classification accuracy of each individual class, calculated from the confusion matrix, ensuring that no class underperforms significantly.

By using these two metrics, the methodology prioritizes models that excel in overall performance while maintaining acceptable accuracy thresholds for each binary class.

```
# Save the model if the F1 score improves and class accuracies are above 90%
if f1 > best_f1_score and class0_acc_val >= 80.0 and class1_acc_val >= 80.0:
    print("Validation F1 score improved and class accuracies are sufficient. Saving best model.")
    best_f1_score = f1
    best_model_checkpoint = {
        'epoch': epoch + 1,
        'model_state_dict': model.state_dict(),
        'optimizer_state_dict': optimizer.state_dict(),
        'loss': epoch_val_regression_loss,
        'f1_score': f1,
        'learning_rate': optimizer.param_groups[0]['lr'], # Save current LR
        'class0_acc_val': class0_acc_val, # Save class-wise accuracies
        'class1_acc_val': class1_acc_val,
        'epoch_train_class_accuracy': epoch_train_class_accuracy,
        'epoch_val_tree_accuracy': epoch_val_tree_accuracy,
        'epoch_train_centroid_accuracy': epoch_train_centroid_accuracy,
        'epoch_val_centroid_accuracy': epoch_val_centroid_accuracy,
        'epochs_no_improve': epochs_no_improve # Track no improvement count
    }
    torch.save(best_model_checkpoint, best_model_path)
    print(f"✅ Best model saved at {best_model_path}")

# Save every improved epoch checkpoint in the "checkpoint" folder
epoch_checkpoint_path = os.path.join(checkpoint_folder, f"checkpoint_epoch_{epoch+1}.pth")
torch.save(best_model_checkpoint, epoch_checkpoint_path)
print(f"📁 Checkpoint saved at {epoch_checkpoint_path}")
```

Figure 10: Evaluation Metrics for Model Selection

- Model Checkpointing

To prevent overfitting and save computational resources, a model checkpointing strategy was implemented alongside early stopping. This combination ensures that the model with the highest validation performance is preserved, while avoiding unnecessary training epochs that could degrade performance.

The checkpointing method was defined as follows:

- **Checkpoint Criteria:** The model was saved only if the validation F1 score improved compared to the previously saved model.

- **Per-Class Accuracy Threshold:** In addition to F1 score improvement, the model was only saved if the accuracy for both classes exceeded 80%. If this condition was not met, even an improved F1 score would not trigger model saving.
- **Early Stopping:** Training was halted if the validation loss did not improve for a predefined number of epochs, helping mitigate overfitting and unnecessary computation.

## 6 Testing and analysis

This chapter presents the evaluation of the trained deep learning models, focusing on their accuracy, reliability, and validity. The outputs were assessed against LiDAR-derived ground truth data using quantitative performance metrics. The study aimed to develop a robust workflow for generating LiDAR-like 3D mapping outputs from satellite imagery, supporting advancements in remote sensing and ecological studies.

### 6.1 Model Training and Evaluation

The trained models' outputs are evaluated against LiDAR-derived ground truth data using quantitative metrics. As a result, the study produces a validated workflow that automates tree cover mapping, tree bole identification, and canopy height estimation, providing a reliable foundation for advancing remote sensing and ecological studies.

To assess the performance of the proposed model, various metrics were tracked during training and validation. The primary evaluation criteria included:

- **Regression Loss:** Monitored to evaluate the accuracy of canopy height prediction. Root Mean Square Error (RMSE) specifically assesses performance by comparing model outputs with LiDAR measurements in regression tasks.
- **Tree Classification Accuracy & F1-Score:** Precision measured the proportion of correctly identified tree cover pixels in classification tasks, while the F1-score provided a balanced measure of precision and recall, offering a comprehensive evaluation of classification performance. Figure 11 shows the F1-score (0.8930) of the decision trees results
- **Centroid Classification Accuracy:** Evaluated for the spatial accuracy of tree centroid predictions.

In below, the results of training and validation metrics of best model in Epoch 40 and are presented, along with the corresponding plots for all epochs of best model. The figure displays key performance metrics from Epoch 40, highlighting improvements in classification accuracy and regression loss. The training accuracy of the tree-based classifier reached 89.0%, while the validation accuracy was 89.2%, demonstrating a well-generalized model. Additionally, the centroid classification accuracy was 76.31%, indicating an almost good performance in tree centroid detection. The F1-score of 0.8930 suggests a balanced trade-off between precision and recall. These results confirm that the model effectively learns to predict canopy height and classify tree cover with high accuracy.

```
Epoch 40/100
Training Regression Loss: 3.1267, Overall tree Classification Accuracy: 89.09% , Overall Centroid Classification Accuracy: 78.28%
Class 0 Tree Training Accuracy: 86.65% | Class 1 Tree Training Accuracy: 90.04%
Class 0 Centroid Training Accuracy: 78.29% | Class 1 Centroid Training Accuracy: 74.06%
Training time: 35.72 seconds

Validation Loss: 3.5970, Tree Accuracy: 89.20%, Centroid Accuracy: 76.33%
Validation Regression Loss: 3.5970, Overall Validation tree Classification Accuracy: 89.20%
Class 0 Tree TrainValidation Accuracy: 83.18% | Class 1 Tree Validation Accuracy: 91.43%
Overall Validation Centroid Classification Accuracy: 76.33%
Class 0 Centroid Validation Accuracy: 76.34% | Class 1 Centroid Validation Accuracy: 74.87%
Validation F1 Score: 0.8930
Validation time: 4.71 seconds
Validation F1 score improved and class accuracies are sufficient. Saving best model.
```

Figure 11: The results of training and validation metrics of best model in Epoch 40

The Figure 12 illustrates the regression loss trend for both training and validation sets over epochs. The train regression loss (blue line) consistently decreases, indicating that the model is effectively learning to predict canopy height. The validation regression loss (orange line) exhibits fluctuations, particularly around early epochs and between epochs 20–40, which may suggest some instability or overfitting tendencies. However, both losses gradually stabilize, with validation loss converging close to training loss, demonstrating that the model is generalizing well.

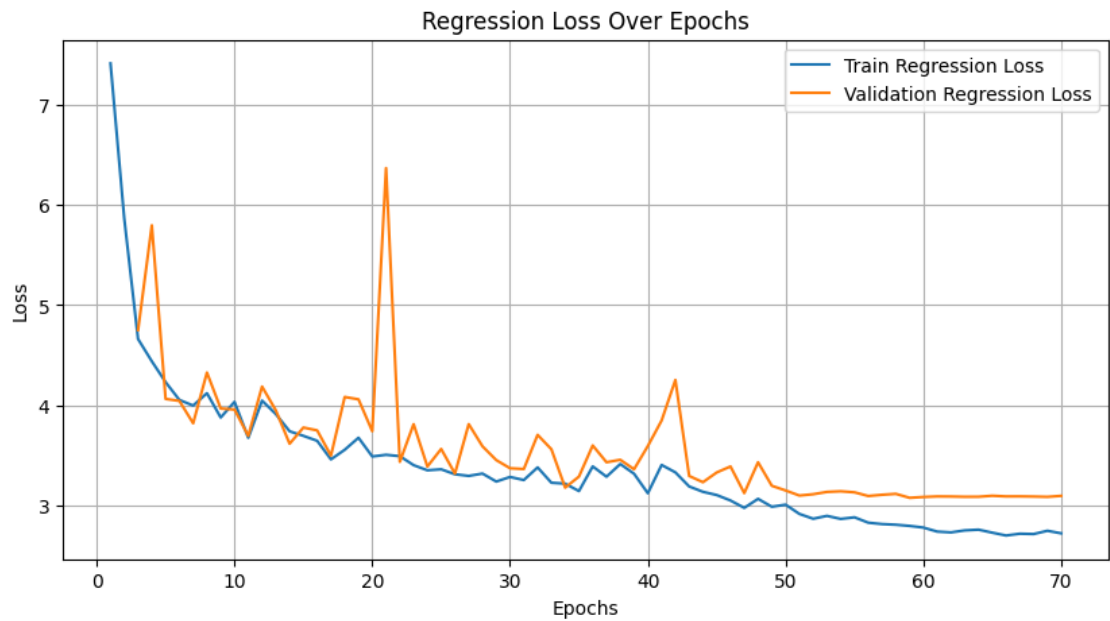


Figure 12: The regression loss of best model over epochs

The

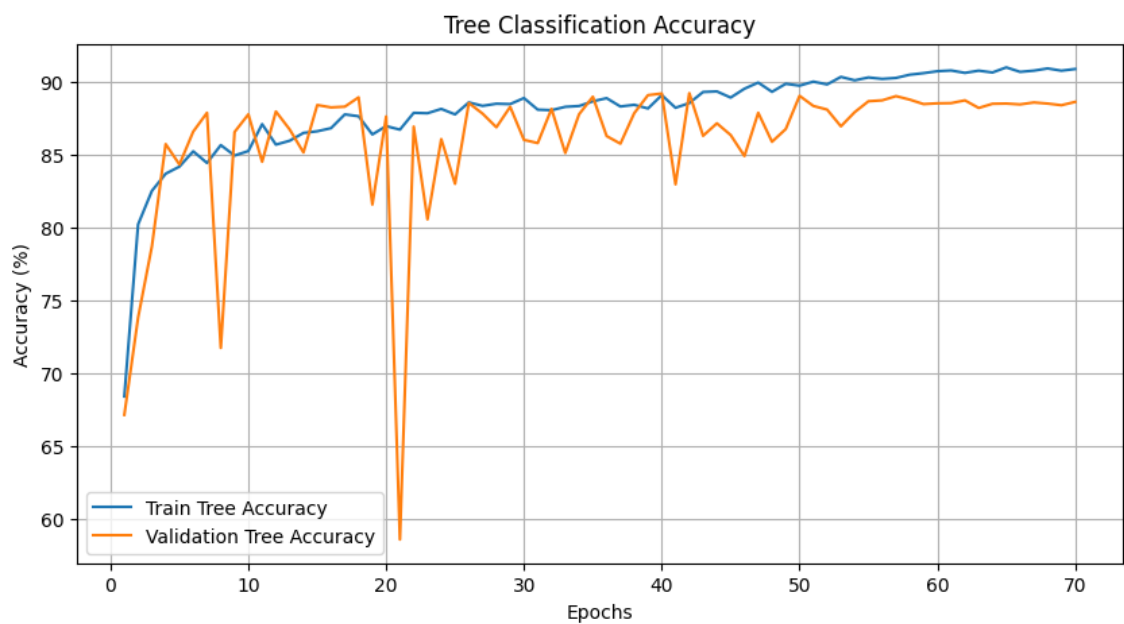


Figure 13 shows the classification accuracy of the tree classifier across epochs for both training and validation data. The train tree accuracy (blue line) steadily improves, reaching around 90%, while the validation tree accuracy (orange line) follows a similar trend but with more fluctuations, particularly in the earlier epochs. The sharp dips in validation accuracy indicate possible variations in the dataset,

but the general upward trend suggests that the model improves its classification performance as training progresses. The final stable accuracy levels indicate that the model achieves high classification performance for tree cover detection.

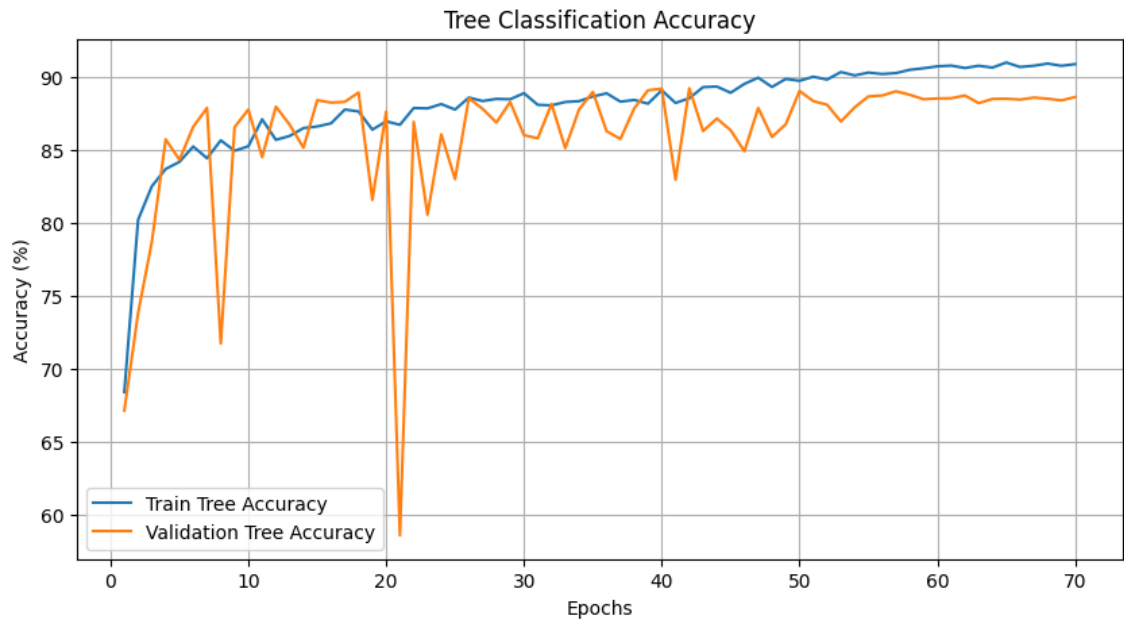


Figure 13: Tree Classification Accuracy of Best Model Over Epochs

To provide a more comprehensive view of the model's performance across training epochs, additional plots illustrating key metrics are included in Appendix 1. These plots track the progression of regression loss, tree classification accuracy, and centroid classification accuracy over time, offering insights into model convergence and stability.

Furthermore, a detailed comparison of all trained models, including metrics such as regression loss, classification accuracy, and centroid accuracy for both training and validation phases, is presented in Appendix 2. This table provides an overview of the performance of different models across various epochs, allowing for a thorough evaluation of their effectiveness.

## 6.2 Reliability and Validity

Reliability and validity are essential for ensuring that the study's findings are consistent, unbiased, and generalizable. This section outlines the measures taken to establish both reliability and validity.

- Reliability

Reliability ensures that the study's results are reproducible and consistent under similar conditions. To achieve this, the following steps were implemented:

1. **Consistent Preprocessing:** Standardized and automated preprocessing steps, including normalization and alignment, ensured data consistency.
2. **Model Stability:** Multiple training runs were conducted using different random seeds to verify that results remained stable.
3. **Comprehensive Evaluation Metrics:** Performance metrics were calculated separately for the training, validation, and testing datasets, ensuring a complete assessment of model effectiveness.
4. **Reproducibility Documentation:** All preprocessing, modeling, and evaluation steps were documented using version control systems, enabling other researchers to replicate the methodology.

- Validity

Validity assesses whether the study accurately measures its intended objectives and whether the results can be generalized beyond the specific study area.

- **Internal Validity**

Internal validity ensures that the study's methods and data are correctly aligned:

- **Data Alignment:** Input satellite imagery and labels were carefully paired to enable precise pixel-wise learning.
- **Weighted Loss Functions:** Adjusted loss functions prioritized key outputs, particularly the CHM Binary Map, which was essential for accurate canopy height modeling.
- **External Validity**

External validity determines how well the findings can be applied to other contexts:

- **Representative Study Area:** The study area, a 35 km<sup>2</sup> forested region near Lappeenranta, Finland, was chosen for its representative forest characteristics, supporting generalizability to similar landscapes.
- **Flexible Model Architecture:** The deep learning models (CNNs and Transformers) were selected for their adaptability, making them suitable for **different regions and datasets** beyond the study area.
- Addressing Potential Bias

To minimize biases and improve model robustness, the following strategies were applied:

- **Overfitting Prevention:** Regularization techniques such as dropout, weight decay, and L2 regularization were used to prevent models from memorizing training data.
- **Data Augmentation:** Various augmentation techniques were applied to enhance dataset diversity and improve model generalization across different forest conditions.

The evaluation process confirmed that the trained deep learning models achieved high accuracy and reliability when validated against LiDAR-derived ground truth data. By employing rigorous testing procedures and mitigating potential biases, this study developed a generalizable and reproducible framework for automated tree cover mapping, tree bole identification, and canopy height estimation, supporting remote sensing applications in forestry and environmental research.

## 7 Discussion

In this section, we present model performances from experiments in subsections for the three experimental objectives: tree cover mapping (most important), canopy height estimation and tree bole identification. For all these experiments we use a batch size of 32 and an input window size of 224x224 pixels. By default, the number of iterations is set to 100, with the learning rate and weight decay set to 1e-3 and 1e-4, respectively. The patience for early stopping is 30, while the patience for reducing the learning rate by half is 3. Different combinations of optimizers, activation functions, attention mechanisms, and other hyperparameters were tested to identify optimal configurations. The overall accuracy and the accuracy of each class for the classification objectives are reported, as well as the RMSE for the regression tasks, using the deep learning methods (Computer vision-based models) on the test dataset. The following subsections address the core research questions, evaluating the feasibility of using deep learning models for tree cover mapping, canopy height estimation, and tree bole identification.

Table 1 presents the performance metrics of different deep learning models for tree cover classification, canopy height estimation, and centroid detection. The table includes results for various optimizers, attention mechanisms, and augmentation strategies

Row	Optimizer	Augmentation	Activation	Dropout	Alpha1 Coeficeint of regression task	Beta1 Coeficeint of tree classification task	Gamma1 Coeficeint of tree centroid classification task	Attention	Model architecture	Regression Loss (m)	Tree cover Classification Accuracy (%)	Tree cover Class 0 Accuracy (%)	Tree cover Class 1 Accuracy (%)	Tree Centroid Accuracy (%)	Tree Centroid Class 0 Accuracy (%)	Tree Centroid Class 1 Accuracy (%)
1	Adam	No	GELU & ReLU	1*0.5	1	2	2	CBAM_SE_NonLocal_Block	Deeplab + UNet	3.087	89.419	84.024	91.408	76.268	76.277	74.296
2	Adam	No	GELU & ReLU	1*0.5	1	2	2	SAM_CBAM_SE_Block	Deeplab + UNet	3.080	89.782	84.044	91.897	76.599	76.608	74.559
3	Adam	No	2* GELU	2*0.5	1	2	2	SAM_CBAM_SE_NonLocal_Block	Deeplab + UNet	3.097	89.365	84.632	91.109	77.232	77.249	73.476
4	Adam	No	GELU & ReLU	1*0.5	1	2	4	SAM_CBAM_SE_NonLocal_Block	Deeplab + UNet	3.152	89.350	84.923	90.982	75.079	75.080	74.967
5	ADOPT	No	GELU & ReLU	1*0.5	1	2	4	SAM_CBAM_SE_NonLocal_Block	Deeplab + UNet	3.151	89.544	85.080	91.190	76.537	76.542	75.402
6	ADOPT	Yes	GELU & ReLU	1*0.5	1	2	4	SAM_CBAM_SE_NonLocal_Block	Deeplab + UNet	4.585	81.813	78.985	82.856	79.410	79.456	69.170
7	Adam	No	2* GELU	2*0.5	1	2	2	SAM	Deeplab + UNet		26.936	100.000	0.000	99.548	100.000	0.000
8	Adam	No	GELU & ReLU	2*0.5	1	2	2	SAM	Deeplab + UNet	3.110	89.581	84.662	91.394	77.028	77.039	74.659
9	Adam	No	GELU & ReLU	1*0.5	1	2	2	SAM	Deeplab + UNet	3.121	89.529	84.437	91.407	76.676	76.686	74.473
10	Adam	No	GELU & ReLU	1*0.5	1	2	4	CBAM_SE_Block_CBAM_SE_NonLocal_Block	SWIN + UNet	3.084	89.509	86.201	90.728	57.334	57.240	77.980
11	Adam	No	2* GELU	1*0.5	1	2	4	Sam_CBAM_SE_NonLocal_Block	SWIN + UNet	3.126	89.442	85.661	90.836	56.595	56.496	78.458
12	Adam	No	GELU & ReLU	1*0.5	1	2	2	Sam_CBAM_SE_NonLocal_Block	SWIN + UNet	3.171	89.023	86.212	90.059	58.688	58.608	76.245
13	Adam	No	GELU & ReLU	1*0.5	1	3	8	Sam_CBAM_SE_NonLocal_Block	SWIN + UNet	3.136	89.458	85.267	91.002	58.230	58.147	76.598
14	Adam	Yes	GELU & ReLU	1*0.5	1	2	2	Sam_CBAM_SE_NonLocal_Block	SWIN + UNet	4.173	84.888	84.827	84.911	41.919	41.738	81.784
15	Adam	No	GELU & ReLU	1*0.5	1	2	2	Sam_CBAM_SE_NonLocal_Block	SWIN + UNet	3.077	89.714	84.701	91.562	58.258	58.174	76.833
16	ADOPT	No	GELU & ReLU	1*0.5	1	2	4	Sam_CBAM_SE_NonLocal_Block	SWIN + UNet	3.223	89.009	85.512	90.299	58.893	58.817	75.640
17	Adam	No	GELU & ReLU	1*0.5	1	2	2	CBAM_SE_Block_Sam_CBAM_SE_NonLocal_Block	SWIN + UNet	3.160	89.238	85.764	90.519	58.298	58.215	76.621

Row	Optimizer	Augmentation	Activation	Dropout	Alpha1 Coeficeint of regression task	Beta1 Coeficeint of tree classification task	Gamma1 Coeficeint of tree centroid classification task	Attention	Model architecture	Regression Loss (m)	Tree cover Classification Accuracy (%)	Tree cover Class 0 Accuracy (%)	Tree cover Class 1 Accuracy (%)	Tree Centroid Accuracy (%)	Tree Centroid Class 0 Accuracy (%)	Tree Centroid Class 1 Accuracy (%)
18	ADOPT	No	GELU & ReLU	1*0.5	1	2	2		Deeplab + UNet	3.065	89.735	85.344	91.353	77.285	77.297	74.714
								CBAM_SE_Block_Sam_CBAM_SE_NonLocal_Block								
19	Adam	No	GELU & ReLU	1*0.5	1	2	2		Deeplab + UNet	3.119	89.641	84.851	91.406	77.654	77.670	74.107
								CBAM_SE_Block_Sam_CBAM_SE_NonLocal_Block								

Table 1- Performance metrics of different deep learning models for tree cover classification, canopy height estimation, and centroid detection

## 7.1 Canopy height

The Validation Regression Loss, expressed as RMSE, is a crucial metric for evaluating how well models predict continuous values, such as canopy height. Among the tested configurations, the ADOPT optimizer, SAM and CBAM\_SE\_Block attention mechanism, integrated with the DeepLabV3 model as the backbone achieved the lowest RMSE of 3.065 meters. This result indicates a significant improvement in accurately predicting continuous canopy height values. The observed performance suggests that the ADOPT approach, when paired with advanced attention mechanisms and a CNN-based architecture like DeepLabV3, provides an effective solution for canopy height estimation, addressing Research Question 2 by demonstrating that deep learning models can reliably infer canopy height from VHR satellite imagery and multispectral data.

Furthermore, this experiment also provides an answer to Research Question 3, indicating that LiDAR-derived canopy height models can indeed be leveraged to train deep learning algorithms to predict canopy height from 2D imagery. As shown in Table 1 and Figure 14, the RMSE of 3.065 meters, the lowest among tested configurations, suggests that CNN-based architectures, such as DeepLabV3, are particularly well-suited to this task. In contrast, models using the SWIN transformer backbone consistently produced higher RMSE values (3.126–3.160 meters), suggesting that, for this specific regression task, convolutional neural networks may outperform transformers, which tend to capture global dependencies but may struggle with fine-grained spatial predictions.

```

Testing: 100%|██████████| 67/67 [00:36<00:00, 1.81it/s]
Test time: 36.96 seconds

Test Regression Loss: 3.0646
Test Classification Accuracy: 89.73%
Class 0 Test Accuracy: 85.34% | Class 1 Test Accuracy: 91.35%
Test Centroid Accuracy: 77.29%
Centroid Class 0 Test Accuracy: 77.30% | Centroid Class 1 Test Accuracy: 74.71%
/run/nvme/job_26585477/tmp/ipykernel_1755830/2279415961.py:1543: FutureWarning: The behav
df = pd.concat([df, test_results_df], ignore_index=True)

```

Figure 14: Performance results of model 18 (The row number in Table 1)

Interestingly, when data augmentation was introduced, the regression performance deteriorated, with the RMSE increasing to 4.173 meters (Table 1). This reinforces the observation that temporal discrepancies between the very high-resolution (VHR) imagery (captured in 2023) and LiDAR data (collected in 2020–2021) introduced noise that adversely impacted model performance, highlighting the challenges of multi-temporal data integration.

When comparing methodologies across different studies, Wilkes et al. reported RMSE values of approximately 5.6 meters (about 31% of mean canopy height) when using Random Forest models trained on Airborne Laser Scanning data to predict canopy height across 2.9 million hectares of heterogeneous forest in Victoria, Australia (Wilkes et al., 2015). Similarly, Vega et al. achieved an RMSE of 3.6 meters for their canopy height model (Vega et al., 2022). As shown in Table 1, these results indicate that while deep learning approaches often outperform traditional methods, the magnitude of improvement varies based on forest type, data quality, and spatial resolution.

## 7.2 Tree Cover Classification

For tree cover classification, the Validation Classification Accuracy measures the model's ability to distinguish between tree cover and non-tree cover pixels. As presented in Table 1 and Figure 14, the ADOPT optimizer, combined with SAM, CBAM\_SE\_Block, and Sam\_CBAM\_SE\_NonLocal\_Block attention mechanisms

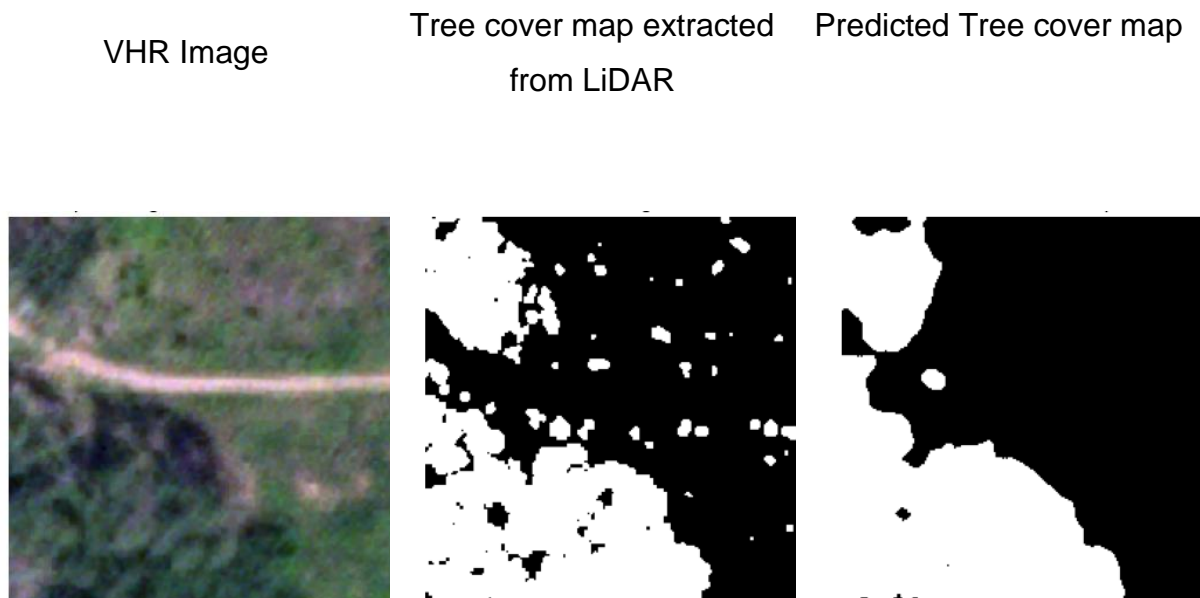
with the DeepLabV3 model, achieved the highest validation classification accuracy of 89.735%, with Class 0 Accuracy of 85.344% and Class 1 Accuracy of 91.353%. This result indicates balanced performance across both classes, with the model demonstrating strong generalization for both tree and non-tree cover areas. This finding directly addresses Research Question 1, confirming that CNN-based deep learning models, particularly when equipped with attention mechanisms, can map tree covers accurately from multispectral and VHR imagery.

However, transformer-based models, despite achieving solid overall classification accuracies (ranging from 89.238% to 89.714%), consistently exhibited lower centroid classification accuracies (approximately 58.258% to 58.893%). This observation suggests that while transformers capture global contextual information effectively, they may struggle with fine-grained spatial tasks such as tree centroid localization, reinforcing the potential advantage of CNN-based architectures for pixel-level segmentation tasks.

While a direct comparison with traditional remote sensing techniques was not performed within this study, the high validation classification accuracy of CNN-based models for tree cover mapping (approaching 90%) suggests that deep learning methods could offer competitive, if not superior, performance, especially in heterogeneous forest landscapes where traditional methods often struggle with feature generalization. A more detailed comparison with conventional pixel-based and object-based image analysis (OBIA) techniques could provide further insights, which remains a promising avenue for future work. However, one study combining OBIA with multiple data sources including LiDAR, very high-resolution satellite imagery, and aerial imagery achieved impressive results with over 95% overall accuracy based on confusion matrix assessment and 70% based on Intersection over Union (IoU) (Timilsina et al., 2020). This demonstrates that traditional methods can still be effective when leveraging diverse, high-quality data sources.

When data augmentation was applied, as with the ADOPT optimizer configuration, the performance dropped significantly, with tree cover classification accuracy falling to 81.813%. This decline suggests overfitting or insufficient regularization strategies to mitigate the temporal and sensor-based discrepancies present in the input data.

To better visualize the effectiveness of the tree cover classification model, we present a comparison between the original high-resolution images and the model's predicted canopy maps. Figure 15 displays two randomly selected 224×224 pixel image patches. The left column contains very high-resolution (VHR) images, the middle column shows tree cover maps extracted from LiDAR data, and the right column presents the predicted tree cover maps from the deep learning model. In both tree cover maps, white pixels represent trees (class 1), while black pixels indicate non-tree areas (class 0). These comparisons illustrate the model's ability to accurately capture tree cover patterns and generalize across different landscapes.



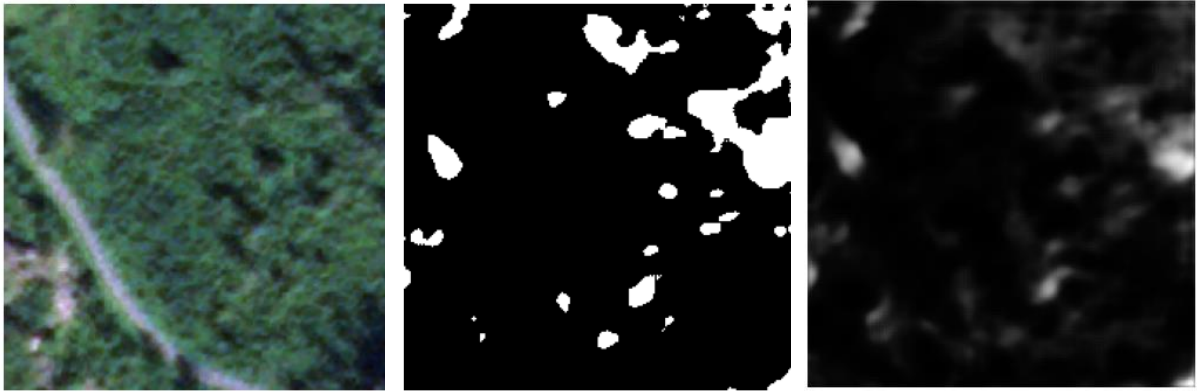


Figure 15: Comparison between original high-resolution images, LiDAR-extracted tree cover maps, and model-predicted tree cover maps. The left column shows VHR images, the middle column represents LiDAR-derived tree cover maps, and the right column displays the pr

### 7.3 Tree Centroid Classification

Beyond tree cover classification, the models were also evaluated on their ability to predict the spatial distribution of tree canopy centers through centroid classification accuracy. As summarized in Table 1 and Figure 14, the best-performing configuration — comprising the ADOPT optimizer, SAM, CBAM\_SE\_Block, and Sam\_CBAM\_SE\_NonLocal\_Block attention mechanisms with the DeepLabV3 model — achieved a centroid classification accuracy of 77.285%, with Class 0 and Class 1 centroid accuracies of 77.297% and 74.714%, respectively. This result suggests a reasonable balance in identifying tree centers across both classes, indicating that the model effectively captures both tree cover and canopy spatial distributions.

Consistent with previous observations, SWIN transformer-based models lagged behind, with centroid classification accuracies between 58.258% and 58.893%. This finding reinforces the notion that while transformers excel at capturing long-range dependencies, they may be less effective than CNN-based architectures for fine-grained spatial tasks, such as predicting tree centroid locations.

Interestingly, when data augmentation was introduced, the centroid classification accuracy experienced a minor increase to 79.410%. However, this improvement came at the cost of lower overall classification accuracy, once again pointing to the challenges posed by temporal and sensor-based discrepancies within the input data.

## 7.4 Validity and Reliability of Results

Ensuring the validity and reliability of the results is essential for producing accurate and trustworthy findings.

- Reliability

Reliability means that the study's results are consistent and reproducible under similar conditions. Several steps were taken to ensure this:

- **Standardized Preprocessing:** All data were processed using the same automated steps, ensuring consistency.
- **Stable Model Training:** The models were trained multiple times with different random seeds to check if results remained stable.
- **Comprehensive Evaluation:** Performance metrics were calculated separately for training, validation, and testing datasets to fully assess model effectiveness.
- **Reproducibility:** The entire process, from preprocessing to evaluation, was carefully documented so that others can replicate the study.

However, some factors may impact the reliability of the results. The temporal gap between the VHR imagery (captured in 2023) and the LiDAR data (collected in 2020–2021) introduced discrepancies, affecting model accuracy when data augmentation was applied. Additionally, while deep learning models showed strong performance, variations in accuracy across different model architectures highlight the sensitivity of results to hyperparameter selection and network design. Future work should explore additional validation techniques, such as cross-validation and independent benchmarking with external datasets, to further enhance the reliability of the findings.

- Validity

Validity ensures that the study accurately measures what it aims to and that the findings can be applied beyond this specific study area.

- **Internal Validity:**

- I. Input data were carefully matched to ensure accurate learning.
- II. Weighted loss functions were used to focus on key outputs, such as canopy height estimation.

- **External Validity:**

- I. The chosen deep learning models (CNNs and Transformers) are flexible and can be applied to different datasets and locations.

- Minimizing Bias

To reduce bias and improve the model's performance, the following techniques were applied:

- **Overfitting Prevention:** Methods like dropout, weight decay, and L2 regularization helped ensure that models did not simply memorize training data.
- **Data Augmentation:** Various techniques were used to make the dataset more diverse and improve the model's ability to work in different conditions.

By following these steps, the study ensured that the deep learning models produced reliable and valid results. The findings support the use of automated deep learning methods for tree cover mapping, tree bole identification, and canopy height estimation in forestry and environmental research.

## 8 Conclusion

This study demonstrated that attention-enhanced deep learning models, particularly those incorporating SAM, CBAM\_SE\_Block, and CBAM\_SE\_NonLocal\_Block with DeepLabV3, offer strong performance for tree cover mapping, canopy height estimation, and tree centroid classification, addressing the core research questions with promising results.

- Canopy height estimation was most accurate using the ADOPT optimizer with SAM and CBAM\_SE\_Block attention mechanisms, achieving a Validation Regression Loss (RMSE) of 3.065. This result indicates that LiDAR-derived canopy height models can be effectively leveraged to train deep learning models on 2D imagery, with CNN-based architectures like DeepLabV3 outperforming SWIN transformers for this task.
- Tree cover classification achieved a high validation accuracy of 89.735%, with balanced performance across tree and non-tree classes. The model demonstrated strong generalization for both tree cover and non-tree areas, supporting the feasibility of CNN-based models for accurate tree cover mapping from multispectral and VHR imagery.
- Tree centroid classification, which measures the ability to identify tree canopy centers, achieved a centroid accuracy of 77.285% with the same ADOPT optimizer and attention-enhanced DeepLabV3 configuration. Although reasonable, transformer-based models consistently underperformed in this spatial prediction task, reinforcing the advantages of CNN-based architectures for pixel-level segmentation tasks.

Overall, these results suggest that deep learning offers a viable and scalable approach to automating forest inventory processes, provided that careful attention is given to mitigating overfitting, domain shifts, and noise in multi-temporal datasets. While data augmentation was found to reduce performance in this context, possibly due to temporal and sensor-based discrepancies, the study highlights the importance of model selection and hyperparameter tuning in optimizing predictive accuracy for forest structure analysis.

## 8.1 Future Work

Several promising avenues for future research emerge from this study, focusing on improving model robustness, generalization, and real-world applicability for large-scale forest monitoring:

- **Domain Adaptation:** Addressing temporal inconsistencies between VHR and LiDAR datasets through domain adaptation techniques could enhance model stability and improve performance on multi-temporal datasets.
- **DTM Integration:** Incorporating Digital Terrain Model (DTM) data with VHR imagery could provide additional spatial context, enhancing tree bole identification and canopy height estimation, particularly in heterogeneous forest landscapes.
- **Advanced Augmentation:** Exploring more sophisticated data augmentation strategies, such as generative adversarial networks (GANs) or self-supervised learning approaches, could help mitigate overfitting and improve model performance on noisy, multi-temporal datasets.
- **Traditional vs. Deep Learning Comparison:** A formal comparison with traditional remote sensing techniques (e.g., OBIA or pixel-based classifiers) for tree cover mapping and canopy height estimation would provide a clearer understanding of the added value deep learning models offer in forestry applications.
- **Hybrid Architectures:** Combining convolutional and transformer-based models could capture both local and global dependencies, potentially improving spatial prediction tasks like tree centroid localization, where transformers currently underperform.
- **Operational Validation:** Testing the model pipeline on larger and more diverse forest areas would help assess its scalability and operational viability for regional and global forest monitoring applications, ensuring the methods developed are robust and efficient for real-world use.

By addressing these challenges, future work could further enhance the accuracy, robustness, and generalization of deep learning models for forest structure

analysis, providing scalable solutions for automated tree cover mapping and forest inventory.

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## Appendix 1: Detailed Training and Validation Metrics Over Epochs

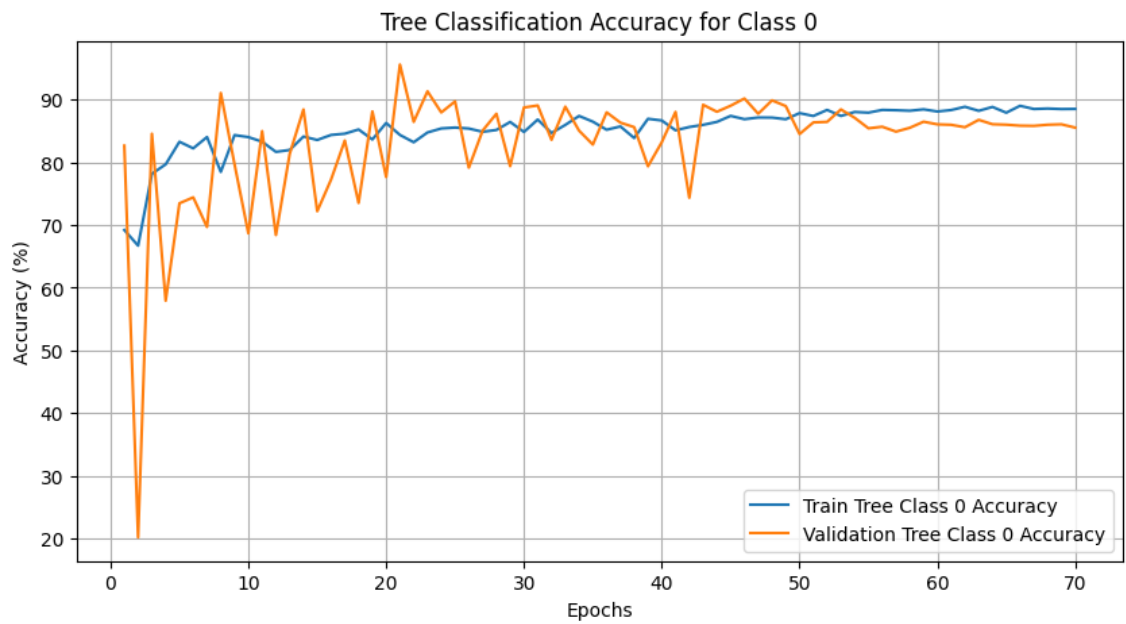


Figure 16: Tree Classification Accuracy for Class 0 of the Best Model Over Epochs

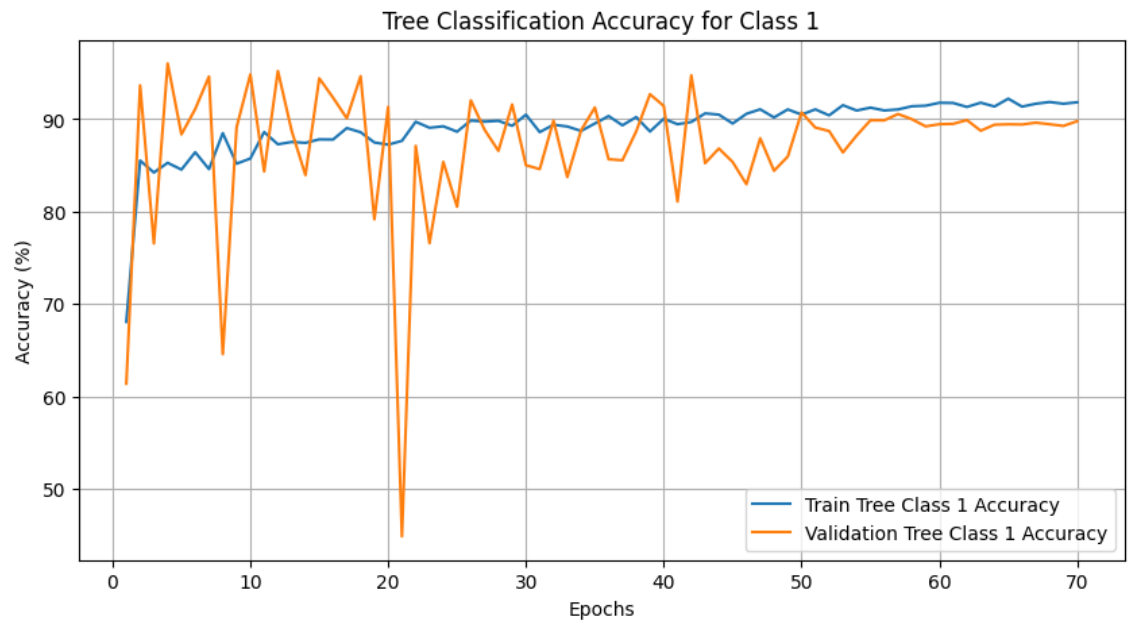


Figure 17: Tree Classification Accuracy for Class 1 of the Best Model Over Epochs

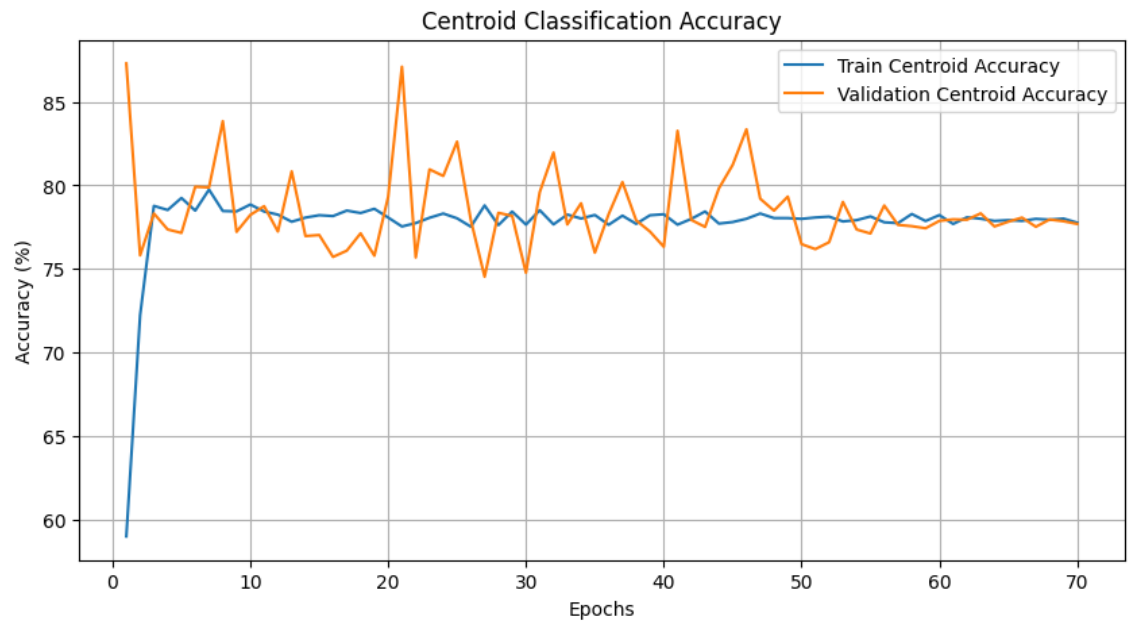


Figure 18: Tree Centroid Classification Accuracy of Best Model Over Epochs

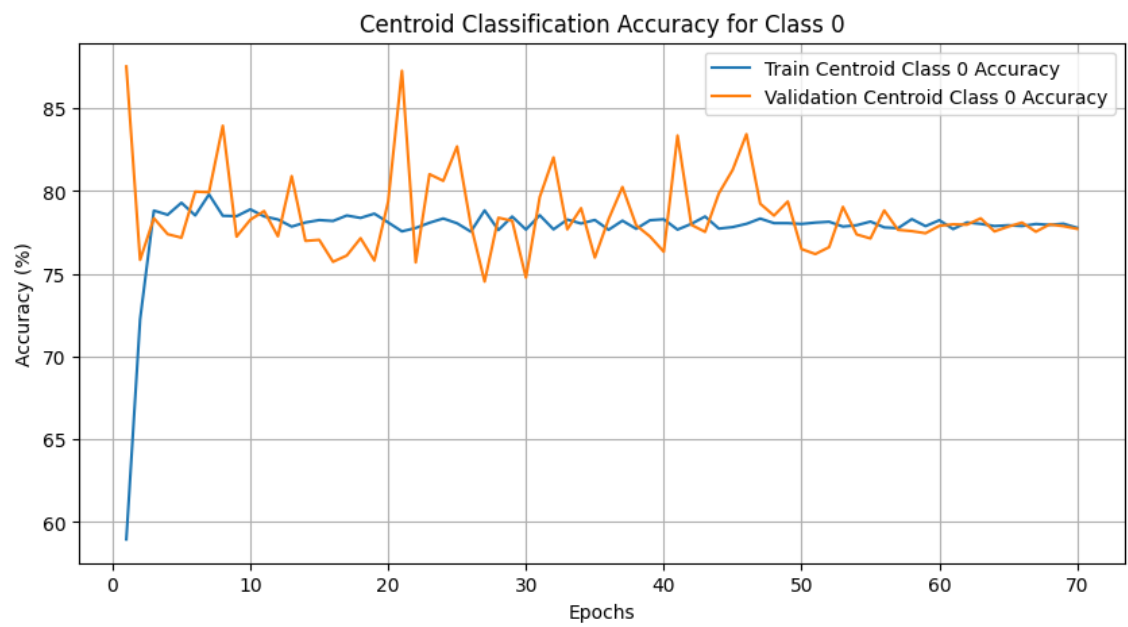


Figure 19: Tree Centroid Classification Accuracy for Class 0 of the Best Model Over Epochs

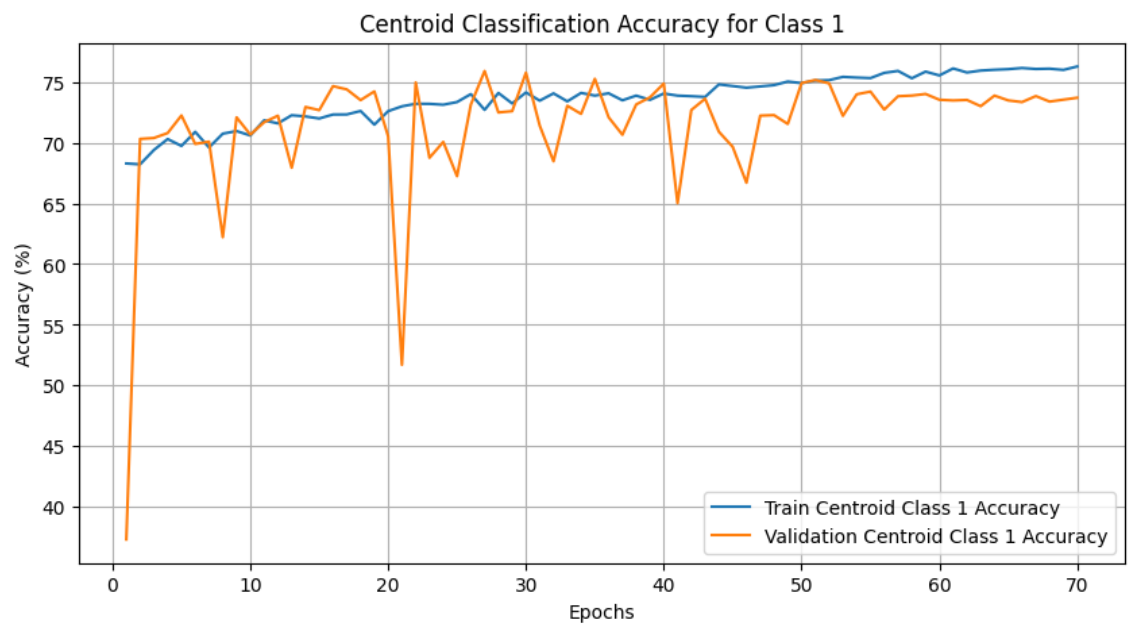


Figure 20: Tree Centroid Classification Accuracy for Class 1 of the Best Model Over Epochs

## Appendix 2: Performance results of all models

The order of the tables is based on the row number in Table 1 in Chapter 7 (Results)

Table 1: Performance Results of Model 1 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	8.41		58.86	68.63	84.40	48.83	60.95	71.47	55.20	36.11	55.18	60.04	35.91	79.77
No	2	5.42	6.91	79.07	71.49	76.12	80.23	75.93	69.85	72.63	82.73	72.67	63.49	82.83	59.71
No	3	4.93	4.48	82.86	84.49	77.48	84.97	70.63	89.62	76.12	78.79	76.14	70.31	78.83	69.30
No	4	4.33	4.20	82.58	85.81	84.55	81.80	71.28	91.19	78.21	77.36	78.25	69.71	77.38	71.96
No	5	4.31	4.20	83.79	82.00	81.00	84.89	89.16	79.35	77.92	70.63	77.95	70.45	70.62	74.87
Yes	6	4.24	4.46	84.78	83.24	81.53	86.06	87.89	81.52	78.25	71.11	78.29	70.69	71.09	74.81
No	7	4.64	4.42	84.59	86.72	83.92	84.86	75.04	91.04	75.37	67.35	75.39	72.39	67.30	79.52
Yes	8	4.67	4.79	85.06	85.24	81.47	86.47	80.96	86.82	78.07	80.97	78.10	70.95	81.03	68.15
No	9	4.36	5.60	83.93	69.36	82.46	84.51	89.16	62.04	77.37	84.25	77.40	70.92	84.36	60.13
No	10	3.96	4.10	86.00	88.19	84.14	86.73	73.27	93.71	79.02	79.12	79.05	70.53	79.16	69.52
No	11	4.51	3.88	80.62	84.76	85.72	78.61	87.58	83.72	80.09	81.21	80.15	64.94	81.27	68.88
No	12	3.80	4.58	86.56	75.91	83.70	87.68	93.37	69.46	79.55	83.82	79.59	70.53	83.91	64.39
No	13	3.89	4.18	85.83	77.79	84.70	86.28	88.51	73.83	79.28	80.66	79.31	70.70	80.72	67.94
Yes	14	3.79	3.63	86.50	87.34	82.66	88.00	84.59	88.35	78.04	80.01	78.06	72.02	80.06	70.45
No	15	4.00	3.88	84.92	87.47	83.38	85.53	77.43	91.19	78.81	74.47	78.84	71.05	74.47	75.05
No	16	3.99	5.07	84.59	79.24	81.33	85.87	82.25	78.12	77.29	80.75	77.31	72.29	80.80	68.80
No	17	4.01	3.81	85.03	81.84	83.16	85.76	85.10	80.64	76.98	81.36	77.00	72.22	81.42	68.47
No	18	3.70	3.65	86.17	83.14	83.83	87.09	86.42	81.93	78.07	74.08	78.10	72.09	74.08	75.40
No	19	3.56	3.58	87.08	84.75	85.26	87.80	87.96	83.57	78.12	79.93	78.15	72.52	79.98	70.55
No	20	3.57	3.99	87.45	78.84	84.47	88.62	92.54	73.77	78.05	81.39	78.07	72.68	81.45	67.98
Yes	21	3.52	3.56	86.99	88.39	85.79	87.46	81.56	90.92	78.69	78.99	78.72	71.97	79.02	71.54
No	22	3.73	4.08	86.77	83.31	85.07	87.43	89.58	80.99	78.52	77.00	78.55	72.02	77.02	72.59
No	23	3.56	3.89	87.29	84.63	84.55	88.37	89.04	83.00	77.56	80.93	77.58	73.06	80.98	69.50
No	24	3.46	3.47	87.59	88.79	85.92	88.24	76.96	93.17	78.33	76.27	78.36	72.78	76.28	74.32
No	25	3.49	3.54	87.42	87.26	85.60	88.14	84.66	88.22	78.59	76.66	78.61	72.53	76.67	74.33
No	26	3.41	3.50	88.40	84.63	85.38	89.58	88.72	83.11	78.51	76.98	78.54	72.88	77.00	73.20
No	27	3.43	3.70	88.06	83.68	84.86	89.32	84.90	83.22	77.94	81.10	77.96	73.35	81.15	69.16

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	28	3.40	3.65	88.24	88.55	84.73	89.61	77.08	92.80	78.52	75.87	78.54	72.84	75.88	74.23
No	29	3.34	3.54	88.50	83.47	84.58	90.03	90.23	80.96	78.12	80.65	78.14	73.40	80.70	69.55
No	30	3.32	3.57	88.34	83.33	85.24	89.56	90.47	80.68	78.49	80.24	78.51	73.03	80.29	69.97
No	31	3.33	3.84	88.81	84.16	85.65	90.05	88.50	82.55	78.07	81.62	78.09	73.58	81.68	68.56
No	32	3.29	3.42	88.55	83.52	85.90	89.59	90.41	80.97	78.75	77.44	78.78	72.93	77.46	72.76
No	33	3.24	3.55	88.45	87.90	86.25	89.31	85.57	88.76	78.20	80.89	78.22	73.60	80.94	69.79
No	34	3.22	3.43	89.16	87.62	85.89	90.45	86.37	88.08	78.49	76.44	78.51	73.38	76.45	74.37
No	35	3.20	3.39	89.06	86.93	86.45	90.08	84.80	87.72	78.02	77.98	78.04	73.92	78.01	72.79
Yes	36	3.26	3.22	88.96	88.99	86.39	89.97	83.58	90.99	78.03	75.49	78.05	73.89	75.49	75.56
Yes	37	3.26	3.38	88.74	89.14	85.73	89.93	81.42	91.99	77.83	80.78	77.85	73.84	80.83	69.60
No	38	3.23	3.35	88.99	87.86	85.57	90.33	86.02	88.54	78.25	76.74	78.27	73.51	76.75	74.16
No	39	3.16	3.24	89.08	88.41	86.48	90.11	84.74	89.76	78.55	75.13	78.58	73.57	75.13	75.87
No	40	3.12	3.44	89.29	84.21	86.54	90.37	90.95	81.71	77.97	79.74	77.99	74.36	79.78	70.85
Yes	41	3.12	3.55	89.02	89.12	87.20	89.73	82.49	91.57	78.69	75.56	78.72	73.56	75.56	75.21
No	42	3.45	3.62	87.60	82.83	84.63	88.77	90.75	79.90	78.42	82.97	78.45	72.74	83.04	66.59
No	43	3.30	3.64	88.76	89.35	85.43	90.07	77.44	93.76	77.77	77.27	77.79	73.84	77.28	73.76
No	44	3.15	3.24	88.97	88.78	86.48	89.94	84.70	90.29	78.22	79.88	78.23	73.98	79.92	71.57
No	45	3.08	3.98	89.40	85.14	86.90	90.38	88.22	84.00	78.15	83.40	78.16	74.13	83.48	65.22
No	46	3.07	3.30	89.38	86.57	86.51	90.50	88.53	85.85	78.31	81.18	78.33	73.98	81.23	69.79
No	47	3.05	3.25	89.45	88.63	87.00	90.41	84.12	90.30	78.28	77.96	78.30	74.25	77.98	73.06
No	48	3.06	3.69	89.64	85.80	86.49	90.88	88.41	84.83	78.09	82.65	78.11	74.47	82.72	67.21
No	49	2.93	3.29	90.06	87.98	87.39	91.10	86.90	88.38	78.15	78.02	78.17	74.53	78.04	73.31
No	50	3.14	3.25	90.12	87.16	87.29	91.23	87.49	87.03	78.37	74.91	78.39	74.51	74.90	75.89
No	51	2.91	3.19	89.88	88.23	88.04	90.61	86.77	88.78	77.87	80.01	77.88	75.10	80.05	71.34
No	52	2.97	3.26	90.37	87.89	87.11	91.65	87.07	88.19	78.23	75.90	78.24	74.93	75.91	75.13
No	53	2.91	3.23	90.27	87.67	87.74	91.26	86.31	88.18	78.04	79.82	78.05	75.13	79.86	71.57
Yes	54	2.83	3.14	90.48	89.27	87.56	91.63	83.52	91.39	78.10	77.00	78.11	75.14	77.01	74.45
No	55	3.15	3.41	89.11	87.20	87.73	89.65	86.71	87.38	78.18	79.23	78.20	74.33	79.26	71.83
No	56	3.12	3.53	89.58	89.10	86.31	90.87	81.42	91.94	77.98	80.47	77.99	74.44	80.51	70.41
No	57	3.03	3.24	89.62	87.59	86.45	90.87	87.35	87.67	78.04	77.30	78.05	74.70	77.32	73.53
No	58	2.86	3.27	89.93	89.26	87.81	90.77	83.16	91.52	78.16	76.19	78.18	74.99	76.20	74.79
No	59	2.86	3.20	90.47	88.62	87.62	91.59	84.75	90.05	77.88	78.29	77.89	75.47	78.31	73.04
Yes	60	2.90	3.27	90.70	89.47	87.49	91.96	82.59	92.01	77.77	78.95	77.78	75.52	78.98	72.26
No	61	2.90	3.36	89.82	87.79	87.64	90.68	86.69	88.19	77.82	78.84	77.83	75.09	78.87	72.27
No	62	2.95	3.41	89.91	88.34	86.96	91.07	81.74	90.78	77.53	80.08	77.54	75.38	80.12	70.68
No	63	3.05	3.33	90.05	88.66	86.83	91.32	84.02	90.38	78.17	78.31	78.19	74.47	78.34	72.82
No	64	2.81	3.23	90.53	87.88	88.21	91.43	86.89	88.24	78.14	78.36	78.16	75.31	78.38	72.49
No	65	2.72	3.14	90.67	89.14	88.41	91.55	83.72	91.14	77.99	75.22	78.00	75.74	75.22	75.54

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	66	2.81	3.17	90.73	88.33	88.14	91.75	85.94	89.21	77.82	77.97	77.83	75.95	77.99	73.05
No	67	2.73	3.21	90.56	87.74	88.17	91.49	87.09	87.98	77.87	79.26	77.88	75.76	79.29	71.91
No	68	2.61	3.34	91.20	88.98	88.68	92.19	84.13	90.78	77.72	78.27	77.73	76.47	78.29	72.90
No	69	2.59	3.25	91.43	88.24	89.04	92.37	86.46	88.90	77.77	74.98	77.77	76.66	74.98	75.11
No	70	2.53	3.22	91.41	88.45	89.18	92.28	85.88	89.40	77.34	77.24	77.34	77.25	77.25	73.75
No	71	2.53	3.23	91.49	88.02	88.94	92.49	85.95	88.79	77.72	78.28	77.73	77.06	78.31	72.25
No	72	2.48	3.12	91.51	88.47	89.55	92.28	84.44	89.96	77.31	76.39	77.31	77.69	76.40	74.20
No	73	2.44	3.11	91.65	88.69	89.52	92.48	84.52	90.23	77.59	76.25	77.59	77.57	76.26	74.59
No	74	2.42	3.12	91.84	88.07	89.43	92.78	85.67	88.95	77.52	77.00	77.52	77.78	77.01	73.51
No	75	2.39	3.12	91.68	88.58	89.90	92.38	85.02	89.90	77.20	77.74	77.20	78.37	77.76	72.89
No	76	2.39	3.12	91.99	88.26	89.59	92.94	84.55	89.63	77.21	78.23	77.21	78.52	78.26	71.93
No	77	2.33	3.11	91.98	87.95	89.74	92.86	85.56	88.84	77.34	77.20	77.33	78.52	77.22	72.98
No	78	2.37	3.13	91.94	88.82	89.90	92.75	83.59	90.75	76.96	77.28	76.95	78.96	77.29	73.28
No	79	2.35	3.13	91.92	88.16	89.82	92.75	85.19	89.25	77.54	78.05	77.54	78.27	78.07	72.04
No	80	2.34	3.14	91.81	88.00	90.02	92.51	84.84	89.16	77.36	75.74	77.36	78.61	75.75	74.08
No	81	2.32	3.16	92.10	87.89	89.96	92.93	85.59	88.74	77.10	77.57	77.09	79.16	77.59	72.08
No	82	2.29	3.13	92.11	88.45	90.13	92.88	83.81	90.16	77.13	76.69	77.12	79.25	76.71	73.37
No	83	2.31	3.11	92.04	88.40	90.22	92.76	84.24	89.94	77.02	76.55	77.01	79.40	76.56	73.36
No	84	2.32	3.13	92.17	88.32	89.80	93.10	83.96	89.93	77.12	76.48	77.11	79.11	76.49	73.34
No	85	2.31	3.12	92.16	88.29	90.02	93.00	84.20	89.81	76.78	77.35	76.76	79.80	77.38	72.49
No	86	2.30	3.12	92.14	88.36	90.15	92.93	83.95	89.99	77.21	76.18	77.20	79.31	76.19	73.55
No	87	2.28	3.12	92.20	88.33	90.02	93.05	84.13	89.88	76.85	77.01	76.84	79.75	77.03	72.66
No	88	2.29	3.13	92.16	88.28	90.20	92.93	84.30	89.76	77.06	76.38	77.04	79.54	76.40	73.26
No	89	2.29	3.13	92.23	88.39	89.77	93.19	83.62	90.16	76.89	76.81	76.88	79.78	76.83	72.93
No	90	2.25	3.13	92.28	88.37	90.10	93.13	83.94	90.02	77.07	76.61	77.05	79.78	76.63	72.96

Table 2: Performance Results of Model 2 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	8.07		56.84	53.14	77.10	48.89	87.02	40.60	80.46	87.49	80.61	47.28	87.69	42.08
No	2	5.73	5.04	79.79	80.24	73.82	82.14	79.22	80.62	70.40	82.77	70.39	72.60	82.87	62.44
No	3	4.88	4.34	81.86	84.01	76.45	83.98	76.89	86.64	79.09	80.00	79.14	68.19	80.06	67.96
No	4	4.74	5.86	82.25	84.79	80.88	82.78	74.77	88.49	77.83	79.57	77.86	70.21	79.62	69.01
No	5	4.40	5.38	82.84	75.08	81.50	83.37	83.63	71.92	78.87	81.70	78.91	69.38	81.77	65.89
No	6	4.55	4.57	83.50	77.71	80.90	84.53	90.65	72.92	77.93	81.05	77.96	70.77	81.11	68.41
Yes	7	4.40	4.08	83.91	85.37	83.81	83.96	81.94	86.64	76.89	80.32	76.92	71.36	80.37	69.50
Yes	8	4.16	3.91	83.57	86.85	85.96	82.62	80.96	89.03	77.85	80.09	77.88	70.92	80.13	69.82
No	9	3.99	3.93	85.34	85.51	84.42	85.70	83.57	86.22	78.83	79.78	78.87	70.55	79.83	70.38
No	10	4.01	4.21	84.75	76.96	84.06	85.02	90.97	71.78	78.74	71.91	78.77	70.75	71.90	73.47
No	11	3.98	5.59	84.61	69.35	86.14	84.01	94.07	60.21	78.00	81.90	78.03	71.23	81.97	65.71
No	12	3.80	5.99	85.89	67.79	82.81	87.09	91.37	59.07	77.48	83.64	77.50	72.45	83.73	62.35
No	13	3.90	4.55	85.69	77.37	84.01	86.35	85.35	74.42	78.69	80.32	78.73	71.10	80.37	69.07
No	14	3.68	3.86	86.65	78.95	84.22	87.61	91.59	74.27	77.98	81.30	78.01	72.34	81.36	68.32
No	15	3.63	4.52	86.60	76.87	84.95	87.24	93.10	70.87	77.93	83.58	77.95	72.62	83.66	65.40
No	16	3.61	3.70	87.42	85.38	83.73	88.86	85.32	85.40	78.11	80.24	78.14	72.51	80.28	70.06
Yes	17	3.61	3.58	86.07	88.22	86.48	85.91	82.07	90.50	78.41	77.12	78.44	72.18	77.14	73.71
No	18	3.73	3.89	86.54	88.40	82.91	87.97	77.90	92.28	77.48	69.16	77.50	72.69	69.12	79.82
No	19	3.60	4.43	87.14	78.51	83.74	88.47	89.01	74.62	77.59	82.05	77.61	72.50	82.12	66.99
No	20	3.69	4.16	87.02	87.79	84.61	87.97	77.20	91.72	77.91	75.67	77.93	72.84	75.68	74.33
No	21	3.61	3.74	87.15	88.21	83.89	88.43	77.20	92.28	77.95	78.15	77.97	72.94	78.17	72.35
No	22	3.68	3.52	86.67	86.43	84.41	87.55	87.14	86.17	77.95	78.19	77.97	72.84	78.21	72.58
No	23	3.39	4.36	88.64	74.55	84.47	90.28	93.34	67.60	78.31	83.75	78.34	73.18	83.85	62.98
No	24	3.41	3.40	88.06	85.86	85.11	89.22	87.60	85.21	78.14	79.25	78.16	73.32	79.29	71.65
No	25	3.36	3.41	88.38	85.61	84.74	89.81	89.47	84.18	77.77	77.59	77.79	73.83	77.61	72.74
Yes	26	3.40	3.68	88.44	88.28	85.33	89.66	84.34	89.74	78.29	72.83	78.31	73.28	72.81	77.30
No	27	3.42	5.95	88.15	63.78	85.15	89.33	93.81	52.67	78.12	85.90	78.14	73.14	86.03	57.05
No	28	3.43	3.75	88.44	82.05	84.78	89.87	84.59	81.10	77.94	80.49	77.96	73.72	80.55	67.90

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	29	3.38	3.31	88.22	86.46	85.04	89.46	87.82	85.96	77.85	78.85	77.87	73.63	78.88	72.14
No	30	3.25	3.93	88.66	80.77	85.76	89.80	92.23	76.53	78.16	80.21	78.18	73.55	80.25	69.60
Yes	31	3.35	3.48	88.90	88.51	86.74	89.74	83.30	90.43	77.79	75.77	77.81	74.05	75.77	75.10
No	32	3.32	4.48	88.35	75.48	85.43	89.49	92.07	69.34	77.68	82.18	77.70	74.04	82.27	63.61
No	33	3.37	3.54	88.05	85.66	86.42	88.69	88.45	84.63	78.32	81.30	78.35	73.21	81.36	67.74
Yes	34	3.27	3.34	88.35	89.39	86.66	89.01	80.87	92.54	77.70	79.95	77.71	74.41	79.99	71.23
No	35	3.27	3.41	88.63	88.39	85.27	89.95	82.73	90.49	77.87	78.11	77.88	73.86	78.14	72.91
No	36	3.34	3.67	88.48	89.05	85.98	89.46	75.00	94.25	77.66	77.19	77.68	74.07	77.21	73.48
No	37	3.37	3.44	88.13	88.04	83.75	89.86	83.51	89.72	77.75	75.32	77.76	73.94	75.32	75.37
No	38	3.34	3.97	88.63	88.53	85.84	89.73	75.48	93.36	78.06	80.33	78.08	73.65	80.38	70.16
No	39	3.35	3.45	88.34	86.58	84.93	89.67	85.68	86.91	77.91	80.27	77.93	73.76	80.31	70.40
No	40	3.19	3.26	88.72	88.97	86.77	89.48	82.75	91.27	78.31	76.40	78.33	73.91	76.41	74.71
No	41	3.19	3.45	88.86	84.41	86.48	89.80	87.75	83.17	77.69	80.94	77.70	74.54	80.99	69.81
No	42	3.20	3.33	89.17	87.87	86.48	90.22	85.68	88.68	77.77	73.90	77.79	74.72	73.89	76.81
No	43	3.10	3.19	89.38	88.39	86.70	90.43	85.96	89.28	78.04	78.25	78.05	74.56	78.28	73.04
No	44	3.08	3.24	89.45	88.00	86.50	90.61	86.60	88.52	78.02	78.59	78.03	74.60	78.62	72.79
No	45	3.10	3.41	89.42	88.44	86.86	90.43	82.58	90.61	77.48	80.09	77.49	75.19	80.13	70.69
No	46	3.02	3.47	89.68	88.51	86.81	90.81	84.49	89.99	78.12	78.72	78.13	74.56	78.75	72.27
No	47	3.03	3.84	89.81	89.33	86.71	91.03	80.36	92.65	78.14	76.44	78.15	74.72	76.44	74.68
No	48	3.05	3.32	88.90	87.91	87.58	89.42	86.70	88.36	78.06	77.99	78.07	74.60	78.01	73.02
No	49	3.05	3.33	89.70	88.31	86.51	90.95	86.63	88.93	77.98	75.11	77.99	74.83	75.11	75.75
No	50	3.02	3.38	89.31	85.36	87.52	90.02	89.82	83.71	77.84	79.88	77.85	74.89	79.93	70.58
No	51	3.04	3.38	89.68	86.80	87.19	90.67	86.91	86.77	77.80	78.04	77.82	75.23	78.07	72.48
No	52	3.04	3.34	89.93	88.87	86.98	91.09	84.35	90.54	77.91	75.55	77.92	75.06	75.55	75.09
Yes	53	2.95	3.13	90.14	89.49	87.92	91.01	82.94	91.92	77.74	76.24	77.75	75.47	76.24	75.04
No	54	3.08	4.07	89.60	78.63	86.55	90.81	92.49	73.50	78.11	82.19	78.13	74.45	82.27	63.38
No	55	3.16	6.07	89.33	57.41	86.04	90.62	97.43	42.60	77.76	87.08	77.77	74.87	87.24	53.44
No	56	3.11	4.58	89.08	88.22	87.73	89.60	77.49	92.19	77.90	72.07	77.92	74.86	72.05	77.50
No	57	3.18	3.90	88.78	89.06	86.92	89.52	79.62	92.55	77.85	74.60	77.87	74.62	74.59	75.76
No	58	3.04	3.23	89.90	88.76	86.54	91.22	84.15	90.46	77.86	78.29	77.88	75.09	78.31	73.05
No	59	3.02	3.36	89.73	88.62	86.61	90.96	82.86	90.75	78.14	77.57	78.15	74.92	77.59	73.16
No	60	2.95	3.29	90.05	89.37	87.33	91.12	81.37	92.32	77.52	76.87	77.53	75.64	76.88	74.47
No	61	2.95	3.47	90.25	86.63	87.48	91.34	87.24	86.41	77.81	79.47	77.82	75.72	79.51	71.55
Yes	62	2.93	3.25	90.26	89.53	87.51	91.34	82.25	92.23	77.84	77.61	77.85	75.55	77.63	73.73
No	63	2.94	3.57	90.24	85.33	87.56	91.29	89.25	83.88	77.94	79.76	77.95	75.55	79.80	70.71
No	64	2.86	3.18	90.42	88.35	87.89	91.42	86.13	89.17	77.66	76.68	77.66	75.96	76.69	74.42
No	65	2.86	3.21	90.50	88.44	88.29	91.36	85.52	89.52	77.92	76.34	77.93	75.76	76.34	74.68

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	66	2.83	3.34	90.47	84.32	88.24	91.34	91.13	81.80	77.75	81.65	77.76	76.04	81.71	68.52
No	67	2.82	3.20	90.33	88.46	88.89	90.89	85.61	89.52	78.16	78.07	78.17	75.88	78.09	73.04
No	68	2.76	3.23	91.11	88.41	88.47	92.14	85.16	89.62	77.54	76.75	77.54	76.67	76.76	74.60
No	69	2.71	3.14	90.98	89.00	88.59	91.91	83.96	90.87	77.68	78.67	77.69	76.66	78.70	72.53
No	70	2.70	3.14	91.26	89.40	88.89	92.18	83.02	91.76	77.73	78.28	77.73	76.78	78.31	73.06
No	71	2.65	3.10	91.37	88.83	88.73	92.41	84.06	90.60	77.59	76.66	77.59	77.20	76.67	74.37
No	72	2.62	3.11	91.45	88.48	89.16	92.36	84.34	90.01	77.60	76.15	77.60	77.36	76.15	74.76
No	73	2.64	3.11	91.48	88.12	89.20	92.38	86.00	88.90	77.66	77.04	77.67	77.29	77.06	73.86
No	74	2.63	3.13	91.59	87.63	89.00	92.60	87.12	87.81	77.69	77.21	77.69	77.21	77.23	73.51
No	75	2.64	3.10	91.39	88.66	89.62	92.09	84.54	90.19	77.27	76.64	77.27	77.89	76.65	74.19
No	76	2.60	3.13	91.66	88.42	89.44	92.54	84.85	89.73	77.51	78.00	77.51	77.81	78.02	72.79
No	77	2.61	3.11	91.76	88.63	89.29	92.73	84.41	90.19	77.72	77.69	77.73	77.56	77.71	73.12
No	78	2.56	3.16	91.79	88.47	89.52	92.68	84.19	90.05	77.60	76.58	77.60	77.80	76.59	73.87
No	79	2.55	3.11	91.82	88.41	89.48	92.75	84.57	89.83	77.36	77.56	77.36	78.28	77.58	73.01
No	80	2.54	3.11	91.79	88.58	89.87	92.54	83.97	90.28	77.47	78.23	77.47	78.18	78.25	72.42
No	81	2.53	3.12	91.98	88.33	89.36	93.02	84.10	89.89	77.57	77.87	77.57	78.23	77.90	72.49
No	82	2.56	3.12	91.82	88.29	89.80	92.61	84.56	89.68	77.39	78.02	77.38	78.33	78.04	72.43
No	83	2.54	3.13	91.94	88.45	89.62	92.85	84.17	90.03	77.48	77.31	77.48	78.33	77.33	73.07
No	84	2.53	3.12	91.89	88.50	89.88	92.68	84.06	90.14	77.45	77.43	77.45	78.51	77.45	73.05
No	85	2.57	3.12	92.03	88.41	89.30	93.10	84.20	89.96	77.36	77.45	77.36	78.46	77.47	72.97
No	86	2.53	3.12	91.95	88.48	89.76	92.81	83.89	90.18	77.32	77.27	77.32	78.58	77.29	73.10
No	87	2.53	3.12	92.00	88.32	89.68	92.91	84.26	89.82	77.45	77.28	77.44	78.51	77.30	72.98
No	88	2.52	3.12	91.92	88.37	89.80	92.75	84.19	89.92	77.24	77.16	77.23	78.71	77.18	73.16
No	89	2.51	3.12	92.01	88.38	89.82	92.87	84.34	89.87	77.35	77.35	77.35	78.70	77.37	72.89
No	90	2.51	3.13	92.02	88.42	89.61	92.97	84.01	90.05	77.36	77.19	77.35	78.67	77.21	73.03
No	91	2.52	3.12	92.01	88.45	89.80	92.88	84.01	90.10	77.13	77.15	77.12	78.89	77.16	73.11
No	92	2.51	3.12	92.00	88.56	89.67	92.92	83.60	90.39	77.34	76.99	77.33	78.75	77.01	73.28

Table 3: Performance Results of Model 3 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	9.20		69.56	74.71	62.11	72.48	39.31	87.81	99.32	90.95	99.76	0.97	91.27	19.54
No	2		7.90	60.03	31.24	74.45	54.36	57.51	21.51	95.81	98.79	96.17	13.11	99.24	0.00
No	3	7.46		76.72	72.77	58.12	84.03	74.56	72.11	94.62	98.00	94.96	18.30	98.41	7.85
No	4	4.66	4.87	83.14	66.88	77.60	85.32	95.02	56.47	94.12	99.55	94.43	24.28	100.00	0.00
No	5	4.52	5.44	82.87	81.48	80.33	83.86	40.62	96.60	94.79	95.30	95.11	21.53	95.64	21.64
Yes	6	4.38	4.23	82.68	81.49	82.65	82.69	83.63	80.69	93.75	92.86	94.05	25.83	93.14	32.04
No	7	4.20	5.93	84.36	59.22	83.89	84.54	96.28	45.51	94.40	99.43	94.71	24.99	99.88	0.74
Yes	8	4.16	3.85	85.27	81.79	82.42	86.39	83.94	80.99	94.48	88.11	94.79	24.38	88.28	49.83
No	9	4.06	4.04	84.81	79.79	83.06	85.49	90.88	75.69	94.12	92.19	94.42	26.51	92.44	36.36
No	10	3.99	3.74	85.61	86.47	83.30	86.52	76.17	90.29	93.93	89.33	94.23	27.11	89.52	46.93
Yes	11	3.96	4.14	85.04	86.65	83.16	85.78	82.01	88.36	93.19	96.10	93.46	32.05	96.45	20.49
No	12	4.09	4.72	85.54	87.92	83.75	86.24	72.12	93.76	93.65	97.76	93.93	30.67	98.15	11.49
No	13	3.86	4.04	86.81	86.32	82.66	88.44	85.34	86.69	94.55	89.68	94.85	26.22	89.87	46.18
Yes	14	4.00	3.99	84.18	87.05	83.88	84.29	81.19	89.21	93.85	96.97	94.14	29.23	97.34	16.12
No	15	4.05	4.21	84.89	76.40	82.91	85.66	92.67	70.38	94.31	92.58	94.60	28.56	92.84	36.37
No	16	4.20		86.31	77.19	79.90	88.83	35.11	92.76	92.69	90.19	92.95	34.60	90.56	9.15
No	17	3.80	3.96	86.27	86.34	82.60	87.72	83.44	87.42	94.02	95.91	94.30	29.57	96.24	21.96
No	18	3.81	3.66	85.78	81.34	85.38	85.94	90.08	78.11	93.86	95.49	94.13	32.00	95.81	24.99
Yes	19	3.75	3.93	85.95	88.52	84.46	86.53	80.38	91.53	93.21	94.18	93.46	36.03	94.46	31.44
No	20	3.79	5.57	86.52	65.01	82.90	87.94	95.35	53.79	93.77	97.60	94.04	33.65	97.98	13.44
No	21	3.99	3.62	83.12	83.69	85.08	82.36	88.28	81.99	94.07	91.22	94.35	31.96	91.44	43.44
No	22	3.86		86.56	71.03	81.74	88.46	93.78	62.62	93.63	94.72	93.90	34.26	95.02	28.03
No	23	5.35	4.14	82.11	87.29	71.57	86.25	81.41	89.47	94.12	92.81	94.41	27.99	93.07	37.00
No	24	3.63	3.81	87.07	87.93	83.44	88.49	81.08	90.47	93.66	95.16	93.92	35.24	95.46	27.65
No	25	3.57	5.32	86.94	66.17	85.74	87.41	95.36	55.37	93.49	96.61	93.75	36.09	96.96	19.05
No	26	3.47	3.49	87.22	88.51	85.18	88.03	79.98	91.66	93.14	92.42	93.39	38.31	92.65	40.47
No	27	3.51	3.84	86.99	88.77	85.15	87.71	78.80	92.46	93.75	91.30	94.01	35.71	91.51	44.63
No	28	3.49	3.58	87.70	86.46	84.87	88.81	83.02	87.73	93.45	95.13	93.70	37.38	95.43	28.70

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	29	3.39	3.38	88.01	87.45	85.01	89.19	86.27	87.89	93.55	91.37	93.81	37.04	91.58	44.91
No	30	3.40	3.41	88.02	87.64	85.79	88.90	84.72	88.72	93.25	94.38	93.49	38.37	94.66	32.65
No	31	3.47	4.11	87.87	80.90	84.62	89.15	90.78	77.25	93.56	94.94	93.81	36.90	95.24	29.40
Yes	32	3.45	3.43	87.63	88.56	83.08	89.42	81.80	91.06	93.35	93.80	93.60	37.71	94.07	35.13
No	33	3.47	3.49	87.29	87.68	85.87	87.85	83.97	89.05	93.32	92.65	93.57	37.61	92.89	39.86
No	34	3.39	3.47	88.10	87.80	85.73	89.02	85.11	88.80	93.44	92.94	93.69	37.81	93.18	38.95
No	35	3.34	3.57	87.98	88.71	85.17	89.09	79.69	92.04	93.31	92.68	93.55	38.54	92.92	39.80
No	36	3.36	3.43	88.02	87.30	85.59	88.97	86.70	87.53	93.49	92.76	93.73	37.71	93.00	39.79
No	37	3.29	3.54	88.41	87.51	86.12	89.31	86.32	87.95	93.29	93.46	93.53	38.81	93.72	36.94
No	38	3.32	3.32	88.67	87.42	85.01	90.11	86.91	87.60	93.19	93.16	93.43	39.31	93.40	38.13
Yes	39	3.25	3.56	88.17	88.63	86.77	88.72	81.79	91.16	93.35	94.37	93.59	38.53	94.65	32.63
No	40	3.38	3.73	87.81	86.57	86.36	88.38	85.38	87.01	93.52	94.04	93.76	37.80	94.32	33.82
No	41	3.21	3.30	88.75	86.81	86.51	89.64	87.88	86.42	93.18	94.02	93.42	39.66	94.29	34.78
No	42	3.22	3.64	88.42	88.93	86.12	89.32	79.62	92.37	93.24	91.84	93.48	39.15	92.06	42.97
No	43	3.23	3.31	88.94	88.03	86.29	89.99	85.95	88.80	93.19	93.06	93.42	39.46	93.31	39.20
No	44	3.27	3.26	88.36	87.49	86.95	88.91	87.16	87.61	93.18	94.32	93.42	39.91	94.59	34.05
No	45	3.18	3.23	88.78	88.11	87.02	89.47	85.18	89.19	93.46	93.32	93.71	38.68	93.57	38.44
No	46	3.20	3.21	88.97	87.10	86.15	90.08	88.33	86.64	93.38	92.79	93.62	39.18	93.03	40.57
No	47	3.15	3.44	88.84	83.96	87.20	89.48	90.40	81.58	93.39	94.22	93.63	39.15	94.50	34.35
No	48	3.15	3.35	89.31	86.05	86.74	90.31	89.34	84.83	93.22	93.55	93.45	39.89	93.80	37.51
Yes	49	3.08	3.22	89.10	89.05	87.29	89.81	84.37	90.78	93.24	92.39	93.48	39.84	92.62	42.31
No	50	3.19	3.29	89.40	86.05	85.55	90.91	89.57	84.75	93.25	93.00	93.49	39.74	93.24	39.47
No	51	3.11	3.37	88.97	88.12	87.03	89.73	85.25	89.19	93.31	93.09	93.55	39.65	93.34	38.77
No	52	3.14	3.75	88.96	79.60	86.87	89.79	91.71	75.12	93.16	93.58	93.40	40.03	93.84	36.21
No	53	3.11	3.78	89.24	89.08	86.64	90.26	74.05	94.64	93.27	93.60	93.50	40.00	93.86	34.87
No	54	3.06	3.19	89.55	88.16	86.89	90.59	86.38	88.82	93.28	93.64	93.51	39.95	93.89	37.16
No	55	3.04	3.16	89.60	88.97	86.91	90.66	85.11	90.39	93.29	94.16	93.53	40.01	94.43	34.69
No	56	3.03	3.23	89.73	88.08	86.87	90.86	87.45	88.31	93.10	92.76	93.33	40.85	93.00	40.81
No	57	3.01	3.21	89.63	88.35	86.63	90.80	86.09	89.18	93.00	93.33	93.22	41.42	93.58	38.44
No	58	2.96	3.25	89.88	88.15	87.73	90.72	87.00	88.57	93.19	93.49	93.42	40.73	93.74	37.82
No	59	3.02	3.19	89.65	88.50	87.94	90.33	86.32	89.30	93.03	92.60	93.26	41.15	92.83	41.77
No	60	2.97	3.25	89.97	87.56	87.37	90.99	87.26	87.67	93.29	93.27	93.52	40.39	93.51	38.88
No	61	2.99	3.32	89.79	89.04	87.49	90.69	84.25	90.81	93.00	93.53	93.23	41.62	93.78	37.01
No	62	2.94	3.14	89.77	88.52	87.80	90.55	86.15	89.40	93.14	93.39	93.37	40.84	93.64	38.45
No	63	2.90	3.12	90.21	87.95	87.54	91.26	86.72	88.40	93.03	93.63	93.26	41.64	93.88	37.58
No	64	2.88	3.22	90.32	88.60	87.76	91.32	86.03	89.55	93.10	93.43	93.33	41.39	93.68	38.21
No	65	2.85	3.12	90.22	87.56	88.33	90.96	87.91	87.44	92.89	93.54	93.12	42.37	93.79	37.85

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
Yes	66	2.89	3.14	90.42	89.14	87.76	91.46	83.78	91.12	93.02	93.05	93.24	41.72	93.29	39.84
No	67	3.19	3.78	88.90	79.83	86.85	89.71	92.52	75.13	93.15	93.83	93.39	40.12	94.09	35.67
No	68	3.00	3.42	89.70	86.87	86.70	90.87	87.22	86.75	93.12	94.20	93.35	40.85	94.47	34.56
No	69	3.14	3.24	89.35	87.22	86.41	90.50	87.86	86.98	93.21	93.26	93.44	40.45	93.50	38.83
No	70	3.01	3.22	89.65	87.26	87.95	90.32	87.63	87.12	93.01	93.98	93.24	41.47	94.25	35.87
No	71	3.00	3.25	89.63	87.77	87.64	90.41	87.61	87.83	93.10	93.68	93.33	40.96	93.93	37.07
No	72	2.88	3.14	90.20	88.71	88.14	91.01	85.35	89.96	93.12	92.10	93.35	41.34	92.32	43.72
No	73	2.82	3.36	90.61	88.62	87.85	91.70	84.50	90.15	92.95	92.17	93.18	42.30	92.39	43.62
Yes	74	2.85	3.13	90.49	89.36	88.34	91.34	82.63	91.86	92.97	92.51	93.19	42.20	92.74	42.27
No	75	3.07	5.64	89.08	60.26	87.22	89.80	94.97	47.41	93.12	97.16	93.35	40.41	97.53	16.55
No	76	3.19	3.32	89.47	89.12	86.30	90.71	83.23	91.30	92.97	93.75	93.20	41.23	94.01	36.49
Yes	77	2.93	3.26	89.98	89.46	87.84	90.82	80.71	92.70	93.25	91.63	93.48	40.61	91.84	44.94
No	78	2.96	3.37	89.84	85.28	86.63	91.09	90.24	83.44	92.92	94.74	93.15	40.67	95.03	31.47
No	79	2.98	3.65	89.43	86.23	87.87	90.04	85.48	86.51	93.12	92.06	93.35	40.90	92.28	42.86
No	80	2.94	3.16	90.20	88.57	87.55	91.25	84.72	89.99	92.85	92.29	93.08	42.33	92.52	43.23
No	81	2.85	3.30	90.47	86.98	87.92	91.47	88.21	86.52	92.83	95.23	93.05	42.81	95.53	29.95
No	82	2.80	3.26	90.49	86.98	88.79	91.16	87.77	86.69	92.96	93.90	93.19	42.21	94.16	35.99
No	83	2.81	3.18	90.32	87.31	88.25	91.14	87.91	87.09	92.84	92.17	93.06	42.79	92.39	43.62
No	84	2.80	3.16	90.74	89.12	89.00	91.43	82.48	91.57	92.94	91.92	93.16	42.61	92.14	44.76
No	85	2.66	3.16	91.20	88.24	88.92	92.09	84.36	89.68	92.73	92.53	92.95	43.85	92.76	42.23
No	86	2.75	3.14	91.16	88.48	88.59	92.17	84.85	89.82	92.80	92.27	93.02	43.36	92.50	43.13
No	87	2.65	3.14	91.26	89.18	89.14	92.10	81.76	91.92	92.81	91.43	93.03	43.42	91.63	46.12
No	88	2.65	3.14	91.43	88.93	89.17	92.31	83.10	91.08	92.67	92.93	92.89	43.97	93.17	40.35
No	89	2.59	3.11	91.41	88.02	89.62	92.11	85.52	88.95	92.58	92.40	92.79	44.59	92.63	42.76
No	90	2.59	3.20	91.61	88.33	89.39	92.48	83.75	90.03	92.70	91.74	92.92	44.23	91.95	45.41
No	91	2.58	3.15	91.75	88.13	89.23	92.74	84.91	89.33	92.47	93.13	92.68	45.28	93.38	39.55
No	92	2.56	3.17	91.71	88.46	90.01	92.38	84.10	90.07	92.56	91.58	92.77	45.08	91.78	46.18
No	93	2.55	3.16	91.85	88.30	89.72	92.69	84.14	89.85	92.52	92.26	92.73	45.37	92.49	43.28
No	94	2.52	3.15	91.92	88.45	89.50	92.88	83.95	90.12	92.42	92.15	92.62	45.83	92.37	43.79
No	95	2.55	3.15	91.85	87.93	89.90	92.61	85.64	88.78	92.51	91.91	92.72	45.36	92.12	44.88
No	96	2.54	3.15	92.02	88.42	90.03	92.80	83.85	90.10	92.36	92.29	92.56	46.04	92.51	43.09
No	97	2.51	3.14	92.07	88.24	89.79	92.96	84.13	89.76	92.44	92.22	92.65	45.72	92.44	43.15
No	98	2.52	3.16	92.06	88.43	89.73	92.98	83.78	90.14	92.35	92.01	92.56	46.13	92.23	44.07
No	99	2.50	3.15	92.07	88.30	89.98	92.89	84.00	89.89	92.44	91.78	92.64	45.95	91.99	45.06
No	100	2.50	3.16	92.03	88.14	89.88	92.87	84.42	89.52	92.38	92.50	92.59	46.13	92.73	42.08

Table 4: Performance Results of Model 4 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	8.33		71.12	54.48	62.54	74.50	87.85	42.14	64.29	78.78	64.27	70.21	78.95	42.24
No	2	5.97	6.83	75.42	68.91	74.36	75.83	81.48	64.26	76.10	79.75	76.14	67.48	79.81	67.42
No	3	4.86	5.52	81.79	81.47	77.14	83.62	38.46	97.39	77.81	63.70	77.84	70.02	63.62	79.85
No	4	4.61	4.82	83.50	82.46	78.33	85.54	72.36	86.20	78.79	76.26	78.84	69.13	76.28	72.15
No	5	5.61	5.61	81.86	74.85	76.94	83.80	91.19	68.80	78.26	78.75	78.30	68.08	78.80	67.78
No	6	4.99	4.81	80.56	84.48	76.33	82.22	68.72	90.31	77.55	72.46	77.58	69.24	72.45	74.75
No	7	4.37	4.32	83.49	80.51	81.12	84.42	84.30	79.11	78.70	80.44	78.74	70.30	80.50	69.02
Yes	8	4.42	4.32	83.82	83.13	81.21	84.84	80.04	84.28	78.20	76.10	78.23	70.63	76.11	73.30
No	9	4.32	4.89	83.60	84.35	79.83	85.08	49.89	97.10	77.72	76.18	77.74	71.25	76.20	72.20
No	10	4.26	4.43	83.96	75.64	82.93	84.36	83.01	72.92	78.63	80.59	78.67	70.72	80.65	67.74
No	11	4.13	4.21	84.29	76.89	82.86	84.85	87.93	72.80	78.28	76.46	78.31	71.14	76.49	71.34
No	12	4.03	4.44	84.42	78.06	82.83	85.05	88.80	74.09	78.06	82.02	78.08	71.68	82.09	67.03
No	13	4.03	3.98	85.09	86.52	83.13	85.86	79.67	89.05	78.41	75.35	78.44	71.41	75.35	74.60
Yes	14	3.99	3.84	85.77	86.19	82.81	86.93	82.93	87.40	77.46	74.48	77.48	72.52	74.47	75.63
No	15	4.08	4.15	85.07	79.26	82.23	86.19	86.87	76.44	77.66	81.32	77.69	72.29	81.38	67.55
No	16	4.06	4.48	85.90	77.04	80.19	88.14	84.45	74.29	77.03	80.99	77.05	73.11	81.05	66.65
No	17	3.92	4.36	85.75	79.14	82.00	87.23	85.89	76.64	77.98	76.02	78.01	72.22	76.03	73.42
No	18	3.92	3.92	85.14	85.40	84.54	85.37	85.52	85.35	77.06	81.70	77.07	73.16	81.77	67.48
Yes	19	3.79	3.90	86.00	87.37	85.34	86.26	81.79	89.44	78.79	73.04	78.83	71.67	73.02	76.65
No	20	3.87	4.57	86.86	87.67	82.53	88.56	78.71	90.99	77.79	75.07	77.81	72.80	75.07	74.99
No	21	3.84	4.01	86.35	87.41	84.63	87.02	76.27	91.54	78.08	75.20	78.10	72.30	75.20	75.17
No	22	3.85	4.13	86.38	87.16	82.47	87.91	80.61	89.58	77.61	76.47	77.63	72.73	76.48	73.85
No	23	3.81	3.92	87.01	82.96	83.39	88.43	86.46	81.66	77.85	79.51	77.87	73.00	79.55	71.04
No	24	3.88	3.93	85.84	83.22	84.80	86.25	88.65	81.22	78.05	80.55	78.07	72.77	80.60	68.65
No	25	3.78	3.83	85.99	86.25	85.02	86.37	79.43	88.78	78.03	78.27	78.06	72.61	78.30	72.09
No	26	3.76	3.80	86.95	85.55	83.37	88.35	78.44	88.18	77.28	81.16	77.30	73.54	81.21	68.76
No	27	3.70	5.24	87.38	71.54	84.19	88.64	91.85	64.03	77.75	80.28	77.77	73.45	80.33	69.36
Yes	28	3.55	3.80	87.49	88.23	85.72	88.19	81.72	90.65	77.96	79.25	77.98	73.29	79.29	71.26
No	29	3.64	3.69	87.17	88.19	83.94	88.44	79.83	91.29	78.27	72.30	78.29	73.05	72.28	76.87
Yes	30	3.57	3.89	87.57	88.33	84.39	88.82	80.68	91.16	77.78	76.77	77.80	73.71	76.79	74.02
No	31	3.64	4.66	86.89	73.87	84.01	88.02	94.94	66.08	78.24	81.38	78.26	72.92	81.44	68.28

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	32	3.60	3.78	87.14	83.63	83.91	88.40	85.89	82.80	77.20	81.87	77.21	74.04	81.93	68.36
No	33	3.56	3.52	88.29	87.05	84.82	89.65	86.03	87.43	78.03	79.86	78.05	73.78	79.90	71.10
No	34	3.38	3.51	88.52	85.02	85.73	89.62	89.07	83.52	78.29	78.74	78.31	73.72	78.77	72.12
No	35	3.38	3.43	88.36	85.00	85.88	89.34	86.73	84.36	77.97	80.73	77.98	74.16	80.78	69.91
No	36	3.35	3.76	88.35	87.05	85.70	89.39	82.43	88.75	78.21	76.59	78.23	73.86	76.61	73.31
No	37	3.46	3.62	87.72	86.21	84.85	88.85	88.01	85.54	77.90	80.35	77.92	74.02	80.40	70.66
Yes	38	3.29	3.82	88.43	88.75	86.74	89.10	82.10	91.21	78.36	75.77	78.38	74.12	75.77	75.06
No	39	3.45	3.85	86.98	81.76	85.11	87.71	91.84	78.03	77.89	79.74	77.91	73.93	79.78	70.62
No	40	3.35	3.52	88.45	86.54	85.32	89.67	84.72	87.22	78.17	77.23	78.18	73.92	77.25	73.42
No	41	3.48	3.80	87.48	88.56	85.62	88.22	78.36	92.33	77.04	72.63	77.05	74.47	72.61	77.59
No	42	3.29	3.51	88.13	87.84	86.77	88.67	85.97	88.53	78.49	78.51	78.51	73.70	78.54	72.76
No	43	3.33	3.45	87.56	87.95	87.07	87.75	84.84	89.10	78.24	76.35	78.26	73.88	76.35	74.60
No	44	3.27	3.72	88.71	87.20	86.41	89.62	87.33	87.15	78.10	80.20	78.12	74.23	80.24	70.53
No	45	3.32	3.58	88.29	89.09	86.55	88.97	79.77	92.54	77.91	77.43	77.92	74.53	77.44	73.69
Yes	46	3.25	3.29	88.54	88.72	85.70	89.66	83.92	90.50	77.57	77.82	77.58	74.89	77.84	73.56
No	47	3.28	3.94	87.79	87.65	86.68	88.23	83.75	89.09	77.96	78.95	77.97	74.29	78.98	72.00
No	48	3.50	4.16	87.49	89.09	85.83	88.14	74.26	94.58	78.80	74.48	78.83	73.03	74.47	75.85
No	49	3.44	3.65	88.01	84.35	86.01	88.80	89.21	82.55	77.58	79.39	77.59	74.56	79.43	70.88
No	50	3.24	3.51	88.83	87.88	86.31	89.81	85.08	88.92	78.09	75.31	78.11	74.56	75.31	75.96
Yes	51	3.25	3.88	88.74	88.97	86.65	89.56	80.58	92.07	77.60	74.19	77.61	75.18	74.18	76.65
No	52	3.25	3.38	88.75	87.96	86.40	89.68	85.83	88.75	78.37	77.71	78.39	74.17	77.73	73.55
No	53	3.29	3.48	88.80	88.31	85.78	89.99	82.63	90.41	77.69	78.44	77.71	74.87	78.47	72.42
No	54	3.44	3.40	87.96	87.79	85.74	88.83	82.67	89.69	77.78	80.52	77.79	74.65	80.57	70.24
No	55	3.33	3.64	88.22	82.02	86.56	88.88	88.95	79.46	77.75	82.21	77.76	74.41	82.28	66.95
No	56	3.22	3.64	88.90	88.89	86.39	89.89	78.52	92.73	78.29	73.64	78.31	74.35	73.62	76.83
No	57	3.12	3.65	88.98	88.91	87.18	89.69	75.78	93.77	77.93	73.69	77.94	75.14	73.68	76.72
No	58	3.22	3.25	89.40	86.66	86.32	90.61	87.97	86.18	77.76	76.81	77.78	75.41	76.82	74.44
No	59	3.12	3.47	88.85	87.56	87.47	89.40	86.18	88.07	77.67	80.21	77.68	75.48	80.25	70.85
No	60	3.07	3.24	89.32	88.72	87.42	90.06	84.92	90.13	77.92	75.13	77.93	75.36	75.13	75.97
Yes	61	3.10	3.34	89.13	89.14	87.71	89.69	81.94	91.81	77.72	73.45	77.73	75.82	73.43	77.06
No	62	3.19	3.39	89.39	88.80	85.44	90.95	79.48	92.25	77.89	76.86	77.91	74.98	76.87	74.12
No	63	3.12	3.44	89.12	85.28	87.11	89.91	89.70	83.64	77.94	77.80	77.95	75.21	77.82	72.24
No	64	3.28	3.53	88.22	88.15	86.43	88.92	85.02	89.30	77.60	79.63	77.61	75.15	79.67	71.29
No	65	3.20	3.58	88.84	87.83	87.19	89.49	86.74	88.24	77.63	78.10	77.64	75.47	78.12	73.04
No	66	3.10	3.32	89.59	88.68	86.64	90.75	84.79	90.12	77.68	74.25	77.69	75.82	74.24	75.96
No	67	3.02	3.29	89.57	87.44	87.53	90.37	86.64	87.73	77.12	76.75	77.13	76.62	76.76	74.42
No	68	3.07	3.21	89.50	87.83	87.49	90.29	87.45	87.97	77.79	75.57	77.80	75.99	75.58	75.16

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	69	2.95	3.17	90.07	88.58	87.58	91.05	85.72	89.64	77.10	75.16	77.10	77.02	75.16	75.63
No	70	2.91	3.20	90.06	88.95	87.99	90.87	84.63	90.55	77.40	77.46	77.41	76.84	77.48	73.70
Yes	71	2.92	3.26	90.12	89.31	87.85	91.01	82.74	91.74	77.19	76.15	77.19	77.24	76.16	75.05
No	72	3.11	3.44	89.39	87.52	87.04	90.32	84.84	88.51	77.37	77.29	77.37	76.26	77.31	73.44
No	73	3.04	3.45	89.77	89.26	87.37	90.71	81.81	92.01	77.15	77.78	77.15	76.91	77.80	73.53
No	74	3.01	3.27	89.64	86.00	87.72	90.39	88.16	85.20	77.09	81.42	77.09	77.07	81.47	68.86
No	75	2.96	3.21	90.23	87.90	87.41	91.33	86.97	88.24	77.02	80.49	77.02	77.02	80.53	70.58
No	76	2.97	3.48	89.80	85.72	87.26	90.80	88.94	84.53	76.80	80.42	76.79	77.36	80.47	68.90
No	77	2.89	3.21	90.06	88.40	88.49	90.67	85.68	89.41	76.91	75.98	76.91	77.84	75.98	74.96
No	78	2.90	3.18	90.57	88.81	87.49	91.78	85.02	90.21	76.92	75.64	76.91	78.02	75.64	74.97
No	79	2.86	3.20	90.36	88.33	88.19	91.21	85.78	89.27	76.47	77.14	76.46	78.42	77.15	73.60
No	80	2.86	3.29	90.40	88.28	88.09	91.31	85.06	89.47	76.93	74.92	76.93	78.31	74.92	75.03
No	81	2.78	3.15	90.60	89.10	88.90	91.27	83.39	91.21	76.40	75.33	76.39	79.17	75.33	75.16
No	82	2.80	3.18	90.67	87.91	88.38	91.57	86.08	88.59	76.65	77.27	76.64	79.00	77.29	73.00
No	83	2.80	3.28	90.74	88.80	88.77	91.52	83.19	90.87	76.13	75.09	76.12	79.76	75.09	75.17
No	84	2.86	3.21	90.91	88.25	87.93	92.08	85.35	89.32	75.94	77.03	75.92	80.11	77.05	73.13
No	85	2.78	3.19	90.77	88.14	88.81	91.54	85.91	88.96	76.52	75.49	76.51	79.66	75.49	74.24
No	86	2.79	3.19	90.97	87.92	88.58	91.90	86.08	88.60	76.02	75.57	76.00	80.27	75.58	74.06
No	87	2.77	3.20	90.80	88.26	89.28	91.40	85.20	89.39	75.83	76.09	75.81	80.54	76.10	73.61
No	88	2.76	3.20	91.07	88.56	88.71	91.99	83.98	90.25	75.76	75.42	75.74	80.89	75.42	74.46
No	89	2.76	3.20	90.95	88.28	88.93	91.74	84.99	89.49	76.00	76.62	75.98	80.69	76.64	73.25
No	90	2.75	3.20	90.83	88.10	89.17	91.48	85.46	89.08	75.89	76.00	75.87	80.89	76.01	73.48
No	91	2.74	3.20	90.99	87.85	88.90	91.81	85.78	88.62	75.92	76.21	75.89	80.90	76.22	73.23
No	92	2.74	3.21	91.11	88.24	88.86	92.00	84.59	89.59	75.62	76.04	75.59	81.36	76.05	73.60
No	93	2.72	3.21	90.97	88.08	89.36	91.60	85.17	89.16	76.06	75.47	76.04	80.97	75.48	73.77
No	94	2.72	3.20	91.13	88.19	89.05	91.94	85.00	89.37	75.69	75.32	75.67	81.53	75.33	74.03
No	95	2.75	3.22	91.23	88.33	88.68	92.23	84.48	89.75	75.37	75.91	75.34	81.91	75.92	73.64
No	96	2.73	3.21	90.96	87.92	89.50	91.54	85.43	88.85	75.72	75.64	75.70	81.69	75.65	73.65
No	97	2.75	3.20	91.08	88.18	88.96	91.91	84.83	89.42	75.43	75.40	75.40	81.68	75.41	73.91
No	98	2.74	3.21	91.06	88.16	89.24	91.78	84.78	89.40	75.53	75.45	75.50	81.76	75.46	73.87
No	99	2.73	3.21	91.09	88.19	88.98	91.91	84.91	89.40	75.78	75.68	75.75	81.42	75.69	73.61
No	100	2.70	3.21	91.11	88.16	89.16	91.88	84.88	89.38	75.48	75.48	75.45	81.93	75.49	73.70

Table 5: Performance Results of Model 5 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	9.10	9.31	51.97	72.99	57.71	49.72	0.00	100.00	45.08	99.55	44.97	69.80	100.00	0.00
No	2			70.97	64.83	71.44	70.78	84.23	57.65	74.07	81.66	74.10	67.19	81.81	48.22
No	3		9.38	64.62	27.01	73.14	61.27	100.00	0.00	74.71	76.62	74.80	53.29	76.64	70.62
No	4	7.24	8.81	62.74	32.91	83.62	54.53	99.05	8.44	76.24	94.55	76.29	63.49	94.88	22.72
No	5	6.64	7.86	73.91	47.83	78.93	71.93	91.69	31.61	78.68	93.16	78.75	62.12	93.47	25.80
No	6	6.64	5.10	72.48	83.30	73.56	72.06	61.60	91.33	75.59	75.50	75.64	64.52	75.52	71.15
No	7	6.65		66.97	65.82	78.20	62.56	88.47	57.45	75.06	85.18	75.12	62.55	85.32	54.32
No	8	5.20	6.00	80.78	74.79	79.57	81.26	84.87	71.06	76.53	77.44	76.56	69.25	77.47	70.65
No	9	7.01	5.69	73.45	60.91	71.02	74.40	95.31	48.18	76.37	87.91	76.41	66.81	88.08	50.75
No	10	5.44	4.39	75.45	76.94	80.16	73.59	90.21	72.03	76.83	75.82	76.86	69.23	75.84	70.90
No	11	4.79	6.80	79.98	54.52	80.24	79.87	97.39	38.66	77.96	82.28	77.99	69.71	82.36	65.05
No	12	4.58	4.30	82.28	76.73	83.04	81.98	86.99	72.93	79.86	79.72	79.91	68.08	79.78	66.56
No	13	4.73	6.49	82.17	58.31	81.11	82.59	92.41	45.69	76.17	81.94	76.19	70.85	82.02	64.65
No	14	5.05	5.26	77.22	73.01	79.27	76.41	79.60	70.58	79.78	81.05	79.84	65.82	81.12	66.80
No	15	4.41	5.60	83.25	63.43	81.35	83.99	91.39	53.08	78.56	75.93	78.60	69.87	75.95	71.07
Yes	16	4.85	4.48	80.84	84.36	78.59	81.72	82.02	85.23	77.22	71.14	77.25	70.71	71.12	76.75
No	17	4.38	4.31	85.00	86.73	80.59	86.73	72.61	91.95	77.92	72.37	77.95	71.09	72.35	76.77
No	18	4.24	4.40	83.92	82.01	83.76	83.99	84.94	80.92	78.36	78.26	78.39	70.66	78.30	71.09
No	19	4.37	6.95	82.50	56.39	84.83	81.58	95.25	42.02	79.14	85.60	79.18	69.40	85.74	54.51
No	20	4.20	4.10	84.70	87.24	82.82	85.43	69.94	93.64	78.06	76.83	78.09	71.72	76.85	72.27
No	21	4.31	4.40	83.53	80.14	80.24	84.82	90.79	76.20	78.12	81.86	78.15	70.61	81.93	67.26
No	22	4.27	4.07	83.47	85.43	84.88	82.91	79.29	87.71	78.82	79.74	78.86	70.34	79.79	69.49
No	23	4.22	5.52	84.44	66.30	82.40	85.24	93.34	56.29	77.88	82.43	77.91	70.63	82.51	64.69
No	24	4.14	4.22	84.40	84.68	82.15	85.28	75.01	88.26	78.43	78.50	78.47	71.13	78.53	71.02
Yes	25	4.21	3.93	84.52	85.65	81.36	85.75	83.96	86.28	77.99	79.06	78.02	71.35	79.09	70.66
No	26	4.10	3.90	85.10	84.01	82.73	86.03	87.28	82.79	77.83	81.46	77.85	71.86	81.52	68.43
No	27	3.92	4.64	84.82	74.10	81.45	86.14	92.40	67.33	77.99	82.55	78.02	71.65	82.64	64.67
Yes	28	4.12	3.70	84.84	86.24	85.14	84.73	84.67	86.82	78.05	80.89	78.08	71.68	80.94	69.02
No	29	3.87	3.88	85.23	87.67	84.16	85.65	77.72	91.35	77.79	79.42	77.82	72.50	79.46	69.93
No	30	3.87	3.90	85.71	81.17	83.36	86.64	87.06	78.99	78.28	80.05	78.30	71.95	80.10	70.11
No	31	3.67	3.65	86.96	88.16	85.06	87.70	75.72	92.77	78.43	74.22	78.46	72.06	74.22	75.80

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	32	4.03	3.90	85.12	80.83	80.93	86.76	88.75	77.90	77.03	82.61	77.05	72.70	82.68	66.56
No	33	3.97	5.39	85.09	64.68	80.66	86.84	89.94	55.34	77.87	84.69	77.89	72.26	84.81	59.04
No	34	3.83	3.77	86.00	81.32	83.33	87.04	89.29	78.37	78.16	76.56	78.19	72.04	76.58	72.92
No	35	3.78	3.99	85.26	85.74	84.67	85.49	80.43	87.71	77.99	73.48	78.01	72.34	73.47	75.81
No	36	3.68	4.22	86.94	88.09	83.73	88.20	77.02	92.19	78.45	74.89	78.48	72.45	74.89	75.34
Yes	37	3.54	3.51	86.93	87.33	86.26	87.20	83.43	88.77	78.48	77.79	78.51	72.68	77.82	73.14
No	38	3.85	4.34	84.16	76.49	85.77	83.53	89.64	71.62	78.58	78.30	78.62	71.26	78.34	69.82
No	39	3.99	3.67	85.65	86.06	83.59	86.46	87.05	85.70	78.08	80.33	78.10	72.41	80.37	70.10
No	40	4.12	3.86	85.07	87.45	81.44	86.50	78.75	90.67	78.10	79.17	78.13	71.76	79.21	71.12
No	41	3.94	4.96	85.87	71.89	82.80	87.08	92.99	64.09	78.20	82.90	78.23	72.59	82.98	65.23
Yes	42	3.76	3.59	86.87	87.96	85.16	87.54	84.23	89.34	78.59	76.71	78.62	72.35	76.72	74.08
No	43	3.83	3.79	85.96	86.61	82.94	87.15	83.54	87.74	77.38	79.78	77.40	73.03	79.82	70.72
No	44	3.71	4.17	86.15	87.64	84.48	86.81	71.92	93.45	77.74	75.59	77.76	73.14	75.60	73.48
No	45	3.77	3.85	86.37	86.77	83.67	87.43	82.10	88.50	78.19	77.73	78.22	72.29	77.76	72.30
No	46	3.63	3.62	85.72	88.03	86.49	85.42	81.62	90.39	78.38	78.46	78.41	72.66	78.49	71.96
No	47	3.40	4.29	87.49	78.83	86.34	87.94	91.23	74.24	78.43	81.49	78.46	73.31	81.55	67.83
No	48	3.45	3.60	87.22	86.39	85.87	87.75	86.34	86.40	78.09	77.56	78.11	73.40	77.58	73.13
No	49	3.42	3.60	88.18	85.72	84.42	89.66	85.60	85.76	78.28	79.95	78.30	73.53	79.99	70.97
No	50	3.43	3.53	87.96	84.86	85.80	88.81	84.34	85.06	78.00	77.94	78.02	73.87	77.96	72.65
No	51	3.43	3.55	86.76	87.79	86.08	87.02	84.52	89.01	77.77	73.09	77.79	74.08	73.07	77.23
No	52	3.32	3.80	88.46	89.08	85.23	89.73	79.24	92.72	77.97	77.25	77.99	74.06	77.27	73.71
No	53	3.38	3.55	88.22	85.53	84.61	89.64	88.90	84.28	77.82	76.91	77.84	74.03	76.92	73.83
Yes	54	3.40	3.57	87.46	88.11	87.14	87.58	82.37	90.23	77.82	76.79	77.83	74.31	76.80	73.50
No	55	3.58	3.56	87.13	84.93	82.90	88.79	86.15	84.48	78.15	77.55	78.18	73.19	77.57	72.83
No	56	3.56	4.15	87.44	74.45	84.91	88.43	94.74	66.94	77.65	82.29	77.67	73.63	82.36	66.22
No	57	3.51	4.64	87.14	86.85	85.96	87.61	60.13	96.74	77.65	77.17	77.66	73.96	77.19	72.40
No	58	3.49	3.58	87.95	85.96	83.05	89.87	85.17	86.25	77.52	78.45	77.53	74.14	78.48	72.04
No	59	3.47	3.43	87.79	85.72	85.56	88.66	89.02	84.50	77.88	79.45	77.90	74.00	79.49	70.97
Yes	60	3.33	3.63	88.31	88.64	85.27	89.50	81.34	91.34	78.38	74.88	78.40	73.78	74.87	75.73
No	61	3.41	3.70	88.11	85.38	86.85	88.61	87.05	84.77	77.72	81.31	77.73	74.21	81.36	69.29
No	62	3.45	3.49	88.06	82.53	84.58	89.42	92.11	78.99	78.14	79.22	78.16	73.87	79.25	71.65
No	63	3.23	3.33	88.35	87.82	87.23	88.79	85.96	88.51	77.96	76.39	77.97	74.52	76.39	74.81
No	64	3.19	3.48	88.83	88.10	86.62	89.69	84.35	89.48	77.92	76.34	77.94	74.59	76.35	74.71
No	65	3.33	3.26	87.74	86.90	86.54	88.21	87.63	86.63	78.29	77.80	78.31	74.25	77.82	73.38
No	66	3.24	3.51	88.92	85.71	85.89	90.11	88.70	84.60	78.09	81.09	78.11	74.42	81.14	69.66
No	67	3.23	3.31	89.09	88.44	86.28	90.20	83.68	90.20	77.79	77.89	77.80	74.83	77.91	72.99
No	68	3.13	3.31	88.85	86.84	86.66	89.71	87.78	86.49	78.34	77.32	78.36	74.56	77.34	73.56

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
Yes	69	3.19	3.25	88.43	88.65	85.74	89.49	84.03	90.36	77.73	77.49	77.74	75.11	77.51	73.86
No	70	3.36	4.41	88.39	86.86	86.02	89.32	65.66	94.70	77.67	76.17	77.68	74.48	76.18	73.37
No	71	3.37	4.07	87.67	83.01	86.26	88.22	88.78	80.87	77.89	77.91	77.90	74.03	77.93	72.30
No	72	3.51	3.99	87.57	79.95	84.52	88.76	90.11	76.19	77.34	83.16	77.36	74.32	83.24	65.61
No	73	3.46	4.03	87.17	87.30	85.93	87.66	75.59	91.63	77.64	78.74	77.65	74.28	78.78	71.68
No	74	3.28	3.29	88.14	88.18	85.86	89.04	83.22	90.02	78.40	75.93	78.42	73.91	75.93	75.36
No	75	3.18	3.33	88.97	86.45	85.98	90.14	88.82	85.57	78.24	74.53	78.25	74.46	74.53	76.13
No	76	3.17	3.43	89.13	85.10	86.19	90.28	90.19	83.21	77.67	79.77	77.69	74.98	79.81	70.76
No	77	3.18	3.42	88.51	87.67	86.56	89.28	86.94	87.95	77.77	79.94	77.78	74.98	79.98	71.05
No	78	3.11	3.28	89.35	86.64	86.56	90.45	88.60	85.92	78.38	78.27	78.40	74.67	78.30	72.74
No	79	3.12	3.33	89.16	86.34	87.40	89.85	88.97	85.36	78.09	76.24	78.10	75.12	76.24	74.78
No	80	3.09	3.28	89.38	86.91	87.64	90.06	87.79	86.59	77.87	79.58	77.88	75.37	79.61	71.77
No	81	3.05	3.23	89.69	86.85	86.63	90.90	88.03	86.42	78.08	79.05	78.10	75.20	79.09	72.00
Yes	82	3.01	3.29	89.59	88.90	87.71	90.33	83.00	91.08	77.92	76.00	77.93	75.59	76.00	75.11
No	83	3.28	3.65	88.21	83.80	85.91	89.11	87.59	82.40	77.86	81.90	77.88	74.33	81.96	67.93
No	84	3.22	3.47	89.12	88.47	85.54	90.53	75.94	93.10	78.07	77.69	78.09	74.34	77.71	72.20
No	85	3.26	3.27	88.57	87.01	86.97	89.20	87.09	86.98	77.76	77.81	77.78	74.76	77.84	72.80
No	86	3.08	3.26	89.30	87.24	86.32	90.48	87.71	87.06	77.81	78.73	77.82	75.34	78.75	72.71
No	87	3.09	3.56	89.33	80.54	87.12	90.19	93.03	75.91	77.70	81.68	77.71	75.56	81.74	67.88
No	88	3.11	3.82	89.25	88.52	87.19	90.06	84.54	89.98	77.67	80.45	77.68	75.58	80.49	70.84
No	89	3.07	3.42	89.37	87.37	87.05	90.28	83.92	88.64	78.28	76.44	78.29	74.97	76.45	73.69
No	90	3.02	3.31	89.54	87.38	86.87	90.59	86.67	87.65	77.35	79.74	77.36	76.17	79.78	71.36
No	91	2.94	3.34	89.90	87.17	87.49	90.85	87.68	86.99	77.83	78.48	77.84	75.91	78.51	72.48
No	92	2.96	3.30	89.68	88.67	87.77	90.44	84.45	90.23	77.77	77.89	77.78	76.05	77.91	73.33
No	93	3.02	3.18	89.77	87.97	87.61	90.61	86.53	88.51	77.70	78.68	77.71	76.03	78.71	72.40
No	94	2.92	3.24	90.30	86.50	86.97	91.60	88.17	85.89	77.79	77.57	77.80	76.22	77.59	73.04
No	95	2.94	3.25	90.22	87.68	87.48	91.29	86.76	88.02	77.44	79.39	77.44	76.53	79.42	71.53
No	96	2.91	3.19	89.79	86.75	87.79	90.58	88.30	86.17	77.98	77.71	77.99	76.07	77.73	73.25
No	97	2.89	3.20	90.36	87.43	87.45	91.50	87.01	87.59	77.53	78.35	77.54	76.69	78.38	72.69
No	98	2.89	3.18	90.11	87.95	88.04	90.92	86.03	88.66	77.56	78.18	77.57	76.63	78.21	73.02
No	99	2.87	3.18	90.30	88.10	87.99	91.21	85.69	89.00	77.82	77.48	77.83	76.54	77.49	73.59
No	100	2.87	3.20	90.27	88.35	87.71	91.27	85.09	89.56	77.44	76.99	77.45	76.80	77.00	74.20

Table 6: Performance Results of Model 6 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	8.57	8.91	39.00	59.99	82.17	22.03	62.40	59.10	81.03	54.27	81.20	43.42	54.32	43.34
No	2	7.72		66.73	51.65	61.73	68.70	86.88	38.62	74.31	90.19	74.35	65.21	90.45	33.63
No	3	7.51	6.42	62.67	76.65	56.93	64.93	75.58	77.04	79.41	76.62	79.50	57.37	76.65	70.54
No	4	6.49	7.84	68.76	83.13	56.40	73.61	55.87	93.22	74.50	75.19	74.52	69.74	75.21	71.07
No	5	6.72	6.08	63.70	70.04	62.79	64.06	82.00	65.61	72.76	75.26	72.77	70.29	75.27	71.07
No	6	6.23	5.71	70.60	82.61	58.57	75.33	53.27	93.46	75.27	75.19	75.30	68.78	75.21	71.07
No	7	6.19	6.50	72.34	78.88	58.17	77.91	55.70	87.46	76.51	75.20	76.54	69.45	75.21	71.07
No	8	7.49	9.85	52.01	27.47	70.17	44.88	99.89	0.68	73.68	75.19	73.75	57.57	75.20	71.07
No	9	6.43	6.53	66.17	67.08	60.68	68.33	85.92	60.11	75.47	78.48	75.50	67.29	78.53	68.96
No	10	6.48	5.15	67.17	78.33	64.21	68.33	82.27	76.87	75.95	75.75	75.99	67.44	75.77	71.06
No	11	6.08	5.60	71.26	74.75	60.61	75.45	51.27	83.44	76.04	73.73	76.08	68.87	73.78	62.28
No	12	6.46	5.37	65.42	76.88	62.50	66.57	61.31	82.64	76.67	75.19	76.71	68.98	75.21	71.07
No	13	6.21	5.31	67.92	62.36	62.02	70.24	87.22	53.16	76.98	76.54	77.02	67.62	76.56	70.76
No	14	5.88	5.33	73.71	82.20	62.05	78.29	50.47	93.95	76.85	75.85	76.89	69.09	75.87	71.02
No	15	6.04	5.84	67.18	81.40	69.18	66.40	34.06	98.92	76.15	75.79	76.18	69.77	75.82	71.06
No	16	5.86	7.50	72.32	29.54	68.67	73.76	98.61	3.98	76.74	77.17	76.78	69.02	77.20	70.81
No	17	5.78	5.36	72.75	81.68	68.58	74.39	64.30	88.11	76.59	75.94	76.62	69.30	75.96	71.01
No	18	6.07	4.70	68.03	82.36	64.92	69.25	75.23	85.00	76.70	77.76	76.73	69.38	77.79	70.59
No	19	5.82	4.92	72.99	75.16	61.89	77.34	89.40	69.89	77.03	79.66	77.07	69.09	79.70	69.31
No	20	5.75	5.12	72.33	85.31	66.71	74.54	63.83	93.25	76.52	76.10	76.56	69.40	76.13	71.00
No	21	5.84	4.43	71.67	78.49	62.42	75.30	87.77	75.06	77.34	81.27	77.38	68.79	81.34	66.80
No	22	5.75	4.65	73.46	83.28	66.93	76.03	67.34	89.17	76.60	75.52	76.63	69.10	75.54	71.06
No	23	5.50	6.13	75.19	50.80	68.82	77.69	96.76	33.80	77.74	78.91	77.78	68.87	78.96	69.62
No	24	5.48	4.88	74.48	72.77	68.56	76.81	80.26	70.00	77.37	81.00	77.40	69.17	81.06	66.64
No	25	5.41	4.71	74.12	84.56	72.88	74.61	75.43	87.93	77.68	76.56	77.72	68.84	76.59	70.97
No	26	5.57	5.26	73.54	66.44	68.73	75.43	83.88	59.99	78.08	77.28	78.13	67.84	77.31	70.55
No	27	5.42	4.74	73.01	79.39	74.28	72.51	68.19	83.54	77.10	77.42	77.13	69.50	77.45	70.68
No	28	5.33	4.74	75.25	81.92	74.65	75.48	67.92	87.10	77.83	76.62	77.87	68.97	76.65	70.96
No	29	5.31	4.85	75.20	73.66	72.69	76.19	84.58	69.61	78.16	79.87	78.20	69.11	79.92	67.90
No	30	5.16	4.62	77.05	79.61	75.15	77.79	78.66	79.96	78.06	79.62	78.10	69.19	79.67	68.66

Table 7: Performance Results of Model 7 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	8.79		70.53	34.30	70.33	70.61	99.00	10.35	56.00	91.47	56.02	52.80	91.83	12.93
No	2	5.94	6.67	72.73	63.03	79.55	70.05	84.25	55.18	52.88	99.44	52.84	62.91	99.89	0.13
No	3	4.86	4.92	82.04	76.87	74.71	84.92	82.89	74.63	57.70	61.91	57.69	59.38	61.93	58.58
No	4	4.49	4.54	82.35	80.06	81.32	82.75	87.53	77.29	53.50	78.17	53.43	69.54	78.35	37.88
No	5	4.49	4.80	82.92	85.73	83.20	82.81	75.12	89.65	58.46	38.00	58.44	62.57	37.79	85.88
No	6	4.39	4.62	83.46	83.98	79.75	84.91	75.69	87.05	50.99	42.67	50.89	72.89	42.49	81.90
Yes	7	4.39	4.17	81.84	83.30	83.38	81.24	84.55	82.84	56.54	74.77	56.49	67.51	74.90	44.74
Yes	8	4.26	4.01	84.08	84.21	82.43	84.73	83.38	84.51	55.51	49.25	55.46	66.63	49.13	75.43
No	9	4.20	4.09	84.47	83.20	82.95	85.07	78.94	84.77	52.42	65.05	52.33	72.76	65.09	56.15
No	10	4.19	3.96	83.99	86.00	83.91	84.03	76.16	89.64	56.65	54.82	56.61	65.27	54.76	68.59
No	11	4.05	4.57	84.80	86.88	83.16	85.44	78.12	90.12	55.83	39.14	55.77	69.31	38.93	85.79
No	12	4.05	4.18	85.00	82.80	83.37	85.65	86.85	81.30	50.87	69.44	50.77	75.11	69.51	52.64
No	13	4.07	4.36	86.01	86.96	82.36	87.44	68.91	93.63	49.52	41.99	49.40	76.87	41.80	84.40
Yes	14	3.88	3.86	85.86	84.21	84.72	86.31	85.03	83.90	51.56	53.59	51.45	75.26	53.50	72.86
No	15	4.06	4.24	85.29	86.73	80.93	87.00	64.62	94.91	58.96	27.79	58.93	65.78	27.49	94.54
No	16	4.08	4.19	85.59	77.72	81.46	87.21	91.10	72.76	55.44	68.24	55.39	67.29	68.31	52.54
No	17	3.96	3.90	85.51	82.68	83.12	86.45	86.30	81.34	54.17	57.51	54.09	72.65	57.47	66.57
Yes	18	4.47	3.84	82.49	84.32	80.36	83.32	84.01	84.43	52.70	64.03	52.61	72.14	64.05	60.06
No	19	3.89	4.05	86.78	87.22	82.69	88.39	69.90	93.63	51.51	55.52	51.40	76.19	55.45	70.68
Yes	20	3.92	3.84	86.13	85.31	82.39	87.60	83.86	85.84	59.54	54.07	59.51	66.64	53.99	72.12
No	21	4.02	4.25	85.28	77.78	82.36	86.42	90.48	73.08	53.83	66.78	53.74	73.14	66.83	56.87
No	22	4.06	5.02	85.79	74.47	82.13	87.23	87.07	69.80	56.70	85.85	56.64	69.99	86.11	28.58
No	23	3.94	5.24	86.15	86.35	82.54	87.56	76.61	89.95	54.68	37.94	54.61	71.93	37.72	86.04
Yes	24	3.98	3.99	85.91	86.98	81.67	87.58	80.62	89.34	54.52	66.70	54.43	73.40	66.74	58.62
No	25	3.81	4.63	86.64	77.09	82.76	88.17	90.12	72.27	55.31	77.26	55.23	73.06	77.41	43.16
No	26	3.68	3.80	86.85	83.13	84.63	87.72	88.72	81.06	55.45	68.50	55.36	74.07	68.55	57.86
Yes	27	3.71	3.80	86.86	87.96	84.53	87.78	80.08	90.87	57.83	53.54	57.76	72.11	53.44	75.76
No	28	3.76	4.75	86.78	72.18	83.35	88.12	92.81	64.54	58.64	78.48	58.58	71.80	78.64	42.53
No	29	3.79	3.92	86.93	82.91	82.95	88.50	86.37	81.63	58.44	58.59	58.38	72.74	58.54	69.42
No	30	13.07	6.71	75.73	82.65	76.79	75.32	38.45	99.01	59.51	57.09	59.49	63.52	56.97	82.60
No	31			67.83935	31.21826	60.20992	70.83673	99.37883	5.999387	67.1094	96.42753	67.19728	47.30842	96.83922	5.514308

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	32			28.80957	27.02974	99.91571	0.874131	99.99908	0.031652	99.17107	99.52803	99.60753	0.827137	99.97859	0.031236
No	33			28.83698	27.04672	99.9112	0.914084	99.99471	0.056537	99.15112	99.50772	99.58745	0.836969	99.95806	0.060069
No	34			28.86325	27.03333	99.91574	0.948882	99.99824	0.03689	99.12624	99.52322	99.56208	0.922387	99.97372	0.038444
No	35			28.86619	27.00699	99.91013	0.955186	100	0.000148	99.11399	99.54921	99.54986	0.902108	100	0
No	36			28.87693	27.00714	99.91206	0.969391	100	0.000356	99.12164	99.54912	99.55752	0.909482	99.99991	0
No	37			28.80236	27.02624	99.91439	0.864612	99.99948	0.02671	99.1809	99.53044	99.61756	0.792724	99.98101	0.028833
No	38			28.76039	27.0071	99.91097	0.807489	100	0.000297	99.20744	99.54916	99.64448	0.73496	99.99996	0
No	39			28.81232	27.00713	99.91134	0.879672	100	0.000341	99.16576	99.54911	99.60231	0.801942	99.9999	0
No	40			28.84729	27.00722	99.91327	0.92762	99.99996	0.000475	99.13604	99.54921	99.57218	0.863393	100	0
No	41			28.84316	27.00695	99.91432	0.921459	100	8.9E-05	99.14491	99.54921	99.58111	0.860321	100	0
No	42			28.84334	27.06911	99.91073	0.923115	99.99414	0.087416	99.14585	99.49267	99.58193	0.887359	99.94273	0.105721
No	43			28.78805	27.00688	99.91634	0.843909	100	0	99.19167	99.54921	99.62836	0.796411	100	0
No	44			28.77674	27.00844	99.91397	0.82908	99.99968	0.002256	99.20188	99.54917	99.63897	0.71591	99.99997	0
No	45			28.66554	27.00688	99.93658	0.665317	100	0	99.2472	99.54921	99.68493	0.616973	100	0
No	46			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	47			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	48			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	49			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	50			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	51			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	52			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	53			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	54			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	55			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	56			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0
No	57			28.20577	27.00688	100	0	100	0	99.55815	99.54921	100	0	100	0

Table 8: Performance Results of Model 8 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	9.05		69.29	53.29	53.91	75.34	94.42	38.08	54.17	79.58	54.11	68.05	79.68	56.65
No	2	5.35	5.76	80.33	78.59	75.42	82.25	85.41	76.06	72.15	77.94	72.16	70.12	77.98	67.89
No	3	4.70	4.60	82.76	85.48	80.45	83.67	65.77	92.77	76.00	78.40	76.02	70.69	78.44	70.44
No	4	4.67	4.58	81.90	84.19	82.75	81.57	59.91	93.17	77.45	76.17	77.48	70.15	76.19	71.02
No	5	4.42	5.34	82.18	82.81	82.94	81.88	56.41	92.58	78.26	77.71	78.29	70.23	77.74	70.38
Yes	6	4.30	4.02	85.05	83.82	81.33	86.51	85.71	83.12	77.88	80.98	77.91	70.87	81.04	67.96
No	7	4.21	4.87	84.26	71.25	84.01	84.36	93.52	63.01	79.04	84.23	79.08	69.92	84.34	61.94
Yes	8	4.20	3.85	84.16	85.51	82.14	84.96	82.43	86.65	78.51	80.19	78.55	70.05	80.24	69.56
No	9	4.19	3.93	84.79	81.57	82.99	85.50	89.59	78.61	78.44	79.61	78.47	70.60	79.65	69.98
No	10	4.01	4.50	84.35	87.30	85.72	83.81	69.73	93.79	79.74	78.73	79.78	69.67	78.77	70.22
No	11	3.99	4.89	85.55	87.33	82.50	86.75	67.73	94.59	78.60	77.62	78.63	70.87	77.64	71.94
No	12	3.93	5.23	85.21	66.49	83.93	85.71	94.99	55.94	79.47	84.96	79.51	70.14	85.07	59.75
No	13	3.76	3.93	86.04	87.97	85.16	86.39	69.96	94.64	78.72	76.86	78.75	71.41	76.87	72.75
Yes	14	3.76	3.59	86.79	87.58	82.62	88.43	80.15	90.33	78.31	78.62	78.34	71.94	78.65	71.56
No	15	3.73	3.66	86.80	86.11	84.26	87.80	86.30	86.04	78.68	79.37	78.71	71.74	79.41	70.96
No	16	3.86	3.78	86.37	87.19	83.63	87.45	84.49	88.19	78.62	77.59	78.65	71.50	77.61	72.99
No	17	3.90	3.67	85.89	85.38	83.38	86.87	87.34	84.65	78.26	78.62	78.28	71.95	78.65	71.83
No	18	3.69	3.60	87.09	87.93	84.64	88.05	79.20	91.17	77.99	79.38	78.01	72.36	79.42	70.48
No	19	3.79	4.00	86.75	87.66	84.25	87.73	64.94	96.07	78.33	76.73	78.36	71.94	76.75	72.50
No	20	3.74	4.37	87.58	76.83	83.80	89.07	92.16	71.16	78.23	81.73	78.25	72.37	81.79	68.32
Yes	21	3.51	3.45	87.83	87.92	85.68	88.67	83.50	89.55	78.72	77.65	78.75	72.39	77.67	73.23
No	22	3.64	3.57	87.53	88.47	83.17	89.24	78.27	92.24	77.92	80.25	77.94	72.83	80.30	69.51
No	23	3.58	3.71	87.48	86.65	85.81	88.14	80.86	88.79	78.31	79.20	78.34	72.52	79.24	71.34
No	24	3.54	3.51	88.17	87.08	85.00	89.41	85.69	87.59	78.21	78.28	78.24	72.80	78.31	72.44
No	25	3.53	3.68	87.56	84.98	84.77	88.65	88.28	83.77	78.09	81.29	78.11	72.82	81.35	68.48
No	26	3.51	3.58	87.85	88.55	84.87	89.02	78.99	92.09	78.13	73.04	78.16	72.96	73.02	76.94
No	27	3.50	3.46	87.80	88.97	86.12	88.47	75.87	93.82	78.00	76.05	78.02	73.32	76.06	74.85
No	28	3.68	3.58	87.14	86.81	84.34	88.24	75.82	90.88	77.43	80.55	77.45	73.25	80.60	69.57
No	29	3.46	4.20	88.29	79.86	84.78	89.67	91.28	75.64	78.35	81.79	78.38	72.96	81.86	67.27
No	30	3.34	3.35	88.62	87.74	85.74	89.76	85.68	88.50	77.93	79.24	77.95	73.75	79.27	71.68
Yes	31	3.40	3.31	88.87	88.44	86.18	89.92	84.46	89.92	78.32	79.41	78.34	73.43	79.44	71.66

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	32	3.41	4.46	88.14	79.61	84.66	89.50	92.41	74.87	77.84	82.32	77.85	73.37	82.39	67.33
No	33	3.42	3.57	88.23	88.80	85.73	89.22	79.96	92.07	78.22	80.75	78.25	73.32	80.80	69.47
No	34	3.28	3.37	88.93	86.52	86.03	90.06	85.67	86.84	77.69	79.29	77.71	74.04	79.33	71.17
No	35	3.35	3.42	88.46	88.15	85.59	89.59	85.50	89.14	77.90	76.32	77.92	73.75	76.33	74.76
No	36	3.28	3.81	88.73	80.30	85.91	89.84	92.23	75.88	78.34	81.34	78.36	73.67	81.40	68.52
No	37	3.20	3.29	88.71	88.31	87.31	89.26	85.09	89.50	78.16	78.83	78.17	73.95	78.86	72.39
No	38	3.24	3.29	89.25	88.20	87.08	90.10	86.66	88.78	78.01	77.90	78.03	74.27	77.92	73.19
No	39	3.16	3.40	89.14	86.20	86.59	90.14	89.50	84.98	78.31	77.99	78.32	74.03	78.02	72.92
No	40	3.19	3.26	89.32	85.70	87.41	90.07	89.09	84.44	77.85	77.08	77.87	74.35	77.09	74.10
No	41	3.12	3.55	89.62	82.73	87.06	90.63	90.02	80.04	77.94	81.49	77.95	74.55	81.56	67.28
No	42	3.22	3.63	89.53	88.64	87.31	90.40	75.15	93.63	78.19	75.14	78.21	74.25	75.14	75.31
Yes	43	3.17	3.38	89.68	89.45	85.76	91.22	80.91	92.61	77.73	78.50	77.74	74.85	78.53	72.78
No	44	3.31	3.87	88.39	80.61	86.35	89.19	91.03	76.75	77.97	76.41	77.98	74.15	76.43	71.26
No	45	3.33	3.52	88.61	89.23	86.88	89.30	74.46	94.70	77.55	80.20	77.57	74.09	80.25	70.03
No	46	3.20	4.00	89.10	83.19	85.49	90.52	90.34	80.54	78.14	80.52	78.15	74.14	80.58	68.04
No	47	3.22	3.40	89.32	89.19	87.42	90.06	78.28	93.22	77.99	77.24	78.00	74.30	77.26	73.76
No	48	3.16	3.35	89.65	87.36	87.13	90.64	87.38	87.35	77.91	77.24	77.92	74.75	77.26	73.75
No	49	3.14	3.21	89.41	89.18	87.01	90.35	83.68	91.21	78.05	76.07	78.06	74.49	76.07	74.99
No	50	3.05	3.63	89.87	89.15	87.30	90.88	83.00	91.42	78.13	76.15	78.14	74.69	76.16	74.62
No	51	3.02	3.24	90.00	89.18	87.74	90.89	82.19	91.77	77.59	75.78	77.60	75.44	75.78	75.26
No	52	3.00	3.21	90.09	89.16	87.77	91.00	83.87	91.11	77.89	76.74	77.90	75.13	76.75	74.60
No	53	2.96	3.12	90.43	88.75	87.14	91.72	85.72	89.87	77.49	78.73	77.50	75.81	78.76	72.80
No	54	2.98	3.15	90.34	89.05	88.10	91.21	84.11	90.88	77.83	75.90	77.84	75.41	75.90	75.45
No	55	2.89	3.13	90.61	89.04	88.27	91.53	84.14	90.85	77.66	77.42	77.67	75.83	77.43	74.10
No	56	2.86	3.22	90.89	88.73	87.97	92.04	83.88	90.52	77.85	77.48	77.86	75.72	77.49	73.94
No	57	2.86	3.15	90.58	87.65	88.46	91.42	87.77	87.61	78.00	77.11	78.01	75.56	77.12	73.96
No	58	2.86	3.15	90.88	88.80	88.13	91.97	84.90	90.25	77.22	77.47	77.22	76.47	77.48	73.92
No	59	2.83	3.14	90.99	88.08	88.38	92.01	86.38	88.71	78.04	78.07	78.05	75.77	78.09	73.20
No	60	2.82	3.12	91.08	88.47	88.56	92.07	85.60	89.53	77.77	78.15	77.77	76.09	78.17	73.20
No	61	2.81	3.16	91.14	88.61	88.45	92.19	84.77	90.03	77.58	77.48	77.58	76.28	77.49	73.81
No	62	2.80	3.14	91.05	88.30	88.70	91.98	85.95	89.17	77.88	78.08	77.88	76.08	78.10	73.13
No	63	2.79	3.14	91.07	88.47	88.79	91.96	85.27	89.65	77.63	77.69	77.63	76.41	77.71	73.53
No	64	2.84	3.14	91.22	88.45	88.66	92.23	84.98	89.74	77.53	77.52	77.53	76.53	77.54	73.69
No	65	2.77	3.15	91.06	88.90	88.85	91.93	83.73	90.82	77.84	77.06	77.84	76.27	77.07	74.24
No	66	2.74	3.15	91.24	88.38	89.18	92.04	85.29	89.53	77.63	77.54	77.64	76.52	77.56	73.57
No	67	2.76	3.15	91.28	88.51	88.81	92.25	84.68	89.93	77.78	77.53	77.79	76.39	77.55	73.62
No	68	2.75	3.16	91.40	88.46	88.83	92.41	84.78	89.82	77.66	77.68	77.66	76.60	77.70	73.47

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	69	2.74	3.16	91.35	88.46	89.08	92.24	84.82	89.81	77.59	77.73	77.60	76.73	77.75	73.37
No	70	2.75	3.16	91.34	88.40	89.17	92.19	85.03	89.65	77.69	77.51	77.70	76.72	77.53	73.51
No	71	2.75	3.17	91.45	88.59	88.82	92.48	84.34	90.16	77.60	77.52	77.60	76.68	77.54	73.63
No	72	2.74	3.16	91.20	88.27	89.28	91.96	85.21	89.41	77.92	77.68	77.93	76.43	77.70	73.31
No	73	2.74	3.16	91.34	88.40	88.97	92.28	84.76	89.75	77.53	77.58	77.53	76.85	77.60	73.48

Table 9: Performance Results of Model 9 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	7.05		68.73	71.83	57.51	73.14	79.19	69.11	75.35	82.91	75.45	52.33	83.02	59.70
No	2	4.88	5.37	81.05	76.28	79.62	81.61	87.23	72.23	77.75	79.26	77.79	68.47	79.31	69.09
No	3	4.79	5.66	82.54	85.96	79.18	83.86	69.84	91.93	77.68	79.26	77.71	70.27	79.30	69.93
No	4	4.38	5.66	84.16	73.00	80.60	85.56	77.31	71.41	79.85	76.81	79.89	68.83	76.84	71.46
No	5	4.47	4.21	84.12	85.89	79.23	86.03	76.00	89.55	77.93	78.82	77.96	70.71	78.86	70.30
No	6	5.25	4.76	77.70	80.58	80.48	76.61	84.71	79.05	77.52	82.99	77.55	69.80	83.08	63.00
No	7	36.45	5.73	74.89	84.95	59.22	81.04	76.71	87.99	77.69	66.42	77.75	63.84	66.38	75.19
No	8	4.76	5.14	83.85	76.88	78.13	86.09	84.57	74.04	78.37	80.83	78.40	69.65	80.88	68.29
Yes	9	4.22	4.02	84.29	83.81	83.61	84.55	86.75	82.72	78.75	75.02	78.78	70.44	75.02	73.73
Yes	10	3.96	3.85	86.18	84.38	84.40	86.88	85.40	84.00	79.52	79.65	79.56	70.25	79.69	70.55
Yes	11	3.92	3.95	85.07	85.71	83.52	85.68	83.79	86.42	78.41	80.62	78.44	70.95	80.68	68.90
Yes	12	3.87	3.64	86.03	85.95	83.04	87.20	82.08	87.39	79.63	74.72	79.67	70.31	74.72	74.83
No	13	3.88	3.68	86.52	85.34	82.88	87.94	83.23	86.12	77.88	80.54	77.90	71.92	80.58	69.54
No	14	3.86	4.19	85.94	84.34	83.65	86.84	80.06	85.92	78.91	79.57	78.95	70.76	79.61	70.42
No	15	3.93	3.86	86.35	82.09	82.76	87.77	88.93	79.57	78.46	83.22	78.49	71.43	83.30	65.09
Yes	16	3.59	3.53	87.57	87.49	84.18	88.90	82.60	89.30	78.50	76.69	78.52	72.09	76.71	73.64
Yes	17	3.92	3.57	86.78	87.57	82.00	88.65	83.83	88.95	77.69	63.58	77.72	72.11	63.49	82.86
No	18	3.60	4.83	87.06	87.51	84.65	88.00	60.84	97.38	77.67	78.68	77.69	72.74	78.72	70.62
Yes	19	3.84	3.67	86.61	87.86	83.13	87.98	81.22	90.32	78.72	71.24	78.75	71.54	71.21	78.42

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	20	3.71	5.10	86.78	68.10	84.78	87.57	89.08	60.33	78.04	82.29	78.06	72.39	82.37	63.51
No	21	3.68	3.92	86.88	88.61	84.63	87.76	71.89	94.80	77.67	72.57	77.69	72.82	72.55	76.61
Yes	22	3.44	3.62	88.13	88.54	85.25	89.26	82.77	90.68	77.64	76.59	77.66	73.36	76.60	73.99
No	23	3.63	3.65	87.34	87.75	82.54	89.22	77.20	91.65	78.11	80.25	78.13	72.37	80.30	69.94
No	24	3.50	3.43	87.34	87.87	85.34	88.13	83.45	89.50	77.65	78.31	77.67	73.08	78.33	72.52
No	25	3.45	3.60	88.02	86.23	85.18	89.14	84.49	86.87	77.72	80.15	77.74	73.32	80.20	70.50
No	26	3.52	3.72	87.51	86.19	84.94	88.52	81.99	87.74	78.38	77.49	78.40	72.67	77.51	73.03
No	27	3.51	3.52	87.82	88.45	84.98	88.94	81.35	91.08	78.48	78.94	78.50	72.53	78.97	71.76
No	28	3.43	5.38	87.62	67.69	86.31	88.14	95.24	57.50	78.08	84.42	78.10	72.93	84.52	60.91
Yes	29	3.41	3.38	87.73	88.71	86.23	88.32	83.05	90.80	77.86	76.14	77.88	73.51	76.15	74.69
No	30	3.42	3.89	87.42	88.17	84.95	88.40	76.68	92.42	78.08	78.81	78.10	73.09	78.85	71.29
No	31	3.46	4.20	87.86	88.54	85.13	88.94	73.90	93.95	77.59	75.52	77.61	73.85	75.52	74.88
No	32	3.55	4.15	87.91	87.36	84.36	89.30	76.70	91.31	77.88	75.26	77.90	73.30	75.26	75.29
No	33	3.41	3.61	88.12	82.40	85.48	89.15	91.52	79.02	78.30	79.93	78.32	73.15	79.98	69.70
No	34	3.26	3.33	88.81	88.47	85.53	90.10	83.34	90.36	77.90	76.28	77.92	73.87	76.28	74.72
No	35	3.20	3.31	88.74	86.41	86.22	89.73	87.81	85.89	78.39	78.01	78.41	73.52	78.03	73.07
No	36	3.19	4.06	89.10	82.02	86.38	90.17	91.34	78.57	77.86	82.47	77.88	74.18	82.55	66.30
No	37	3.18	3.24	89.31	87.97	86.46	90.43	86.39	88.56	78.28	78.73	78.30	73.89	78.76	72.43
No	38	3.21	3.34	89.01	89.04	86.39	90.04	78.91	92.78	78.12	76.02	78.13	73.80	76.02	74.74
Yes	39	3.20	3.89	88.61	88.91	86.33	89.51	80.34	92.09	78.10	76.15	78.11	74.06	76.15	74.37
No	40	3.37	3.53	88.36	88.22	84.53	89.86	82.74	90.24	77.63	80.06	77.64	74.18	80.10	70.85
No	41	3.36	3.54	88.55	87.56	86.08	89.51	82.08	89.59	78.05	79.42	78.07	73.63	79.46	70.74
No	42	3.15	3.44	88.94	87.75	86.99	89.71	84.85	88.82	78.02	78.80	78.04	74.28	78.83	72.32
No	43	3.17	3.26	89.36	86.87	86.35	90.54	88.50	86.27	78.09	79.26	78.11	74.42	79.30	71.33
No	44	3.09	5.06	89.53	66.29	86.81	90.61	94.84	55.73	77.86	85.08	77.87	74.82	85.21	56.98
No	45	3.17	3.66	88.96	88.79	86.82	89.81	82.43	91.14	78.09	77.76	78.10	74.26	77.78	73.29
No	46	3.17	3.21	89.42	88.46	86.40	90.61	85.60	89.52	77.88	78.20	77.90	74.71	78.22	73.06
No	47	3.04	3.15	89.61	88.42	87.44	90.46	86.13	89.27	78.22	77.39	78.24	74.60	77.41	74.05
No	48	2.93	3.23	90.04	88.03	87.34	91.10	86.49	88.60	78.04	77.91	78.06	75.06	77.94	73.28
No	49	2.98	3.17	89.90	88.32	87.65	90.79	85.30	89.43	78.36	77.07	78.37	74.62	77.08	74.20
No	50	2.96	3.16	89.99	86.92	87.19	91.10	88.38	86.38	77.93	78.77	77.94	75.18	78.80	72.42
No	51	2.95	3.26	89.96	88.57	87.42	90.96	84.96	89.91	77.96	76.43	77.97	75.25	76.44	74.55
No	52	2.93	3.15	90.00	88.58	87.93	90.81	85.03	89.90	78.05	78.50	78.07	75.17	78.53	72.81
No	53	2.89	3.21	90.33	88.49	87.45	91.46	86.12	89.37	78.19	75.08	78.20	75.10	75.08	75.57
No	54	2.92	3.11	90.12	88.75	88.00	90.96	85.41	89.98	77.96	77.74	77.97	75.46	77.76	73.61
Yes	55	2.88	3.11	90.52	88.91	87.43	91.73	84.70	90.47	78.06	78.21	78.08	75.51	78.23	72.94
No	56	3.09	3.38	89.45	89.14	86.84	90.47	77.05	93.61	77.79	81.01	77.80	74.95	81.07	67.08

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	57	3.14	3.78	88.87	82.85	86.70	89.73	89.38	80.43	78.08	80.26	78.10	74.40	80.31	69.11
No	58	3.01	3.27	89.64	88.27	86.18	91.01	84.98	89.48	77.78	76.76	77.80	75.08	76.77	74.02
No	59	3.05	3.28	89.65	85.49	86.88	90.73	89.92	83.85	78.13	78.44	78.15	74.84	78.47	72.18
Yes	60	2.97	3.36	89.91	89.31	87.71	90.77	82.94	91.67	78.34	76.67	78.36	74.85	76.68	74.46
No	61	3.09	3.78	89.40	87.15	86.65	90.48	85.08	87.92	77.85	69.06	77.86	74.84	69.02	78.78
No	62	3.03	3.18	89.74	88.17	87.05	90.80	85.69	89.08	77.31	78.50	77.32	75.54	78.53	72.80
No	63	2.96	3.22	90.07	89.18	87.65	91.03	82.68	91.58	77.74	78.38	77.75	75.82	78.40	72.89
No	64	2.93	3.41	90.34	85.56	87.30	91.53	89.34	84.17	78.06	77.62	78.07	75.32	77.65	71.33
No	65	2.90	3.35	90.30	85.42	87.78	91.29	89.73	83.82	77.46	81.37	77.46	75.76	81.43	68.98
No	66	2.89	3.15	90.43	88.24	87.51	91.58	86.83	88.76	77.86	76.44	77.87	75.82	76.45	74.69
No	67	2.81	3.14	90.78	88.39	88.20	91.80	85.93	89.31	77.38	76.29	77.39	76.68	76.30	74.92
No	68	2.77	3.14	90.83	89.02	88.43	91.77	83.34	91.12	77.98	75.41	77.99	76.13	75.41	75.55
No	69	2.78	3.23	91.13	88.45	88.24	92.27	86.10	89.32	77.88	78.99	77.89	76.24	79.02	72.16
No	70	2.77	3.13	91.04	87.88	88.87	91.89	86.76	88.29	77.77	78.02	77.78	76.67	78.05	72.94
No	71	2.70	3.14	91.21	88.76	88.97	92.09	84.64	90.28	77.66	75.95	77.66	77.03	75.95	74.95
No	72	2.68	3.14	91.33	88.83	88.81	92.31	84.01	90.62	77.40	77.63	77.40	77.34	77.65	73.25
No	73	2.66	3.21	91.38	88.70	89.03	92.30	84.71	90.17	77.76	77.11	77.77	77.11	77.12	73.89
No	74	2.64	3.15	91.52	88.85	89.19	92.43	83.78	90.73	77.50	76.95	77.49	77.63	76.96	74.04
No	75	2.64	3.16	91.51	88.29	89.10	92.46	84.83	89.57	77.86	77.25	77.87	77.25	77.27	73.52
No	76	2.61	3.16	91.62	88.54	89.21	92.57	84.43	90.06	77.30	77.00	77.29	78.03	77.01	73.79
No	77	2.63	3.15	91.49	88.33	89.37	92.33	85.53	89.37	77.57	77.62	77.56	77.72	77.65	72.97
No	78	2.60	3.15	91.71	88.30	89.50	92.58	85.10	89.48	77.41	77.54	77.41	78.01	77.56	73.11
No	79	2.60	3.15	91.64	88.67	89.56	92.45	84.32	90.28	77.54	77.24	77.54	77.91	77.26	73.40
No	80	2.61	3.14	91.76	88.46	89.40	92.69	84.64	89.87	77.53	76.82	77.53	77.97	76.83	73.72
No	81	2.61	3.17	91.73	88.51	89.30	92.68	84.33	90.05	77.45	77.45	77.45	78.07	77.47	73.15
No	82	2.60	3.16	91.80	88.50	89.65	92.64	84.49	89.98	77.23	77.33	77.22	78.46	77.35	73.24
No	83	2.62	3.16	91.72	88.28	89.49	92.60	85.08	89.46	77.51	76.91	77.50	78.07	76.92	73.50
No	84	2.58	3.16	91.79	88.45	89.49	92.69	84.63	89.86	77.43	77.18	77.43	78.28	77.20	73.27
No	85	2.57	3.16	91.69	88.45	89.78	92.45	84.43	89.93	77.34	77.36	77.34	78.49	77.38	73.12
No	86	2.57	3.16	91.90	88.41	89.54	92.82	84.65	89.80	77.35	77.29	77.34	78.43	77.31	73.12
No	87	2.57	3.17	91.78	88.28	89.83	92.55	84.99	89.50	77.52	77.20	77.51	78.33	77.22	73.07
No	88	2.59	3.17	91.82	88.37	89.63	92.68	84.61	89.76	77.18	77.28	77.17	78.63	77.30	73.13
No	89	2.57	3.16	91.80	88.40	89.51	92.69	84.64	89.80	77.46	77.07	77.46	78.26	77.09	73.34
No	90	2.57	3.16	91.87	88.42	89.57	92.77	84.54	89.85	77.13	77.16	77.13	78.66	77.18	73.27

Table 10: Performance Results of Model 10 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	7.25	6.90	58.36	77.73	52.26	60.76	70.07	80.56	38.75	40.18	38.63	67.28	40.02	76.96
No	2	7.31	5.05	75.20	83.31	51.71	84.43	69.16	88.55	57.43	32.98	57.44	54.79	32.74	86.60
No	3	5.11	5.98	83.10	72.92	74.52	86.47	92.32	65.74	41.50	65.36	41.33	79.71	65.41	53.47
Yes	4	4.76	4.62	83.05	82.77	79.90	84.29	83.54	82.48	49.40	61.03	49.28	74.62	61.02	63.65
Yes	5	4.71	4.35	82.75	84.27	79.57	83.99	83.42	84.59	56.53	56.18	56.47	69.40	56.12	70.44
Yes	6	4.64	4.43	83.76	85.16	84.02	83.66	81.23	86.61	58.48	57.95	58.43	69.47	57.90	69.51
No	7	4.53	4.67	84.21	81.05	82.38	84.93	88.81	78.18	58.46	60.54	58.41	69.54	60.51	67.22
Yes	8	4.41	4.16	85.57	86.23	81.45	87.19	81.05	88.15	55.25	57.46	55.16	73.83	57.41	69.46
No	9	4.21	4.00	84.53	83.36	83.90	84.78	85.84	82.45	58.89	62.22	58.84	70.08	62.21	65.39
No	10	4.06	4.05	85.48	85.20	82.87	86.51	84.23	85.55	58.31	59.07	58.25	71.36	59.03	69.60
No	11	4.09	3.99	85.33	83.90	83.83	85.92	85.97	83.13	58.58	58.78	58.52	71.42	58.73	70.25
No	12	4.00	4.01	85.71	87.50	84.34	86.25	70.24	93.89	57.25	49.95	57.18	73.22	49.82	78.66
No	13	3.90	3.94	86.17	84.41	84.44	86.86	84.30	84.45	57.53	61.62	57.46	73.13	61.60	67.03
No	14	4.08	4.03	85.26	83.48	83.69	85.88	85.68	82.66	57.17	58.64	57.10	72.69	58.59	70.58
Yes	15	3.92	3.71	86.12	87.33	83.85	87.01	82.74	89.03	56.76	54.34	56.68	74.11	54.24	76.05
No	16	3.88	3.80	87.00	85.17	83.35	88.44	86.30	84.75	56.19	56.77	56.10	75.44	56.70	73.71
No	17	3.84	3.98	86.30	85.22	84.66	86.94	86.03	84.92	56.89	61.27	56.81	74.31	61.24	68.76
No	18	4.58	4.08	81.59	83.73	83.40	80.88	85.32	83.14	57.57	53.44	57.51	71.17	53.34	75.91
No	19	4.25	4.01	84.48	81.92	84.29	84.56	88.16	79.62	57.17	55.17	57.10	73.64	55.09	74.46
No	20	3.97	4.00	86.22	81.76	84.00	87.09	89.31	78.97	56.45	60.67	56.37	75.29	60.63	69.34
No	21	3.71	3.62	86.95	87.05	85.07	87.69	83.67	88.30	57.44	56.12	57.36	75.09	56.04	74.20
No	22	3.74	3.64	87.03	87.04	84.72	87.94	81.92	88.94	57.33	53.52	57.25	75.30	53.42	76.52
No	23	3.63	3.57	87.75	86.40	84.65	88.97	86.26	86.45	56.52	56.89	56.43	76.44	56.81	74.76
No	24	3.58	3.59	87.90	87.05	85.26	88.94	82.16	88.86	57.79	57.14	57.71	75.72	57.07	73.76
No	25	3.54	3.54	87.77	85.87	85.25	88.75	87.11	85.42	57.09	58.55	57.01	76.57	58.49	73.06
No	26	3.49	3.72	87.88	83.89	84.91	89.04	89.63	81.77	56.71	58.17	56.62	77.09	58.10	73.72
Yes	27	3.42	3.47	88.04	87.53	86.33	88.71	82.30	89.46	57.09	57.26	57.00	77.07	57.18	74.14
No	28	3.75	3.58	87.01	87.09	82.10	88.94	83.00	88.60	56.38	52.12	56.29	75.73	52.00	78.80
No	29	4.17	3.93	86.28	82.50	83.18	87.50	87.91	80.49	57.68	60.20	57.60	74.19	60.16	70.06
No	30	3.94	3.74	85.64	85.13	84.73	86.00	85.84	84.86	58.91	60.21	58.85	72.56	60.16	71.09
No	31	4.00	3.88	85.98	80.51	83.14	87.10	88.68	77.48	57.44	61.85	57.37	73.48	61.82	68.03

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	32		3.815723	86.67079	85.24614	84.78721	87.41079	81.93476	86.47133	55.79319	59.65948	55.70399	75.89074	59.61024	70.53269
No	33	3.746355	3.652389	87.17445	83.86942	84.8078	88.10424	88.45274	82.17363	56.70374	59.40671	56.61663	76.33012	59.3487	72.21702
No	34	3.541588	3.501193	87.83054	86.92142	85.07343	88.91372	85.70466	87.37161	57.627	60.44491	57.54427	76.26928	60.39475	71.52022
No	35	3.581041	3.562628	87.77096	85.99605	84.85623	88.91606	87.08969	85.59142	57.98384	57.92604	57.9053	75.6818	57.8525	74.16565
Yes	36	3.466511	3.484199	88.29339	88.31665	86.01657	89.18788	80.81944	91.09055	57.10099	55.28166	57.01065	77.45529	55.18644	76.3089
No	37	3.504725	3.523251	88.22078	86.21293	85.46334	89.30409	85.21633	86.58167	55.95204	57.16031	55.85342	78.17305	57.08248	74.34585
No	38	3.538865	3.619984	87.79304	86.94769	84.91628	88.92323	84.32609	87.91767	57.14486	57.7706	57.05758	76.81067	57.69726	73.96622
No	39	3.695425	3.790648	87.73731	87.5994	84.3943	89.05068	77.48108	91.3431	55.87331	54.94963	55.77676	77.6292	54.85573	75.68659
No	40	4.631064	3.66946	80.50878	87.47274	85.4859	78.55342	82.01561	89.49183	58.46519	53.31893	58.40596	71.81098	53.20578	78.30558
No	41	3.566228	3.713601	88.12836	84.06989	84.95219	89.37619	89.97457	81.8852	55.35715	61.95205	55.25403	78.59215	61.91813	69.44184
Yes	42	3.457845	3.577462	88.38573	88.60381	85.85396	89.38038	80.55614	91.58138	57.85193	56.12922	57.7685	76.65151	56.04323	75.11713
No	43	3.380371	3.741027	88.3641	87.59339	86.32705	89.1644	85.6139	88.32578	57.90245	56.45822	57.8179	76.95201	56.3667	76.66931
No	44	3.329084	3.394762	89.07831	88.08844	85.88273	90.33375	85.09172	89.1972	56.4903	57.49044	56.39084	78.90063	57.41113	75.0042
Yes	45	3.297715	3.337815	88.78565	88.58521	85.8271	89.94798	82.59013	90.80335	56.51056	57.535	56.4119	78.74086	57.45403	75.41507
No	46	3.460686	3.639339	88.33472	86.74788	86.35968	89.11066	85.37751	87.2549	55.69968	59.09451	55.60001	78.15707	59.03156	72.99551
No	47	3.473865	3.408868	88.46232	87.60531	85.30359	89.70328	84.32677	88.81835	56.63274	56.76784	56.53842	77.88484	56.68177	75.77549
No	48	3.378568	3.45959	88.50915	88.03474	86.21751	89.40946	82.71137	90.00434	58.34704	54.21883	58.26653	76.48866	54.11016	78.21668
No	49	3.453923	3.620363	88.81753	85.86788	85.29517	90.20136	87.53759	85.25009	56.05294	59.45921	55.95174	78.85577	59.3992	72.71198
No	50	3.410374	3.333627	88.6085	87.87361	85.60672	89.78781	84.94745	88.95626	57.24872	55.99111	57.15701	77.91249	55.89464	77.29402
No	51	3.40455	3.520331	88.59342	87.48718	86.62556	89.36653	84.56612	88.56794	56.82495	51.88713	56.72766	78.74762	51.75451	81.17446
No	52	3.38268	3.39343	89.10562	85.40927	85.46463	90.53606	88.9744	84.0902	56.60534	59.37411	56.50785	78.57187	59.3098	73.57697
No	53	3.256417	3.343079	88.8431	86.81341	86.80266	89.64472	87.42393	86.58752	57.36379	58.17926	57.27047	78.3912	58.1038	74.84322
No	54	3.177134	3.278726	89.38547	87.34316	86.02798	90.70453	86.23382	87.75361	57.24131	55.16501	57.14456	79.04197	55.06013	78.32721
No	55	3.20355	3.340129	89.03153	86.21108	86.75103	89.92747	88.35913	85.41632	57.77334	58.61241	57.68024	78.75069	58.53964	74.68224
No	56	3.223073	3.328336	88.95805	86.36341	86.99474	89.72938	88.43934	85.59534	57.3281	61.30504	57.23052	79.3142	61.26119	70.98921
No	57	3.148636	3.290536	89.3712	88.1091	87.04256	90.28605	85.81591	88.95755	57.19294	60.15271	57.09471	79.32649	60.09405	73.10603
No	58	3.117959	3.221679	89.39202	87.60836	86.97478	90.34168	86.30385	88.09102	57.18956	52.28932	57.08993	79.63867	52.1586	81.15764
No	59	3.050365	3.222389	89.50769	87.82136	87.43321	90.3227	86.10989	88.45459	56.9841	58.19581	56.88136	80.13335	58.11815	75.3454
No	60	3.083331	3.24966	89.55797	86.76957	87.41042	90.40168	88.41556	86.16057	57.44664	61.00927	57.34732	79.82671	60.95737	72.4693
No	61	3.056817	3.289731	89.4807	87.20452	87.48001	90.26671	87.55777	87.07382	57.77391	60.01457	57.67621	79.78738	59.95321	73.56496
No	62	3.02679	3.2281	89.56849	88.33599	87.49997	90.38115	85.46194	89.39937	57.22344	57.73082	57.12056	80.40312	57.64745	76.1407
No	63	3.057643	3.318268	89.56123	87.09683	87.37836	90.41882	88.1675	86.70069	57.62333	59.64506	57.52375	80.06145	59.57832	74.3843
No	64	3.020585	3.229816	89.65929	87.22019	87.7708	90.40122	87.99882	86.93211	57.92429	57.42499	57.82618	80.03011	57.33898	76.41942
No	65	2.979792	3.185469	89.68307	87.56784	87.68582	90.46773	87.44888	87.61185	57.2686	58.27723	57.16358	80.93283	58.19823	75.72263
No	66	2.982791	3.169462	89.78902	87.89405	87.4683	90.70075	86.6847	88.3415	57.42038	57.61036	57.31698	80.71837	57.52419	76.64048
No	67	2.980587	3.210169	89.82809	87.41775	87.57234	90.7143	87.63237	87.33834	57.26245	58.14088	57.15639	81.15897	58.06081	75.82114
No	68	2.987286	3.162235	89.66207	88.44772	87.83928	90.37818	85.52992	89.52728	57.36105	56.83297	57.25542	81.16266	56.74173	76.98167

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	69	2.950272	3.152929	89.77486	87.73852	87.90317	90.51018	87.17403	87.94738	57.57927	57.93695	57.47532	80.99982	57.85413	76.2272
No	70	2.951487	3.178406	89.74567	87.9145	87.99743	90.4325	86.62113	88.39303	57.82768	57.5189	57.72601	80.73496	57.43209	76.69093
Yes	71	2.977423	3.166471	89.61918	88.66231	87.91614	90.28825	84.64666	90.14807	57.84995	56.01937	57.74829	80.75647	55.92027	77.90192
No	72	3.294259	3.575084	89.20176	85.9702	87.06206	90.04238	88.59664	84.99844	55.40591	56.6866	55.29165	81.15037	56.59398	77.14025
No	73	3.246756	3.362095	89.19219	85.68586	86.14238	90.39037	87.4729	85.02467	56.84758	58.7032	56.74511	79.93486	58.6311	74.62457
Yes	74	3.209769	3.372527	88.97821	88.80584	86.86005	89.81038	83.34092	90.82782	57.07214	49.55026	56.97256	79.50962	49.39905	82.94048
No	75	3.09264	3.220843	89.59112	88.32723	86.96596	90.62247	85.42283	89.40183	56.87344	55.5622	56.76837	80.54815	55.45853	78.45695
No	76	3.059479	3.197607	89.63517	88.04352	87.34039	90.53672	86.09161	88.76572	57.4195	59.8003	57.31679	80.56228	59.73542	74.1272
No	77	3.023448	3.329427	89.57184	88.33107	87.59514	90.34842	83.90806	89.96755	57.39752	56.09151	57.29353	80.82837	55.99434	77.55112
No	78	3.073352	3.231999	89.67818	87.99895	87.43091	90.56106	86.49981	88.55362	57.3316	55.8729	57.22665	80.97831	55.7731	77.91153
No	79	3.031281	3.157724	89.68091	87.56084	87.83197	90.4073	86.97234	87.77858	57.4834	60.43842	57.37805	81.22227	60.37902	73.55535
No	80	2.961816	3.166188	89.83841	88.52208	87.51195	90.75241	84.45876	90.02547	57.82213	56.16634	57.71868	81.12948	56.06892	77.67846
No	81	2.98875	3.172171	89.78355	88.17978	87.93416	90.51012	86.04031	88.97137	57.54581	55.40936	57.43966	81.46316	55.30357	78.77171
No	82	2.968653	3.192965	89.88154	88.05252	87.74349	90.72151	86.59422	88.59208	57.61538	57.42603	57.50858	81.68008	57.34019	76.38338
No	83	2.926208	3.167446	89.94246	87.87483	88.10159	90.66568	87.06222	88.17549	57.93484	58.22852	57.82945	81.68131	58.14909	75.77068
No	84	2.92537	3.183098	90.02303	87.61134	87.92176	90.84856	87.2234	87.75487	56.98085	58.54675	56.86652	82.74012	58.46938	75.63372
No	85	2.910093	3.137887	90.01274	87.97317	88.058	90.78069	86.86209	88.38426	57.67215	57.43608	57.56317	82.227	57.34933	76.59242
No	86	2.924577	3.177675	90.07824	88.03609	87.53582	91.07708	86.70776	88.52756	57.42082	57.96004	57.3094	82.52627	57.87816	76.03979
No	87	2.895241	3.136786	90.01307	87.97063	88.11683	90.75805	86.69051	88.44426	57.73075	58.18672	57.62088	82.48694	58.10542	76.1383
No	88	2.889947	3.127885	90.06021	87.92592	88.03447	90.85606	86.8302	88.33133	57.75734	57.84268	57.6477	82.46052	57.7589	76.34254
No	89	2.888065	3.136471	90.10456	87.87024	88.1135	90.88679	87.03731	88.17842	57.70613	57.4193	57.59555	82.62152	57.33172	76.75821
No	90	2.880081	3.113675	90.10697	88.32465	88.15632	90.87332	85.92917	89.21096	57.68651	57.70775	57.57497	82.81817	57.62232	76.5732
No	91	2.88143	3.120257	90.19998	88.13044	87.87351	91.11398	86.4806	88.74087	58.12136	57.98053	58.01366	82.38739	57.89732	76.35455
No	92	2.874693	3.122309	90.1363	87.94537	88.1016	90.93567	86.92726	88.32206	57.82418	58.43526	57.71382	82.68973	58.35618	75.90043
No	93	2.873081	3.114392	90.11288	88.10773	88.1507	90.88377	86.5961	88.66702	57.84288	56.96421	57.73245	82.7266	56.87179	77.37332
No	94	2.879266	3.1332	90.12362	88.1142	88.1952	90.88124	86.49375	88.71375	57.93566	57.60571	57.82569	82.71493	57.5195	76.64288
No	95	2.875951	3.115232	90.15525	88.03179	88.02443	90.99239	86.74469	88.50801	57.54254	58.13764	57.42879	83.17213	58.05601	76.16473
No	96	2.863772	3.112114	90.12446	88.08829	88.11453	90.91411	86.68325	88.60814	57.99758	57.7683	57.8879	82.71062	57.68351	76.49151
No	97	2.861079	3.113941	90.13739	88.2486	88.21299	90.89343	86.21156	89.00229	57.89503	57.26343	57.7845	82.79973	57.17422	76.96485
No	98	2.866876	3.111463	90.09746	88.23131	88.09046	90.88595	86.19339	88.98532	57.93097	57.14509	57.82072	82.77269	57.05476	77.09219
No	99	2.856202	3.112469	90.20869	88.10882	88.17346	91.00828	86.5414	88.68876	57.79264	57.63965	57.68102	82.9423	57.5537	76.62125
No	100	2.859908	3.110295	90.16339	88.20892	88.17634	90.94404	86.35522	88.89477	57.85106	57.44266	57.73973	82.93677	57.35487	76.83029

Table 11: Performance Results of Model 11 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	7.10	6.17	60.65	80.35	45.12	66.75	35.42	96.97	30.18	25.07	29.99	73.09	24.77	91.52
No	2	5.61	5.67	81.75	82.37	65.62	88.09	73.89	85.51	36.15	40.72	35.95	82.08	40.54	80.61
Yes	3	5.10	4.72	82.91	83.29	74.10	86.38	80.98	84.14	42.22	51.58	42.05	79.83	51.49	72.22
No	4	7.60	5.54	74.16	75.58	81.72	71.18	90.32	70.13	63.63	48.66	63.66	55.38	48.55	74.41
No	5	4.94	4.43	83.65	85.25	80.32	84.95	73.82	89.49	54.11	51.04	54.03	71.61	50.93	75.68
No	6	4.55	4.66	84.17	81.02	81.50	85.22	89.01	78.06	55.29	61.65	55.21	72.27	61.63	65.10
No	7	4.40	4.25	85.30	84.16	82.67	86.33	67.48	90.33	56.64	57.79	56.57	71.75	57.74	68.91
No	8	4.33	4.10	83.94	86.26	81.93	84.74	79.54	88.75	56.10	47.35	56.02	72.48	47.21	80.14
Yes	9	4.31	4.01	84.97	84.79	82.64	85.88	83.97	85.10	56.22	61.00	56.15	72.87	60.97	67.40
Yes	10	4.10	4.01	85.90	84.86	83.39	86.88	85.72	84.54	56.21	58.12	56.13	73.31	58.06	70.79
No	11	4.13	3.97	85.89	83.93	82.92	87.06	87.62	82.56	57.78	60.49	57.72	72.01	60.46	68.15
No	12	4.10	4.70	86.34	84.49	82.46	87.86	85.67	84.05	56.24	54.97	56.16	74.10	54.88	74.74
Yes	13	4.02	3.81	86.38	86.23	83.03	87.69	83.64	87.18	56.98	53.52	56.91	73.70	53.41	76.34
Yes	14	3.98	3.94	86.99	87.41	83.06	88.54	82.16	89.35	55.04	50.32	54.95	75.82	50.19	79.51
Yes	15	3.97	3.87	86.90	87.63	83.34	88.30	80.36	90.32	56.61	54.51	56.53	74.43	54.41	75.52
No	16	3.89	3.80	86.86	87.52	83.76	88.07	83.41	89.04	57.72	50.00	57.65	72.99	49.87	79.87
No	17	3.98	3.70	86.63	87.43	83.52	87.85	83.98	88.70	56.31	56.24	56.23	74.70	56.16	74.14
No	18	3.73	3.72	87.18	88.04	83.33	88.70	79.99	91.02	57.83	53.59	57.76	73.90	53.49	76.41
No	19	3.71	3.73	86.89	87.46	85.05	87.61	82.74	89.21	57.13	58.49	57.05	75.08	58.43	72.03
No	20	3.83	3.81	87.28	86.17	84.03	88.56	82.73	87.44	57.32	56.77	57.25	74.85	56.69	73.38
No	21	3.89	3.78	87.28	87.13	83.92	88.60	85.12	87.87	56.82	57.34	56.74	75.16	57.27	73.82
No	22	3.91	3.81	87.65	88.66	83.69	89.20	76.44	93.19	56.76	52.87	56.67	75.68	52.76	78.19
No	23	3.53	3.60	88.19	86.22	84.36	89.69	86.07	86.28	57.14	58.15	57.06	76.28	58.09	72.50
Yes	24	3.50	3.54	88.17	88.04	85.20	89.34	81.56	90.44	56.63	54.99	56.54	76.86	54.89	76.24
No	25	3.58	3.60	88.12	85.32	84.61	89.50	85.91	85.10	56.59	60.41	56.51	76.44	60.36	70.25
No	26	3.67	3.59	87.77	85.93	85.05	88.84	86.33	85.78	57.61	56.43	57.53	75.39	56.34	75.11
No	27	3.71	3.61	87.70	86.12	84.48	88.97	87.59	85.58	56.07	58.68	55.98	76.92	58.62	72.51
No	28	3.65	3.93	87.58	84.41	84.30	88.86	88.50	82.89	56.59	61.32	56.50	76.40	61.29	69.38
No	29	3.60	3.57	88.26	84.98	84.77	89.62	89.03	83.49	57.80	60.74	57.72	75.77	60.70	69.63
No	30	3.55	3.83	87.75	87.59	85.45	88.65	79.93	90.43	56.82	50.30	56.74	76.76	50.16	81.47
No	31	3.41	3.45	88.80	86.62	85.17	90.23	86.31	86.74	56.51	57.42	56.41	78.00	57.34	74.81

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
Yes	32	3.37	3.46	88.73	88.10	85.82	89.87	82.04	90.34	57.08	56.44	56.99	77.44	56.36	75.96
No	33	3.51	3.63	87.94	86.96	85.65	88.84	85.62	87.46	56.80	58.81	56.71	76.81	58.75	72.99
No	34	3.43	3.62	88.35	85.07	86.11	89.23	86.56	84.52	57.04	58.49	56.95	77.17	58.42	73.50
No	35	3.39	3.57	88.25	87.51	86.09	89.09	81.08	89.89	57.10	56.39	57.01	77.20	56.30	75.33
No	36	3.33	3.40	89.07	86.94	85.98	90.29	87.35	86.79	57.18	58.06	57.09	77.66	57.98	74.68
No	37	3.26	3.34	88.94	86.44	86.48	89.91	88.22	85.79	56.48	56.38	56.38	78.53	56.29	76.27
No	38	3.33	3.47	88.98	87.94	86.37	90.00	83.27	89.67	57.84	56.04	57.75	77.35	55.95	76.98
No	39	3.27	3.39	89.08	87.32	86.41	90.13	86.60	87.59	57.14	57.46	57.05	78.08	57.38	75.50
No	40	3.23	3.28	89.34	87.17	86.60	90.42	87.20	87.16	56.65	57.31	56.55	79.07	57.23	76.02
No	41	3.15	3.39	89.24	86.61	86.92	90.16	87.97	86.11	57.28	59.83	57.19	78.69	59.77	73.07
Yes	42	3.16	3.45	89.37	88.05	86.57	90.47	85.58	88.97	57.12	56.94	57.02	78.96	56.85	76.62
No	43	3.31	3.41	88.90	87.16	86.13	89.99	86.01	87.59	57.60	53.23	57.51	77.25	53.11	79.49
Yes	44	3.31	3.51	88.91	88.62	86.32	89.93	83.47	90.53	56.40	54.16	56.30	78.53	54.05	77.38
No	45	3.28	3.38	89.11	87.43	86.34	90.20	85.40	88.18	57.14	57.18	57.04	78.22	57.10	75.53
No	46	3.18	3.34	89.31	87.98	86.37	90.46	86.47	88.54	56.94	57.55	56.84	78.98	57.46	75.97
No	47	3.17	3.30	89.23	86.98	87.03	90.10	86.91	87.00	57.37	58.77	57.28	78.61	58.70	74.45
No	48	3.22	3.38	89.14	86.36	87.12	89.94	88.58	85.54	57.15	56.95	57.05	79.11	56.86	76.54
No	49	3.14	3.29	89.42	87.98	86.45	90.59	86.45	88.54	57.81	57.75	57.71	78.30	57.67	75.41
No	50	3.16	3.39	89.32	88.57	86.73	90.34	83.87	90.31	57.29	53.82	57.20	79.15	53.70	79.21
No	51	3.17	3.29	89.48	86.71	86.91	90.49	87.78	86.31	57.26	60.86	57.16	79.36	60.81	72.02
No	52	3.12	3.30	89.57	88.09	87.12	90.53	84.59	89.39	57.51	54.71	57.42	79.35	54.60	78.85
No	53	3.04	3.22	89.74	88.11	87.32	90.69	86.39	88.75	57.16	57.68	57.06	80.04	57.60	75.56
No	54	3.05	3.27	89.75	87.93	87.15	90.77	86.39	88.50	57.61	58.58	57.51	79.87	58.50	75.07
No	55	3.03	3.20	89.76	87.34	86.99	90.84	87.39	87.32	56.90	61.58	56.79	80.44	61.53	71.88
No	56	3.02	3.20	89.82	88.46	87.38	90.78	84.96	89.76	58.09	54.59	57.99	79.42	54.48	79.54
No	57	3.02	3.24	89.84	87.86	87.25	90.86	86.58	88.33	57.56	56.00	57.46	80.09	55.90	78.19
No	58	2.98	3.23	89.89	87.16	87.29	90.91	87.27	87.11	57.53	58.19	57.43	80.38	58.11	75.82
No	59	2.95	3.20	90.02	88.11	87.37	91.06	86.19	88.82	57.54	59.10	57.43	80.59	59.03	75.10
No	60	2.94	3.18	89.90	88.54	87.74	90.76	84.89	89.89	58.21	54.70	58.11	80.01	54.58	79.43
No	61	2.97	3.15	90.03	87.76	87.29	91.11	87.00	88.04	56.98	57.25	56.87	81.26	57.16	77.02
No	62	2.94	3.17	90.01	87.82	87.59	90.96	86.86	88.18	57.63	56.46	57.52	80.99	56.36	77.71
No	63	2.92	3.17	90.05	88.14	87.57	91.03	86.25	88.84	57.79	57.40	57.69	80.79	57.31	76.60
No	64	2.91	3.17	90.12	88.30	87.60	91.11	85.64	89.28	57.95	56.84	57.85	80.68	56.75	77.29
No	65	2.91	3.16	90.13	88.17	87.59	91.13	86.03	88.96	57.64	57.82	57.54	81.04	57.73	76.46
No	66	2.90	3.17	90.17	87.87	87.57	91.19	86.63	88.33	57.66	57.38	57.55	81.18	57.30	76.84
No	67	2.89	3.15	90.10	88.45	87.80	91.00	85.55	89.53	57.89	56.90	57.79	80.98	56.80	77.38
No	68	2.89	3.14	90.14	88.21	87.72	91.10	86.18	88.96	57.76	56.41	57.65	81.20	56.31	77.91

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	69	2.89	3.14	90.19	88.21	87.66	91.19	86.10	88.99	58.04	56.51	57.94	80.84	56.42	77.80
No	70	2.89	3.15	90.21	88.31	87.60	91.23	85.91	89.20	57.37	56.62	57.27	81.51	56.52	77.68
No	71	2.90	3.15	90.15	88.18	87.71	91.12	86.19	88.91	57.69	56.94	57.58	81.21	56.85	77.33
No	72	2.89	3.14	90.16	88.22	87.76	91.10	86.03	89.03	58.13	57.01	58.03	80.70	56.92	77.24
No	73	2.89	3.15	90.16	88.25	87.77	91.10	86.00	89.09	57.88	56.76	57.78	81.12	56.66	77.53
No	74	2.89	3.15	90.22	88.17	87.55	91.26	86.17	88.91	57.63	57.07	57.53	81.35	56.98	77.26

Table 12: Performance Results of Model 12 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	7.00	7.67	64.12	68.97	51.26	69.17	84.74	63.14	68.58	48.69	68.72	37.04	48.61	67.38
No	2	5.66	4.82	81.10	81.40	68.42	86.09	77.05	83.01	38.08	48.00	37.90	80.06	47.89	73.13
No	3	4.97	4.82	82.44	80.84	76.76	84.67	85.79	79.01	47.95	50.58	47.84	73.72	50.48	72.62
Yes	4	4.59	4.46	83.21	82.71	82.16	83.62	83.12	82.56	49.68	63.58	49.57	74.54	63.59	60.58
Yes	5	4.59	4.22	83.87	84.45	80.69	85.12	82.07	85.33	58.34	52.62	58.30	68.45	52.52	74.21
No	6	4.43	4.60	84.09	83.55	82.75	84.62	82.80	83.83	58.81	60.79	58.77	68.63	60.76	66.29
No	7	4.70	4.97	83.72	83.73	79.85	85.24	84.23	83.54	58.48	50.70	58.44	69.25	50.58	76.47
No	8	4.33	4.10	84.76	84.09	82.03	85.83	84.73	83.85	56.71	65.34	56.64	71.79	65.35	61.63
No	9	4.18	4.06	85.10	82.59	82.95	85.94	86.92	80.98	57.16	55.28	57.10	71.79	55.20	72.92
No	10	4.09	4.15	85.63	79.52	82.58	86.82	90.01	75.64	56.56	64.81	56.49	72.77	64.81	62.99
No	11	4.08	4.23	85.53	85.84	83.08	86.50	78.65	88.51	57.85	59.09	57.79	71.84	59.05	68.31
No	12	4.14	3.92	85.85	81.77	81.79	87.45	86.84	79.90	56.93	63.24	56.86	72.94	63.24	64.44
No	13	4.01	3.96	85.08	82.43	84.65	85.25	88.88	80.04	58.56	64.75	58.50	72.03	64.75	63.88
No	14	3.90	3.87	86.36	85.92	83.37	87.54	79.87	88.16	56.34	60.74	56.26	74.33	60.71	68.07
Yes	15	3.94	3.88	85.34	84.74	83.97	85.88	82.82	85.45	57.03	60.19	56.96	73.45	60.16	68.65
Yes	16	3.89	4.02	86.02	85.34	83.24	87.11	83.07	86.18	57.60	59.88	57.53	72.80	59.83	69.20
No	17	3.96	4.21	85.96	87.30	83.48	86.94	78.47	90.57	57.44	57.05	57.37	73.67	56.98	72.70
No	18	3.91	3.97	86.81	86.83	82.79	88.40	76.94	90.49	56.41	52.52	56.32	75.09	52.41	77.11

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	19	3.94	3.97	86.45	84.36	82.67	87.94	86.73	83.48	56.19	57.92	56.10	75.47	57.87	70.75
No	20	3.85	3.74	85.97	81.83	84.35	86.61	90.50	78.63	57.79	62.13	57.72	73.60	62.10	68.25
Yes	21	3.80	3.72	86.53	85.99	84.42	87.36	85.19	86.29	57.32	61.33	57.24	74.71	61.30	68.86
No	22	3.83	3.71	86.74	87.44	83.86	87.88	76.60	91.45	57.02	51.42	56.94	75.12	51.30	78.18
No	23	3.78	4.28	87.36	87.77	83.99	88.68	77.82	91.46	56.70	55.78	56.62	75.61	55.70	73.04
No	24	3.82	3.74	86.89	83.57	84.77	87.72	89.13	81.51	56.44	60.97	56.36	75.86	60.93	69.81
No	25	3.93	3.76	85.71	85.36	84.10	86.34	84.22	85.78	58.10	55.16	58.03	73.26	55.07	74.89
No	26	3.73	3.72	87.01	85.46	84.53	87.98	84.78	85.71	56.83	55.60	56.75	75.73	55.51	75.12
Yes	27	3.59	3.62	87.39	87.12	85.10	88.29	83.32	88.52	57.38	58.34	57.30	75.77	58.28	72.43
No	28	3.60	3.70	87.52	84.95	85.08	88.48	87.97	83.83	56.22	60.30	56.13	76.90	60.26	70.10
No	29	3.79	3.61	87.16	86.93	82.84	88.85	83.35	88.25	55.97	58.36	55.88	76.24	58.30	71.39
No	30	3.78	3.66	86.06	86.93	85.47	86.29	84.54	87.81	59.27	61.26	59.21	72.79	61.22	69.63
No	31	3.61	3.67	87.19	85.66	85.64	87.80	87.10	85.13	57.51	55.95	57.43	75.17	55.86	75.38
No	32	3.54	3.52	87.82	86.17	85.00	88.92	85.63	86.37	56.43	60.59	56.34	77.07	60.54	70.70
No	33	3.60	3.58	87.55	87.44	85.25	88.45	79.08	90.53	57.53	55.29	57.44	75.98	55.19	75.75
No	34	3.49	3.53	88.08	86.86	84.38	89.53	85.16	87.49	55.67	59.57	55.57	77.86	59.52	71.76
No	35	3.52	3.60	87.67	85.77	85.30	88.60	86.92	85.35	58.45	57.28	58.38	74.97	57.21	73.84
No	36	3.59	3.81	87.60	84.24	84.85	88.68	88.51	82.66	57.07	55.55	56.99	75.89	55.47	73.66
No	37	3.61	3.54	87.10	86.54	85.02	87.92	85.37	86.97	57.30	58.36	57.22	75.86	58.29	73.29
Yes	38	3.59	3.60	87.80	88.41	85.75	88.61	80.78	91.24	57.51	57.73	57.43	76.56	57.65	74.04
No	39	3.53	3.83	88.07	84.86	85.40	89.12	88.42	83.55	57.16	66.95	57.07	77.18	66.97	62.12
Yes	40	3.51	3.63	87.96	88.42	85.49	88.94	81.31	91.04	57.59	51.64	57.50	76.32	51.51	80.57
No	41	3.48	3.52	88.30	86.91	85.43	89.42	85.66	87.37	57.13	51.34	57.04	76.74	51.22	79.93
No	42	3.34	3.46	88.50	86.88	86.14	89.43	86.23	87.12	56.56	58.96	56.46	78.20	58.89	72.90
Yes	43	3.30	3.39	88.45	88.39	86.85	89.08	82.30	90.65	57.39	56.59	57.30	77.84	56.50	75.73
No	44	3.37	3.42	88.55	87.53	85.93	89.58	84.27	88.74	57.03	54.56	56.93	77.94	54.45	77.48
No	45	3.40	3.50	88.78	88.14	85.54	90.05	83.34	89.91	57.76	58.58	57.68	77.05	58.51	73.36
No	46	3.46	3.42	88.48	87.07	85.81	89.52	85.36	87.70	56.24	57.56	56.15	78.32	57.48	74.70
No	47	3.40	3.37	88.27	86.94	86.21	89.09	85.58	87.45	57.35	59.78	57.26	77.60	59.72	71.58
No	48	3.35	3.64	88.50	87.93	85.70	89.60	81.74	90.23	57.38	56.07	57.29	77.61	55.98	75.91
No	49	3.38	3.56	88.41	88.25	86.69	89.08	83.43	90.04	57.89	53.10	57.81	77.50	52.98	79.21
No	50	3.31	3.43	88.96	87.02	86.64	89.87	86.33	87.28	56.82	62.26	56.72	78.91	62.22	70.01
No	51	3.28	3.33	88.59	87.65	86.93	89.24	84.83	88.69	58.05	56.76	57.97	77.77	56.67	76.31
Yes	52	3.26	3.40	88.80	88.63	86.87	89.55	81.72	91.19	57.43	52.88	57.34	78.55	52.76	79.73
No	53	3.18	3.37	89.01	87.86	86.64	89.95	84.00	89.28	56.77	61.05	56.67	79.62	61.01	71.28
No	54	3.18	3.38	89.09	87.45	86.91	89.95	86.31	87.87	57.55	56.73	57.46	78.98	56.64	75.93
No	55	3.18	3.34	89.05	87.06	86.98	89.86	86.64	87.21	56.80	58.77	56.70	79.83	58.70	74.38

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	56	3.19	3.32	89.10	87.61	86.97	89.94	86.01	88.20	57.83	57.73	57.74	78.99	57.65	75.79
No	57	3.18	3.34	89.15	88.18	86.92	90.02	83.97	89.74	56.76	57.61	56.65	79.98	57.53	75.08
No	58	3.19	3.34	89.25	86.35	86.88	90.18	88.13	85.69	57.43	60.61	57.33	79.18	60.56	71.64
No	59	3.09	3.29	89.35	87.55	87.38	90.13	85.88	88.16	57.65	55.91	57.55	79.57	55.81	77.93
No	60	3.09	3.28	89.53	87.99	87.33	90.40	85.42	88.94	57.13	58.98	57.03	80.51	58.91	74.67
No	61	3.08	3.28	89.41	87.97	87.43	90.20	85.42	88.92	57.91	58.87	57.81	79.81	58.79	74.95
No	62	3.07	3.27	89.48	88.47	87.31	90.34	83.87	90.18	57.30	56.97	57.20	80.59	56.88	76.55
No	63	3.08	3.49	89.45	87.72	87.70	90.14	85.76	88.45	57.73	58.91	57.63	80.27	58.84	74.86
No	64	3.10	3.26	89.70	88.50	87.26	90.66	83.47	90.36	57.41	57.21	57.30	80.93	57.12	76.30
No	65	3.07	3.25	89.28	87.70	87.91	89.82	86.16	88.27	57.66	59.07	57.56	80.48	59.00	74.51
No	66	3.03	3.26	89.82	87.82	87.25	90.83	85.92	88.52	57.72	57.12	57.62	80.77	57.03	76.67
No	67	3.01	3.25	89.64	87.46	87.73	90.39	86.68	87.75	57.55	59.56	57.45	80.98	59.50	74.28
No	68	3.02	3.29	89.71	87.15	87.67	90.52	86.98	87.22	57.71	58.83	57.60	80.82	58.76	74.98
No	69	3.03	3.23	89.75	87.72	87.65	90.58	86.15	88.30	57.53	58.11	57.43	81.03	58.03	75.85
No	70	3.00	3.24	89.76	87.91	87.79	90.53	85.87	88.66	57.18	59.44	57.07	81.64	59.38	74.57
No	71	2.99	3.24	89.72	87.80	88.01	90.39	86.11	88.43	57.92	57.52	57.82	80.93	57.44	76.42
No	72	2.99	3.22	89.91	87.51	87.61	90.81	86.54	87.87	57.78	57.60	57.68	81.26	57.51	76.43
No	73	2.98	3.22	89.84	88.01	87.85	90.62	85.44	88.96	57.91	56.96	57.81	81.10	56.87	77.02
No	74	3.00	3.26	89.81	87.68	87.83	90.58	86.32	88.18	57.61	57.07	57.50	81.42	56.98	76.79
No	75	2.99	3.24	89.83	87.04	87.85	90.61	87.20	86.98	57.53	59.92	57.42	81.64	59.85	73.92
No	76	2.98	3.23	89.83	87.52	87.88	90.59	86.49	87.90	57.78	58.57	57.67	81.44	58.50	75.30
No	77	2.98	3.23	89.86	87.71	87.87	90.64	86.27	88.25	57.48	59.04	57.37	81.84	58.97	74.92
No	78	2.98	3.22	89.83	87.69	87.76	90.65	86.08	88.28	58.25	57.14	58.15	80.96	57.05	76.87
No	79	2.97	3.23	89.87	87.73	87.89	90.65	86.13	88.32	57.26	59.18	57.15	81.98	59.11	74.67
No	80	2.97	3.22	89.87	87.84	87.92	90.64	85.87	88.57	57.86	58.03	57.75	81.35	57.95	75.98
No	81	2.97	3.22	89.92	87.74	87.78	90.75	86.07	88.36	57.63	58.58	57.52	81.79	58.50	75.37
No	82	2.96	3.23	89.89	87.67	87.91	90.67	86.21	88.21	57.90	58.92	57.80	81.36	58.85	75.02

Table 13: Performance Results of Model 13 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	6.73	4.90	72.65	82.70	70.76	73.39	71.22	86.94	53.35	37.26	53.34	55.79	37.05	83.45
Yes	2	5.11	5.44	82.69	82.47	75.78	85.40	85.45	81.36	45.19	52.22	45.05	75.71	52.14	71.64
No	3	4.97	5.17	83.49	77.67	77.01	86.04	89.02	73.48	52.40	56.56	52.31	72.56	56.51	67.59
Yes	4	4.68	4.25	84.43	84.38	82.20	85.30	84.03	84.51	54.49	59.72	54.41	72.63	59.69	67.33
No	5	4.38	4.33	85.05	81.34	81.48	86.45	86.59	79.40	56.66	70.24	56.59	72.01	70.31	54.34
No	6	4.36	4.32	84.50	86.56	83.14	85.04	74.87	90.88	58.96	54.78	58.91	69.80	54.70	73.16
No	7	4.37	4.13	84.66	86.51	83.86	84.98	78.56	89.45	56.01	58.23	55.93	73.55	58.17	70.67
Yes	8	4.20	4.05	86.46	86.29	80.69	88.73	80.29	88.51	57.42	55.23	57.35	72.22	55.15	73.86
No	9	4.34	4.19	85.58	82.06	83.88	86.24	87.21	80.16	56.53	57.23	56.46	73.03	57.16	71.68
No	10	4.29	3.95	86.09	84.21	83.26	87.21	87.53	82.98	55.95	63.02	55.87	74.52	63.01	64.55
Yes	11	4.12	3.76	86.19	86.75	83.57	87.21	82.98	88.15	55.80	58.39	55.71	74.54	58.33	71.77
No	12	4.04	4.20	85.92	80.35	84.00	86.68	90.68	76.52	57.16	67.07	57.09	73.37	67.10	60.24
No	13	4.30	3.98	85.60	86.64	83.55	86.41	80.21	89.02	57.16	49.45	57.08	73.52	49.31	79.67
No	14	4.10	3.87	85.89	84.90	84.10	86.60	81.28	86.25	55.50	60.34	55.41	75.29	60.30	68.47
No	15	4.10	3.97	84.85	87.09	85.06	84.77	77.86	90.51	58.76	53.22	58.70	71.69	53.13	75.26
No	16	3.81	3.78	86.99	85.16	85.35	87.64	85.82	84.92	57.56	62.80	57.48	74.32	62.78	67.33
No	17	3.71	4.32	87.68	84.91	84.41	88.96	87.99	83.77	56.34	58.74	56.25	76.07	58.68	71.79
Yes	18	3.84	3.73	87.93	88.21	84.29	89.36	80.17	91.18	56.82	55.65	56.73	75.56	55.56	75.40
No	19	3.85	4.17	87.14	87.76	85.04	87.96	80.55	90.43	55.15	50.91	55.05	76.59	50.78	80.00
No	20	3.87	3.85	87.34	85.57	83.56	88.83	87.10	85.00	57.01	57.80	56.93	74.94	57.74	72.66
No	21	3.72	3.67	87.81	84.90	84.39	89.15	88.46	83.58	56.00	54.30	55.91	76.52	54.20	77.05
No	22	3.65	3.81	87.75	85.07	85.27	88.73	88.10	83.95	55.72	58.31	55.62	77.34	58.24	73.25
No	23	3.69	3.82	87.70	87.85	85.39	88.61	75.61	92.38	56.90	47.46	56.81	76.32	47.30	82.65
No	24	3.96	3.89	87.14	88.60	85.08	87.95	75.95	93.28	56.84	47.53	56.76	76.30	47.38	82.43
No	25	3.65	3.55	87.82	87.87	84.76	89.02	81.65	90.17	56.20	53.81	56.10	77.37	53.70	78.17
No	26	3.47	3.60	88.72	84.80	84.94	90.21	87.19	83.91	56.90	61.53	56.80	77.26	61.49	70.01
No	27	3.47	3.48	88.56	86.82	86.09	89.53	84.65	87.62	56.67	57.14	56.58	77.68	57.06	74.74
No	28	3.42	3.42	88.97	87.09	85.73	90.24	85.57	87.65	55.95	60.05	55.85	78.67	60.00	71.81
No	29	3.33	3.49	88.92	85.70	85.84	90.13	88.20	84.78	55.95	57.34	55.84	78.95	57.26	75.08
No	30	3.40	3.45	88.65	88.92	86.30	89.57	79.36	92.46	56.60	52.15	56.50	78.20	52.03	79.53
No	31	3.35	3.52	89.12	87.71	85.79	90.43	84.95	88.73	56.01	57.89	55.91	79.15	57.82	74.95

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	32	3.27	3.34	89.32	87.57	86.44	90.45	85.82	88.22	56.59	55.92	56.49	79.19	55.82	77.32
No	33	3.20	3.44	89.38	85.22	86.57	90.49	88.38	84.06	56.59	60.58	56.49	79.34	60.53	72.07
No	34	3.19	3.33	89.24	87.49	86.94	90.15	85.27	88.32	56.81	57.68	56.71	79.30	57.60	75.41
No	35	3.19	3.39	89.50	87.75	86.51	90.67	85.98	88.41	57.03	59.07	56.93	79.12	59.01	73.64
Yes	36	3.15	3.32	89.38	88.25	87.00	90.31	83.76	89.91	56.23	56.49	56.13	80.14	56.40	76.73
Yes	37	4.08	3.52	87.29	88.28	85.74	87.90	83.29	90.12	55.62	56.24	55.53	77.52	56.15	75.53
No	38	3.49	3.49	88.44	87.75	84.94	89.81	81.43	90.09	55.83	55.00	55.73	78.84	54.90	77.45
No	39	3.45	3.57	88.05	85.67	85.47	89.06	86.46	85.37	57.15	58.22	57.06	77.46	58.15	73.65
Yes	40	3.34	3.37	88.94	88.77	86.36	89.95	81.08	91.61	56.93	55.44	56.83	78.82	55.33	77.83
No	41	3.30	3.38	88.87	87.87	86.07	89.97	83.49	89.49	56.42	49.26	56.32	79.00	49.11	83.19
No	42	3.38	4.04	88.67	82.66	85.60	89.88	90.24	79.85	57.52	60.27	57.43	77.61	60.22	71.62
No	43	3.38	3.52	88.62	87.79	86.80	89.34	81.57	90.10	55.87	52.19	55.77	79.89	52.07	80.01
No	44	3.32	3.35	89.20	88.03	86.43	90.29	84.39	89.38	56.90	57.67	56.79	79.54	57.58	75.74
No	45	3.22	3.34	89.40	88.05	86.28	90.63	83.56	89.71	56.16	55.74	56.06	80.64	55.65	77.42
No	46	3.14	3.28	89.70	87.06	86.51	90.96	87.03	87.06	56.67	53.91	56.56	80.32	53.80	79.22
No	47	3.14	3.28	89.47	88.66	87.18	90.37	82.94	90.77	56.04	56.94	55.93	81.11	56.85	76.19
No	48	3.11	3.26	89.82	87.87	86.91	90.96	84.79	89.01	56.91	56.70	56.80	80.52	56.61	76.83
No	49	3.10	3.28	89.83	87.58	86.96	90.96	84.94	88.56	56.23	56.57	56.12	81.43	56.48	76.85
Yes	50	3.04	3.28	90.02	88.71	87.13	91.15	83.55	90.62	56.76	56.17	56.65	81.53	56.08	77.32
No	51	3.24	3.39	89.06	87.26	86.44	90.09	86.16	87.66	56.34	51.48	56.23	80.61	51.34	81.09
No	52	3.19	3.36	89.39	86.14	87.08	90.30	87.13	85.77	56.37	56.56	56.26	80.71	56.47	76.24
No	53	3.23	3.43	89.28	86.90	86.89	90.22	87.61	86.64	56.12	58.90	56.01	80.60	58.84	73.66
No	54	3.11	3.34	89.68	87.71	87.05	90.71	84.54	88.89	57.31	54.74	57.21	80.50	54.63	78.14
No	55	3.14	3.28	89.70	87.14	87.10	90.72	85.84	87.62	57.41	57.13	57.31	80.83	57.04	76.52
No	56	3.09	3.27	89.71	87.56	86.95	90.79	86.98	87.77	56.25	59.42	56.14	82.22	59.36	74.11
Yes	57	3.00	3.27	90.06	88.86	87.16	91.20	82.03	91.39	57.32	54.58	57.21	81.70	54.47	78.64
No	58	3.07	3.44	90.06	86.22	87.21	91.18	87.73	85.66	56.74	59.04	56.63	82.20	58.98	74.08
No	59	3.11	3.23	89.90	87.80	88.07	90.62	86.26	88.37	57.14	57.60	57.03	82.23	57.52	76.04
No	60	2.98	3.25	90.21	88.29	87.61	91.23	84.41	89.72	57.18	57.68	57.07	82.47	57.60	75.99
No	61	2.98	3.23	90.23	87.93	87.48	91.31	85.79	88.72	57.18	58.19	57.06	82.77	58.11	75.46
No	62	2.96	3.21	90.28	88.27	87.77	91.26	85.19	89.41	57.54	58.02	57.43	82.91	57.94	75.74
No	63	2.92	3.22	90.55	87.48	87.66	91.68	86.39	87.89	57.11	58.47	56.99	83.86	58.40	75.17
No	64	2.89	3.22	90.40	87.97	88.00	91.34	85.77	88.78	57.38	56.77	57.26	83.77	56.67	77.02
No	65	2.90	3.25	90.57	87.85	87.62	91.73	86.06	88.52	57.42	59.30	57.30	83.84	59.23	74.12
No	66	2.87	3.19	90.55	88.23	88.05	91.54	84.27	89.70	57.59	56.22	57.47	84.35	56.13	77.33
No	67	2.86	3.20	90.58	87.84	88.14	91.53	86.18	88.45	57.82	58.84	57.70	84.20	58.77	74.94
No	68	2.86	3.18	90.66	88.12	87.99	91.71	85.25	89.19	57.84	57.76	57.72	84.40	57.67	75.99

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	69	2.85	3.20	90.60	88.23	88.09	91.59	84.66	89.55	57.60	57.04	57.48	84.74	56.95	76.70
No	70	2.83	3.18	90.74	88.20	88.12	91.77	84.73	89.48	57.63	57.06	57.51	85.00	56.97	76.54
No	71	2.83	3.17	90.74	88.05	88.02	91.82	85.40	89.03	57.66	57.98	57.54	85.12	57.90	75.71
No	72	2.82	3.17	90.73	88.31	88.18	91.73	84.38	89.77	57.90	56.89	57.78	84.92	56.80	76.78
No	73	2.82	3.18	90.73	88.30	88.14	91.75	84.52	89.70	57.38	58.66	57.26	85.47	58.59	74.85
No	74	2.81	3.17	90.72	88.10	88.18	91.72	85.08	89.22	58.42	58.64	58.31	84.70	58.56	75.08
No	75	2.82	3.18	90.80	88.20	88.16	91.84	84.77	89.46	57.82	58.36	57.70	85.26	58.29	75.21
No	76	2.81	3.17	90.78	88.02	88.27	91.76	85.44	88.98	57.95	58.90	57.83	85.28	58.82	74.73
No	77	2.81	3.16	90.85	88.19	88.09	91.94	85.18	89.30	58.10	57.80	57.98	85.10	57.72	75.84
No	78	2.81	3.17	90.77	88.04	88.19	91.79	85.33	89.04	57.96	58.54	57.84	85.21	58.47	75.03
No	79	2.81	3.17	90.80	88.17	88.36	91.77	84.95	89.37	58.08	58.22	57.96	85.12	58.15	75.45
No	80	2.81	3.17	90.80	88.10	88.24	91.81	85.27	89.15	58.10	58.65	57.98	85.30	58.58	74.94
No	81	2.80	3.17	90.78	88.09	88.25	91.77	85.31	89.12	57.86	58.53	57.74	85.54	58.46	75.03
No	82	2.80	3.17	90.81	88.10	88.19	91.85	85.29	89.15	57.97	58.38	57.85	85.40	58.31	75.22
No	83	2.80	3.17	90.77	88.10	88.22	91.78	85.19	89.17	57.89	58.40	57.77	85.46	58.32	75.21
No	84	2.79	3.17	90.78	88.11	88.38	91.73	85.18	89.19	58.09	58.60	57.97	85.38	58.52	74.97
No	85	2.80	3.17	90.86	88.08	88.12	91.94	85.27	89.12	58.19	58.54	58.07	85.28	58.46	75.07
No	86	2.80	3.17	90.76	88.10	88.25	91.75	85.19	89.17	58.04	58.34	57.92	85.29	58.26	75.26
No	87	2.80	3.17	90.80	88.13	88.32	91.78	85.12	89.24	58.01	58.30	57.89	85.49	58.23	75.31

Table 14: Performance Results of Model 14 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	7.14	5.47	61.39	76.74	38.36	70.44	77.58	76.43	34.28	37.17	34.11	72.39	36.97	80.95
No	2	6.15	5.11	69.39	83.41	60.72	72.79	66.96	89.50	38.35	42.74	38.18	74.86	42.58	77.84
No	3	5.97	4.97	72.96	83.24	59.28	78.33	65.08	89.96	46.72	26.70	46.64	65.55	26.41	90.81
No	4	5.89	4.75	72.39	76.86	62.77	76.17	86.21	73.40	39.97	43.39	39.82	73.21	43.23	78.20
No	5	5.85	5.39	74.71	72.68	63.10	79.27	87.39	67.24	42.35	57.92	42.22	71.36	57.92	59.19

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	6	6.17	5.01	75.06	82.45	57.76	81.85	78.39	83.95	40.55	45.50	40.40	73.46	45.36	76.13
No	7	5.95	4.78	74.91	83.40	62.95	79.60	67.99	89.10	41.83	61.12	41.70	72.37	61.13	56.92
No	8	5.96	4.52	72.81	79.07	62.73	76.77	83.53	77.42	43.15	48.06	43.03	70.08	47.95	72.70
No	9	5.68	5.24	75.10	84.85	65.61	78.83	58.13	94.74	42.85	29.29	42.72	72.26	29.02	90.76
No	10	5.87	4.47	73.14	84.65	62.13	77.47	71.12	89.65	42.51	38.30	42.38	71.64	38.10	83.31
No	11	5.67	4.84	75.85	84.74	61.17	81.62	66.29	91.56	38.21	25.21	38.04	76.39	24.90	92.91
No	12	5.72	4.80	74.36	79.74	65.23	77.94	81.39	79.13	41.27	44.38	41.13	72.83	44.23	77.18
No	13	5.62	4.58	75.34	85.39	60.79	81.05	72.79	90.05	39.47	33.77	39.31	75.08	33.53	87.69
No	14	5.58	4.51	75.26	81.43	64.48	79.50	77.83	82.77	40.95	45.78	40.80	74.06	45.65	75.58
No	15	5.78	4.54	72.64	84.15	66.56	75.03	78.47	86.25	43.84	47.76	43.72	70.52	47.65	73.67
No	16	5.65	4.42	75.61	84.62	61.79	81.04	76.01	87.81	42.87	37.67	42.75	71.62	37.46	84.24
No	17	5.63	5.05	75.35	75.31	64.93	79.44	88.78	70.32	42.36	72.18	42.22	72.45	72.32	42.61
No	18	5.55	4.40	75.81	85.85	65.45	79.88	65.73	93.29	43.35	33.15	43.22	71.43	32.90	88.58
No	19	5.53	4.46	76.20	84.72	62.51	81.57	70.58	89.96	42.39	40.38	42.26	72.59	40.20	81.37
No	20	5.55	4.52	74.76	80.14	63.97	79.00	84.58	78.50	42.38	37.54	42.24	72.26	37.33	84.40
No	21	5.47	4.50	76.04	78.97	64.67	80.51	84.54	76.91	39.96	50.24	39.80	75.56	50.15	70.84
No	22	5.43	4.40	75.96	85.30	66.80	79.56	72.57	90.00	43.05	35.64	42.92	72.21	35.41	86.41
Yes	23	5.54	4.55	75.99	83.15	63.11	81.06	82.46	83.41	38.04	40.87	37.87	77.27	40.68	82.00
No	24	5.45	4.52	75.98	85.76	66.74	79.60	68.91	91.99	43.43	30.48	43.31	71.99	30.21	90.83
No	25	5.44	4.34	76.35	84.98	64.85	80.87	78.28	87.46	41.34	36.10	41.20	74.23	35.87	86.23
No	26	5.40	4.53	76.40	84.18	65.84	80.55	76.69	86.95	41.29	38.73	41.15	74.46	38.53	82.65
No	27	5.39	4.25	76.47	85.19	65.51	80.78	76.53	88.40	41.77	39.88	41.63	74.00	39.68	82.55
No	28	5.40	4.33	76.72	85.32	64.35	81.58	71.95	90.27	39.82	33.08	39.66	75.95	32.83	88.62
No	29	5.51	4.70	76.35	80.97	63.15	81.54	83.52	80.03	38.69	43.28	38.52	76.89	43.11	78.88
No	30	5.47	4.40	76.11	82.81	64.02	80.86	80.62	83.62	41.31	41.40	41.16	74.14	41.23	80.24
Yes	31	5.38	4.27	76.14	84.60	66.07	80.09	80.02	86.30	41.53	39.54	41.38	74.43	39.34	83.20
No	32	5.45	4.30	76.00	84.44	65.31	80.20	75.92	87.59	41.13	35.95	40.98	74.17	35.72	85.89
No	33	5.53	4.65	75.52	83.80	65.22	79.56	81.20	84.76	40.91	43.24	40.76	74.11	43.08	78.64
No	34	5.47	4.63	76.00	85.09	67.16	79.47	68.60	91.19	41.42	31.66	41.28	74.38	31.39	89.64
No	35	5.47	4.29	75.58	84.19	63.33	80.39	76.24	87.13	38.23	45.13	38.06	76.81	44.99	77.05
No	36	5.54	5.02	76.21	82.03	64.34	80.87	82.75	81.76	41.70	45.50	41.56	73.73	45.35	76.79
No	37	5.52	4.36	75.73	86.07	66.67	79.29	71.14	91.60	44.66	35.98	44.54	70.66	35.75	86.59
No	38	5.37	4.30	77.29	84.96	64.59	82.27	74.68	88.76	40.20	37.45	40.04	75.91	37.24	84.94
No	39	5.33	4.29	76.07	85.04	67.35	79.50	77.32	87.90	41.36	39.36	41.21	74.90	39.16	83.05
No	40	5.40	4.26	75.37	82.50	65.83	79.12	80.62	83.20	42.77	43.87	42.64	72.81	43.71	78.28
No	41	5.30	4.18	76.59	82.50	66.86	80.42	83.08	82.29	41.84	41.55	41.70	74.34	41.38	81.07
No	42	5.33	4.24	76.22	83.07	67.21	79.76	81.04	83.81	42.17	43.61	42.03	73.97	43.45	78.69

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	43	5.33	4.23	76.72	85.40	66.42	80.77	78.34	88.01	40.71	34.89	40.55	75.43	34.65	87.85
No	44	5.27	4.19	77.38	84.86	67.49	81.26	77.71	87.50	39.44	37.72	39.27	77.13	37.50	84.92
No	45	5.31	4.23	77.19	83.35	65.27	81.87	80.41	84.44	39.41	41.39	39.24	76.82	41.21	81.12
No	46	5.34	4.14	76.45	85.04	66.21	80.47	78.92	87.31	40.90	39.59	40.74	75.20	39.39	83.42
No	47	5.29	4.22	77.40	84.04	66.11	81.83	82.39	84.65	39.81	41.94	39.64	76.38	41.76	81.13
No	48	5.25	4.19	78.18	83.91	65.36	83.22	80.44	85.19	38.97	40.85	38.80	77.55	40.66	82.13
No	49	5.25	4.12	76.95	84.19	66.48	81.06	80.58	85.52	41.51	41.16	41.36	74.62	40.98	81.70
No	50	5.26	4.17	77.10	81.39	65.39	81.69	84.93	80.08	39.59	47.72	39.42	76.77	47.60	74.22
No	51	5.23	4.13	76.52	84.01	67.29	80.15	80.86	85.17	43.39	42.59	43.26	73.32	42.42	80.30
No	52	5.32	4.15	76.63	84.79	65.63	80.95	79.48	86.75	40.95	39.46	40.79	75.28	39.26	83.63
Yes	53	5.20	4.12	77.11	84.60	67.51	80.87	80.29	86.19	40.96	39.89	40.81	75.92	39.69	83.18
No	54	5.39	4.12	77.09	84.72	66.44	81.27	79.91	86.50	38.91	38.65	38.74	77.55	38.44	84.35
No	55	5.50	4.39	74.56	74.42	64.33	78.57	91.53	68.09	40.65	52.88	40.50	74.23	52.81	68.11
No	56	5.37	4.23	75.20	84.92	67.51	78.22	77.98	87.49	43.84	38.48	43.72	71.79	38.27	84.58
No	57	5.34	4.48	76.55	76.86	65.27	80.98	87.40	72.96	40.10	54.26	39.94	75.95	54.20	66.10
No	58	5.36	4.21	75.71	85.47	65.93	79.55	76.07	88.94	44.51	37.96	44.39	71.11	37.75	84.93
No	59	5.27	4.16	77.53	85.48	66.01	82.06	77.92	88.28	40.27	37.20	40.11	76.16	36.98	85.91
No	60	5.26	4.15	77.11	85.26	66.31	81.35	77.56	88.11	40.79	39.93	40.64	75.64	39.74	82.83
No	61	5.26	4.10	76.83	84.21	66.83	80.76	81.28	85.30	40.98	40.58	40.83	75.18	40.39	82.25
No	62	5.29	4.12	76.98	84.35	66.73	81.01	80.96	85.60	41.19	37.76	41.04	75.20	37.54	84.98
Yes	63	5.24	4.14	76.99	84.61	66.62	81.07	80.58	86.10	38.78	41.24	38.61	77.79	41.05	81.79
No	64	5.41	4.41	77.45	85.14	64.96	82.36	76.56	88.31	39.42	34.67	39.25	77.00	34.43	88.10
No	65	5.43	4.52	75.93	83.97	65.28	80.11	78.23	86.09	42.22	40.97	42.08	73.30	40.79	81.35
No	66	5.39	4.47	76.90	74.47	63.41	82.19	90.12	68.68	39.04	55.71	38.87	76.51	55.67	64.32
No	67	5.42	4.33	76.07	79.24	66.00	80.03	84.19	77.41	41.93	49.48	41.79	73.62	49.38	71.73
No	68	5.34	4.20	75.79	85.61	68.21	78.76	75.89	89.21	44.05	35.37	43.93	71.67	35.14	87.24
No	69	5.31	4.17	76.88	83.77	66.53	80.94	83.05	84.04	39.28	41.66	39.12	76.97	41.48	81.59
No	70	5.29	4.16	76.85	83.93	66.94	80.74	80.37	85.24	41.51	42.06	41.37	74.87	41.88	80.73
No	71	5.22	4.11	77.14	81.89	67.21	81.05	84.78	80.82	41.90	44.40	41.75	74.59	44.24	78.21
No	72	5.22	4.14	77.48	84.67	67.90	81.24	78.98	86.77	40.18	39.75	40.01	76.61	39.55	83.19
No	73	5.21	4.20	77.54	84.01	67.14	81.63	80.38	85.35	40.42	40.64	40.26	76.46	40.45	82.26
No	74	5.28	4.10	77.07	84.70	65.29	81.69	79.77	86.52	40.01	39.25	39.85	76.20	39.05	83.81
No	75	5.17	4.04	78.24	83.36	67.05	82.63	83.51	83.30	40.12	42.76	39.95	76.74	42.59	80.47
No	76	5.27	4.07	76.98	81.87	66.29	81.18	83.61	81.23	40.02	45.41	39.86	76.62	45.27	77.15
No	77	5.23	4.19	77.25	85.63	67.42	81.11	77.94	88.48	40.20	38.82	40.04	76.47	38.61	84.18
Yes	78	5.30	4.01	76.54	84.69	65.69	80.81	82.39	85.54	41.33	43.69	41.18	74.91	43.52	79.59
No	79	5.41	4.21	75.88	81.02	65.95	79.78	85.69	79.29	41.87	50.08	41.73	73.67	49.99	71.58

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	80	5.37	4.26	76.67	85.29	65.22	81.17	73.81	89.53	40.43	41.72	40.28	75.48	41.55	80.84
No	81	5.26	4.50	77.04	86.49	66.50	81.19	67.29	93.59	42.44	27.57	42.30	73.72	27.27	93.29
No	82	5.47	4.42	76.39	86.04	64.52	81.05	74.46	90.32	39.80	37.64	39.64	75.73	37.42	85.37
No	83	5.35	4.20	76.10	86.46	67.21	79.59	73.50	91.26	44.43	33.98	44.31	71.53	33.73	88.96
No	84	5.32	4.10	76.80	83.48	64.69	81.56	82.52	83.84	41.22	41.12	41.07	74.91	40.93	82.10
No	85	5.28	4.02	77.08	83.77	65.54	81.61	82.57	84.22	39.60	44.83	39.44	76.81	44.68	78.13
No	86	5.22	4.07	77.40	84.27	66.58	81.65	83.03	84.73	42.81	45.55	42.67	73.65	45.41	77.18
No	87	5.17	4.04	77.70	84.41	66.91	81.94	81.20	85.60	40.61	42.12	40.45	76.20	41.94	81.12
No	88	5.22	4.19	76.62	86.28	68.08	79.97	74.40	90.67	42.51	34.10	42.37	73.88	33.85	89.02
No	89	5.24	4.09	77.31	85.62	66.30	81.64	78.43	88.28	40.44	38.21	40.29	76.21	38.00	85.06
No	90	5.32	4.07	76.56	85.34	66.10	80.67	78.11	88.01	40.88	37.30	40.72	75.23	37.08	85.99
No	91	5.18	4.11	77.12	84.20	67.90	80.74	83.64	84.41	41.80	45.82	41.65	75.00	45.68	77.48
Yes	92	5.23	4.01	76.94	85.35	65.89	81.28	80.50	87.14	41.73	37.92	41.58	74.51	37.70	85.86
No	93	5.32	4.32	76.61	86.28	65.77	80.86	74.17	90.76	41.00	32.78	40.85	75.41	32.52	90.04
No	94	5.35	4.31	77.41	83.97	64.87	82.33	81.97	84.70	38.91	41.45	38.74	77.42	41.26	81.54
No	95	5.51	4.23	75.78	84.27	64.95	80.04	73.73	88.17	40.95	37.48	40.80	74.61	37.27	84.47
No	96	5.24	4.03	76.72	84.32	67.83	80.21	82.50	85.00	43.98	41.84	43.85	72.41	41.66	81.56
No	97	5.29	4.07	76.57	84.51	68.03	79.93	83.09	85.04	40.57	36.72	40.41	75.99	36.49	86.66
No	98	5.26	4.15	76.75	85.09	66.06	80.95	79.68	87.10	39.89	43.07	39.72	76.48	42.90	80.14
No	99	5.25	4.13	77.58	85.16	65.98	82.13	76.45	88.38	40.92	38.96	40.76	75.49	38.76	83.52
No	100	5.27	4.10	76.66	82.99	65.77	80.93	85.29	82.15	40.78	44.77	40.62	75.62	44.62	78.47

Table 15: Performance Results of Model 15 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	8.23	6.34	62.27	80.35	35.73	72.70	73.13	83.03	60.80	87.86	60.89	41.67	88.20	13.24
No	2	5.25	4.79	82.57	83.80	65.71	89.20	75.71	86.79	43.73	39.51	43.59	74.82	39.32	81.17
Yes	3	5.27	4.38	82.84	84.63	77.37	84.99	82.39	85.46	38.79	40.07	38.60	82.39	39.87	82.93

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	4	4.61	4.38	84.40	79.63	81.48	85.55	89.86	75.84	40.42	50.06	40.23	83.26	49.95	74.18
No	5	4.47	4.33	84.56	83.80	81.04	85.95	85.84	83.04	44.69	60.80	44.53	80.62	60.79	63.29
Yes	6	4.34	4.10	84.68	85.47	83.41	85.18	82.79	86.46	53.56	49.84	53.47	72.91	49.71	77.33
No	7	4.21	4.05	84.84	85.04	84.16	85.11	84.52	85.24	56.43	55.12	56.36	71.75	55.03	73.05
No	8	4.26	3.97	84.88	83.35	83.64	85.36	84.92	82.77	56.00	63.55	55.93	72.67	63.55	63.50
Yes	9	4.26	4.02	85.77	87.11	81.44	87.48	80.86	89.42	54.54	54.45	54.45	74.66	54.36	74.21
No	10	4.26	4.29	84.29	83.66	83.15	84.74	85.14	83.11	56.30	61.92	56.22	72.73	61.90	65.50
No	11	3.96	4.02	86.39	86.09	83.46	87.55	81.91	87.64	55.54	51.06	55.46	74.34	50.94	77.57
Yes	12	4.00	3.83	85.37	87.70	84.82	85.58	80.14	90.50	57.78	47.62	57.72	71.87	47.47	80.73
No	13	4.03	4.57	86.12	79.34	83.22	87.25	88.15	76.07	55.53	63.34	55.45	74.08	63.34	64.91
No	14	4.07	3.89	86.41	86.90	83.23	87.67	81.91	88.74	56.52	54.32	56.44	73.90	54.22	75.64
No	15	3.96	4.12	86.81	86.16	83.12	88.26	85.35	86.46	55.71	52.50	55.62	75.21	52.38	77.28
No	16	3.85	3.89	86.44	83.09	84.03	87.39	85.23	82.30	56.02	62.22	55.93	75.20	62.20	66.35
No	17	3.90	4.43	86.32	82.53	82.80	87.71	89.44	79.97	57.02	60.94	56.95	73.67	60.91	68.58
No	18	3.89	3.98	86.27	85.86	84.82	86.85	85.73	85.91	55.54	59.96	55.45	75.56	59.92	69.95
No	19	3.68	3.63	87.47	85.87	83.48	89.04	87.16	85.40	55.81	57.19	55.72	75.97	57.12	73.74
No	20	3.59	3.89	87.68	87.81	85.66	88.48	79.85	90.76	56.32	54.71	56.23	75.95	54.61	75.89
No	21	3.56	3.60	88.13	87.16	85.04	89.34	84.57	88.12	55.92	57.72	55.83	76.82	57.65	73.44
No	22	3.53	3.59	88.22	86.89	85.02	89.48	84.53	87.76	56.14	54.36	56.05	76.71	54.26	76.63
No	23	3.48	3.55	88.03	85.07	85.52	89.01	85.04	85.08	55.66	60.76	55.56	77.24	60.72	70.08
No	24	3.48	3.58	87.97	88.20	85.14	89.08	78.89	91.64	55.99	53.88	55.89	77.05	53.78	77.00
Yes	25	3.48	3.53	88.13	87.85	85.19	89.29	82.10	89.98	57.25	51.06	57.17	75.86	50.93	79.86
No	26	3.49	3.50	87.70	84.50	85.24	88.66	89.34	82.71	56.66	59.14	56.58	76.29	59.09	71.48
No	27	3.55	3.59	87.63	84.58	85.05	88.65	87.75	83.40	56.67	64.76	56.58	75.92	64.77	63.62
No	28	3.62	3.74	87.89	83.79	85.11	88.98	89.45	81.70	56.60	62.24	56.52	75.76	62.21	68.48
No	29	3.46	3.58	88.28	86.75	85.93	89.20	85.21	87.33	56.41	54.55	56.32	76.36	54.45	75.71
No	30	3.56	3.55	88.36	87.92	85.02	89.67	79.58	91.00	56.29	53.80	56.20	76.98	53.69	77.35
No	31	3.50	3.60	88.13	87.34	84.92	89.39	85.26	88.11	55.55	60.65	55.45	77.90	60.60	70.10
No	32	3.51	3.49	87.86	86.80	85.46	88.80	83.97	87.84	56.69	61.71	56.61	76.26	61.67	68.75
No	33	3.53	3.50	88.36	87.76	84.89	89.73	84.43	88.99	56.61	57.88	56.52	76.59	57.81	73.38
No	34	3.36	3.45	88.72	87.75	85.67	89.92	83.18	89.44	56.09	56.75	55.99	77.84	56.67	74.96
Yes	35	3.28	3.40	88.94	87.87	86.07	90.07	85.23	88.85	56.21	60.17	56.11	78.33	60.12	71.22
No	36	3.35	3.44	88.91	86.55	85.31	90.33	86.79	86.46	56.07	56.47	55.97	77.84	56.38	75.41
Yes	37	3.40	3.44	88.57	88.15	85.77	89.67	81.47	90.62	56.92	53.32	56.83	77.34	53.21	78.62
No	38	3.25	3.47	88.82	87.25	86.63	89.69	85.64	87.84	56.94	58.71	56.85	77.82	58.64	73.63
No	39	3.33	3.41	88.95	88.04	85.61	90.26	84.19	89.46	56.74	55.94	56.64	78.24	55.85	76.35
No	40	3.19	3.33	89.33	87.84	86.63	90.38	83.26	89.54	56.59	54.84	56.50	78.61	54.73	77.79

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
Yes	41	3.14	3.30	89.37	88.36	86.75	90.40	84.51	89.79	56.47	56.55	56.38	78.95	56.46	76.58
No	42	3.25	3.44	88.76	87.38	86.98	89.46	83.01	89.00	57.02	51.36	56.93	78.04	51.23	79.91
No	43	3.44	3.41	88.43	87.48	85.80	89.46	83.47	88.96	56.09	52.53	56.00	77.82	52.41	79.54
No	44	3.35	3.47	88.78	88.32	86.57	89.65	83.27	90.19	55.94	52.25	55.84	78.62	52.13	79.77
No	45	3.28	3.36	88.76	86.97	86.19	89.77	84.51	87.88	57.14	53.91	57.05	77.79	53.79	78.83
Yes	46	3.12	3.36	89.08	88.57	86.57	90.07	82.14	90.96	56.74	53.10	56.64	78.83	52.98	79.29
No	47	3.24	3.35	89.47	88.39	86.56	90.61	84.41	89.87	55.77	55.18	55.67	79.71	55.08	77.97
No	48	3.22	3.94	88.99	87.81	86.86	89.82	80.10	90.67	56.49	55.21	56.39	78.68	55.12	75.87
No	49	3.38	3.81	88.70	86.11	85.98	89.77	89.08	85.01	57.29	59.92	57.20	77.76	59.86	72.61
Yes	50	3.19	3.31	89.27	88.57	86.55	90.34	82.84	90.69	56.73	58.49	56.63	79.20	58.42	74.64
Yes	51	3.19	3.42	89.67	88.66	86.52	90.91	83.41	90.60	57.08	53.46	56.98	78.75	53.35	78.54
No	52	3.24	3.36	89.49	88.09	86.37	90.72	83.94	89.63	56.01	58.63	55.91	79.68	58.56	74.26
Yes	53	3.20	3.56	89.61	88.90	86.99	90.64	80.71	91.93	57.09	54.16	57.00	78.69	54.05	78.29
No	54	3.13	3.30	89.59	88.04	86.83	90.68	85.54	88.96	56.30	53.82	56.20	79.84	53.71	78.40
No	55	3.05	3.26	89.59	87.37	87.62	90.37	86.52	87.69	56.30	56.79	56.20	80.24	56.70	76.48
No	56	2.99	3.17	90.02	88.46	87.21	91.13	84.91	89.77	56.60	54.02	56.49	80.58	53.90	79.58
No	57	2.97	3.25	90.04	88.71	87.67	90.97	84.48	90.27	56.69	58.98	56.58	80.82	58.91	74.20
No	58	2.99	3.36	90.04	88.29	88.14	90.78	83.81	89.94	56.74	56.02	56.64	80.81	55.92	77.55
No	59	2.99	3.22	90.04	88.70	87.59	91.00	84.78	90.15	56.72	55.29	56.61	81.03	55.19	77.91
No	60	2.97	3.24	90.06	87.62	87.65	91.01	86.97	87.86	56.83	56.98	56.73	81.10	56.89	76.54
No	61	2.87	3.17	90.31	88.62	88.07	91.19	85.08	89.92	56.76	57.85	56.65	81.69	57.77	76.17
No	62	2.86	3.18	90.61	88.34	87.96	91.65	85.33	89.46	57.39	55.75	57.28	81.18	55.65	77.62
No	63	2.85	3.25	90.49	88.69	88.32	91.34	84.54	90.23	56.60	57.03	56.49	82.03	56.94	76.48
No	64	2.86	3.18	90.62	88.35	88.15	91.59	86.05	89.20	57.07	56.21	56.96	81.71	56.11	77.87
No	65	2.81	3.18	90.80	87.98	88.06	91.87	86.53	88.51	56.90	57.04	56.79	82.17	56.95	76.93
No	66	2.79	3.18	90.73	88.31	88.51	91.60	85.44	89.38	55.90	59.93	55.78	83.44	59.87	73.31
No	67	2.77	3.15	90.76	88.33	88.41	91.69	85.82	89.26	57.82	55.08	57.72	81.37	54.97	78.84
No	68	2.76	3.17	90.85	88.45	88.41	91.81	85.19	89.66	56.30	56.91	56.18	83.28	56.82	76.98
No	69	2.75	3.16	90.93	88.11	88.39	91.93	86.35	88.76	57.03	58.49	56.92	82.66	58.41	75.29
No	70	2.73	3.17	90.97	88.56	88.63	91.89	85.03	89.86	57.22	57.31	57.10	83.01	57.22	76.72
No	71	2.71	3.11	91.03	88.15	88.39	92.07	86.63	88.71	56.87	58.77	56.75	83.44	58.69	75.50
Yes	72	2.71	3.13	91.02	88.85	88.74	91.92	84.40	90.50	57.18	57.50	57.07	83.30	57.41	76.69
No	73	3.03	3.25	90.07	88.15	87.65	91.02	84.85	89.37	55.83	60.42	55.71	82.05	60.36	72.96
No	74	2.90	3.21	90.61	87.75	87.56	91.82	85.85	88.45	57.10	58.28	56.99	82.14	58.20	75.20
No	75	2.81	3.17	90.66	87.38	88.31	91.59	86.78	87.60	57.44	58.71	57.33	82.23	58.64	74.97
No	76	2.79	3.25	90.63	87.61	88.39	91.51	86.67	87.96	57.06	59.29	56.94	82.78	59.23	74.20
No	77	2.76	3.17	90.87	88.80	88.39	91.84	83.94	90.59	56.57	58.41	56.45	83.60	58.33	75.56

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	78	2.70	3.13	91.17	88.27	88.62	92.17	85.91	89.14	57.53	56.77	57.42	83.37	56.68	77.24
No	79	2.71	3.12	91.18	88.56	88.76	92.13	85.54	89.67	57.50	58.08	57.38	83.75	58.00	75.67
No	80	2.69	3.13	91.32	88.18	88.67	92.36	86.44	88.83	56.96	59.42	56.84	84.40	59.35	74.58
No	81	2.68	3.16	91.13	88.69	89.05	91.94	83.87	90.47	57.46	56.30	57.34	83.95	56.20	77.50
No	82	2.63	3.13	91.39	88.79	89.03	92.33	84.56	90.35	57.50	57.31	57.38	84.51	57.22	76.62
No	83	2.61	3.16	91.50	88.77	89.00	92.48	84.20	90.46	57.74	57.92	57.62	84.45	57.84	75.90
No	84	2.64	3.14	91.39	88.11	89.14	92.27	86.37	88.76	57.52	59.12	57.40	84.64	59.05	74.81
No	85	2.62	3.14	91.47	88.03	88.83	92.51	86.53	88.58	57.59	58.37	57.47	84.73	58.29	75.63
No	86	2.58	3.10	91.44	88.63	89.06	92.37	85.11	89.93	57.56	58.08	57.44	85.13	58.00	76.00
No	87	2.58	3.13	91.57	88.83	89.15	92.52	84.13	90.57	57.93	56.99	57.81	84.96	56.90	77.03
No	88	2.57	3.11	91.56	88.84	89.12	92.52	84.25	90.53	57.74	57.60	57.62	85.26	57.52	76.53
No	89	2.56	3.11	91.64	88.44	89.06	92.65	85.59	89.49	57.62	58.92	57.50	85.37	58.85	75.27
No	90	2.56	3.11	91.62	88.49	89.23	92.55	85.31	89.67	57.89	59.07	57.77	85.29	59.00	74.98
No	91	2.55	3.11	91.60	88.50	89.26	92.53	85.13	89.75	58.04	58.74	57.92	85.16	58.66	75.34
No	92	2.55	3.12	91.67	88.73	89.23	92.63	84.48	90.30	57.85	57.97	57.73	85.44	57.89	76.06
No	93	2.55	3.12	91.64	88.68	89.18	92.60	84.47	90.24	58.05	57.58	57.93	85.23	57.50	76.30
No	94	2.55	3.11	91.65	88.55	89.11	92.65	85.10	89.83	57.97	58.33	57.85	85.41	58.25	75.77
No	95	2.55	3.12	91.60	88.59	89.22	92.54	84.92	89.94	57.82	58.08	57.70	85.50	57.99	75.97
No	96	2.54	3.11	91.67	88.67	89.28	92.61	84.59	90.18	58.02	58.14	57.89	85.45	58.06	75.81
No	97	2.53	3.12	91.68	88.77	89.27	92.63	84.27	90.44	57.95	57.72	57.83	85.43	57.64	76.26
No	98	2.54	3.11	91.70	88.67	89.19	92.68	84.66	90.15	57.89	58.09	57.76	85.63	58.00	75.88
No	99	2.54	3.11	91.62	88.68	89.22	92.57	84.58	90.19	57.98	57.97	57.86	85.43	57.88	75.97
No	100	2.53	3.11	91.66	88.63	89.29	92.59	84.77	90.06	58.04	58.35	57.92	85.54	58.28	75.62

Table 16: Performance Results of Model 16 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	8.02	5.59	57.72	82.35	70.46	52.71	64.11	89.10	57.76	23.87	57.80	47.91	23.56	92.47

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	2	6.70	5.03	75.71	81.72	65.43	79.75	73.63	84.71	44.93	27.52	44.83	67.73	27.24	90.90
No	3	5.87	5.26	75.26	83.17	72.66	76.29	45.77	97.01	51.44	29.15	51.39	63.31	28.88	90.59
No	4	6.17	5.18	77.07	82.52	72.80	78.74	76.87	84.61	51.52	39.80	51.47	62.64	39.61	82.14
No	5	5.64	4.74	78.79	83.05	77.87	79.15	69.44	88.09	52.20	23.00	52.14	66.95	22.67	94.60
No	6	6.96	4.83	79.08	84.53	73.46	81.29	74.35	88.29	42.74	27.61	42.59	77.54	27.32	91.16
No	7	6.16	5.82	75.22	80.98	80.66	73.08	85.26	79.40	59.69	57.69	59.68	61.37	57.66	65.67
No	8	6.06	5.34	77.84	70.63	74.70	79.07	92.64	62.49	60.85	65.89	60.85	60.47	65.92	58.24
No	9	5.55	5.05	76.40	76.86	82.03	74.18	89.33	72.25	60.23	65.65	60.21	64.19	65.68	58.95
No	10	4.80	4.37	81.69	81.61	82.09	81.53	86.44	79.82	59.36	60.94	59.33	66.82	60.92	65.31
No	11	4.76	4.93	82.23	69.83	83.01	81.92	92.93	61.29	58.90	80.22	58.86	68.20	80.41	38.85
No	12	4.94	4.91	78.20	84.73	82.02	76.69	71.36	89.68	60.24	50.29	60.22	64.51	50.18	74.43
No	13	4.71	4.66	80.99	86.07	81.61	80.74	71.77	91.36	59.38	51.98	59.35	67.45	51.88	74.18
No	14	4.55	4.53	83.18	84.21	81.02	84.03	72.91	88.39	59.73	44.58	59.70	67.79	44.41	80.76
Yes	15	4.95	4.21	78.80	84.27	82.72	77.26	82.23	85.03	59.42	59.89	59.38	66.91	59.86	67.58
No	16	4.53	4.36	82.51	86.36	82.30	82.59	73.64	91.07	60.50	49.72	60.48	67.06	49.60	76.29
No	17	4.47	5.00	82.95	72.89	82.58	83.09	85.88	68.08	59.20	74.29	59.16	68.22	74.41	47.86
No	18	4.65	4.36	81.78	85.06	81.83	81.76	79.24	87.22	60.55	50.48	60.52	66.54	50.36	77.15
No	19	4.72	4.17	80.02	82.48	83.83	78.53	84.82	81.62	59.53	55.48	59.49	68.08	55.41	72.64
No	20	4.28	4.46	83.64	74.13	82.46	84.10	92.46	67.35	58.71	76.69	58.66	70.27	76.84	45.29
No	21	4.34	4.26	83.08	84.59	82.98	83.12	77.68	87.15	60.11	55.66	60.07	67.60	55.59	71.03
No	22	4.24	4.10	84.24	82.26	82.24	85.03	86.82	80.57	56.79	59.78	56.72	72.56	59.74	67.86
No	23	4.21	4.28	83.69	80.26	82.21	84.27	88.08	77.36	59.23	62.90	59.18	69.44	62.89	64.88
No	24	4.31	4.66	83.81	70.30	83.38	83.98	94.19	61.46	59.99	65.29	59.95	68.93	65.31	61.14
Yes	25	4.21	3.98	83.97	86.74	82.61	84.50	81.01	88.85	58.80	58.19	58.75	70.09	58.13	70.38
No	26	4.18	3.99	84.25	85.19	83.14	84.69	83.48	85.82	59.08	53.67	59.03	70.00	53.58	74.78
No	27	4.17	4.16	84.54	80.48	82.77	85.24	88.68	77.45	58.89	66.86	58.84	70.62	66.89	59.77
No	28	4.29	3.96	83.64	83.77	82.47	84.10	83.71	83.79	58.30	60.29	58.24	71.04	60.26	68.22
No	29	4.11	4.01	84.09	84.15	83.13	84.47	84.45	84.04	59.37	60.36	59.32	70.02	60.33	67.28
No	30	4.10	4.07	85.55	83.08	83.27	86.45	84.38	82.60	58.10	61.80	58.04	72.03	61.78	66.32
No	31	3.97	3.88	85.11	86.67	84.14	85.50	80.72	88.87	57.74	56.93	57.67	72.86	56.86	71.83
No	32	4.08	4.07	84.33	86.91	83.23	84.77	78.19	90.13	57.93	56.49	57.87	71.67	56.42	72.59
Yes	33	3.95	4.01	85.68	87.12	83.79	86.42	80.16	89.69	59.88	56.00	59.83	71.08	55.92	72.98
No	34	3.95	4.01	85.94	83.58	83.21	87.02	82.19	84.09	57.95	61.54	57.88	73.05	61.52	66.53
No	35	4.08	3.95	84.81	84.65	82.69	85.64	85.40	84.38	58.76	55.16	58.70	71.61	55.08	74.25
No	36	3.97	3.82	85.74	85.41	82.31	87.09	81.20	86.97	57.12	59.20	57.05	73.62	59.15	70.34
No	37	3.85	3.94	85.56	81.98	84.16	86.12	88.36	79.63	58.33	60.22	58.27	72.53	60.18	68.40
No	38	3.86	4.21	85.98	86.15	84.48	86.57	79.81	88.49	58.58	56.16	58.52	72.73	56.08	73.32

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	39	3.84	3.92	86.49	86.37	83.05	87.84	81.28	88.25	58.01	53.46	57.94	73.21	53.36	76.45
No	40	3.90	3.81	84.81	86.57	85.91	84.39	83.02	87.88	58.64	56.83	58.57	72.69	56.75	73.33
No	41	3.90	4.03	85.99	82.17	83.67	86.91	89.51	79.45	58.24	60.59	58.18	73.34	60.56	68.42
No	42	3.88	3.85	86.04	87.09	84.07	86.81	78.86	90.13	58.41	51.51	58.35	73.08	51.38	78.72
No	43	3.79	3.75	86.19	86.12	84.20	86.97	84.06	86.89	58.75	58.32	58.68	72.98	58.26	71.81
No	44	3.88	3.78	86.25	85.97	84.52	86.93	84.82	86.40	58.63	61.53	58.57	73.08	61.50	68.71
No	45	3.79	3.67	86.66	86.68	83.63	87.85	82.16	88.35	57.96	56.23	57.89	74.19	56.14	74.93
No	46	3.78	3.75	86.88	84.86	84.08	87.98	86.52	84.24	58.33	65.20	58.26	74.29	65.21	63.86
No	47	3.78	3.73	85.93	84.62	84.53	86.47	85.64	84.24	58.99	61.05	58.93	72.56	61.02	69.75
No	48	3.72	3.71	87.07	86.07	83.28	88.56	82.91	87.24	57.71	59.34	57.64	74.98	59.28	71.33
No	49	3.81	3.80	86.59	83.78	84.19	87.53	88.22	82.13	58.07	62.55	57.99	74.31	62.53	67.82
No	50	3.66	3.68	87.14	86.90	84.66	88.11	83.86	88.02	57.74	58.40	57.66	75.17	58.34	73.15
Yes	51	3.63	3.60	86.47	87.41	85.97	86.66	81.79	89.49	59.59	57.85	59.53	73.67	57.78	72.53
No	52	3.85	3.92	86.33	82.08	82.73	87.75	87.60	80.04	57.26	63.43	57.19	74.68	63.41	66.90
No	53	3.71	3.73	86.91	84.97	84.67	87.79	87.76	83.94	58.20	56.50	58.12	74.24	56.42	75.06
No	54	3.62	3.73	87.03	85.22	85.30	87.71	86.60	84.71	57.84	61.83	57.76	75.42	61.80	69.28
Yes	55	3.59	3.66	87.37	87.86	85.51	88.10	81.31	90.29	58.87	54.16	58.80	74.42	54.05	77.47
No	56	3.72	3.79	86.38	83.00	85.40	86.76	87.93	81.17	58.71	63.39	58.64	74.12	63.38	65.84
No	57	3.63	3.62	87.15	86.72	84.51	88.19	84.73	87.45	57.90	56.03	57.82	75.04	55.94	75.69
No	58	3.52	3.53	87.38	86.85	85.86	87.97	85.46	87.37	58.86	55.73	58.79	75.07	55.63	76.27
No	59	3.47	3.56	87.75	86.06	85.39	88.68	85.79	86.16	58.85	59.93	58.78	75.17	59.87	71.85
No	60	3.46	3.54	87.72	86.22	85.19	88.71	86.33	86.18	58.37	59.65	58.30	75.88	59.60	72.18
No	61	3.46	3.49	87.72	86.97	85.98	88.40	84.71	87.80	58.32	58.57	58.24	76.14	58.50	73.95
No	62	3.42	3.59	88.00	87.76	85.28	89.07	82.10	89.85	58.39	56.64	58.31	76.07	56.56	74.71
Yes	63	3.48	3.57	87.82	88.10	85.89	88.58	81.38	90.59	57.99	56.38	57.91	76.69	56.29	75.60
No	64	3.61	3.64	86.97	86.32	85.86	87.41	84.80	86.89	58.67	57.08	58.60	74.59	57.00	74.63
No	65	3.60	3.59	87.33	85.40	84.81	88.32	87.45	84.64	57.91	58.38	57.83	75.75	58.31	73.45
No	66	3.49	3.59	87.78	87.34	85.90	88.52	84.17	88.51	58.26	59.66	58.18	76.19	59.60	72.39
Yes	67	3.40	3.60	87.87	88.22	86.49	88.41	82.12	90.47	58.48	55.11	58.40	76.10	55.01	77.18
No	68	3.50	3.68	87.89	88.14	85.45	88.85	81.87	90.46	58.27	53.18	58.19	75.87	53.07	78.26
No	69	3.53	3.54	87.75	87.23	85.62	88.58	84.84	88.12	57.92	61.34	57.84	76.26	61.30	70.48
No	70	3.45	3.46	87.87	87.24	86.02	88.61	84.90	88.11	58.18	60.67	58.10	76.48	60.62	71.35
No	71	3.34	3.46	88.35	86.91	85.98	89.28	86.52	87.06	58.30	60.35	58.22	76.56	60.30	72.16
Yes	72	3.34	3.46	88.45	88.34	86.12	89.36	81.57	90.85	58.33	59.21	58.25	76.98	59.15	73.46
Yes	73	3.46	3.55	87.70	88.44	85.29	88.65	81.15	91.13	58.20	56.01	58.12	76.37	55.92	76.26
No	74	3.49	3.81	87.91	88.35	85.40	88.89	78.71	91.91	57.71	54.49	57.63	76.56	54.40	76.00
No	75	3.63	3.53	86.93	88.21	85.97	87.31	81.24	90.79	59.36	53.30	59.30	74.63	53.18	78.56

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	76	3.44	3.59	88.27	88.42	84.38	89.80	79.43	91.74	57.59	55.41	57.51	77.06	55.31	77.06
No	77	3.36	3.38	88.28	87.15	86.41	89.01	86.14	87.53	58.26	58.93	58.18	77.31	58.86	73.28
No	78	3.28	3.40	88.56	86.39	86.01	89.56	87.61	85.94	58.89	60.89	58.81	76.70	60.84	71.30
No	79	3.37	3.40	88.58	87.35	85.85	89.66	85.92	87.88	58.12	58.38	58.03	77.40	58.30	74.85
No	80	3.30	3.39	88.34	87.42	86.49	89.06	84.95	88.34	58.51	59.17	58.42	77.23	59.10	73.29
No	81	3.30	3.44	88.48	87.99	85.84	89.52	83.14	89.78	58.38	59.52	58.30	77.70	59.46	73.06
No	82	3.23	3.41	88.88	86.88	86.07	89.99	86.81	86.91	58.66	61.97	58.57	77.75	61.93	70.84
No	83	3.19	3.37	88.69	86.55	86.88	89.39	86.94	86.40	58.71	59.78	58.62	77.92	59.71	73.49
No	84	3.17	3.34	88.88	88.28	86.63	89.77	83.79	89.95	58.83	56.45	58.74	77.96	56.36	76.78
No	85	3.17	3.33	89.09	87.84	86.22	90.21	84.84	88.95	58.31	59.47	58.22	78.72	59.40	73.69
No	86	3.18	3.34	88.76	87.90	86.88	89.50	84.91	89.01	59.04	58.13	58.96	77.87	58.05	75.47
No	87	3.17	3.33	89.06	87.77	86.60	90.02	85.46	88.63	58.47	58.00	58.38	78.62	57.92	75.54
No	88	3.15	3.32	89.06	87.69	86.85	89.93	85.41	88.53	58.61	58.29	58.52	78.68	58.21	75.25
No	89	3.14	3.32	89.07	87.46	86.65	90.02	85.66	88.12	59.04	58.54	58.95	78.45	58.46	75.04
No	90	3.13	3.32	89.08	87.95	87.08	89.86	84.74	89.14	58.77	57.30	58.68	78.82	57.22	76.05
No	91	3.12	3.37	89.19	87.05	86.67	90.18	86.76	87.15	58.80	57.57	58.71	78.79	57.48	75.90
No	92	3.13	3.31	89.18	87.40	86.89	90.07	85.73	88.01	58.76	58.37	58.67	78.84	58.30	75.26
No	93	3.11	3.31	89.26	87.83	86.77	90.24	85.03	88.86	58.51	58.73	58.42	79.30	58.65	74.82
No	94	3.10	3.30	89.27	87.31	86.84	90.22	86.35	87.67	58.91	59.42	58.82	79.00	59.35	74.18
No	95	3.11	3.32	89.14	87.00	86.80	90.05	86.95	87.02	58.98	59.30	58.90	78.88	59.23	74.27
No	96	3.10	3.31	89.11	87.98	87.29	89.82	84.66	89.21	58.87	58.78	58.78	79.07	58.71	74.77
No	97	3.09	3.31	89.25	87.75	86.91	90.17	85.33	88.65	58.89	58.23	58.80	79.14	58.16	75.36
No	98	3.08	3.31	89.28	87.68	86.97	90.18	85.30	88.56	59.22	58.18	59.14	78.84	58.10	75.44
No	99	3.08	3.29	89.23	87.46	87.10	90.07	85.91	88.03	58.48	58.80	58.39	79.62	58.73	74.76
No	100	3.08	3.30	89.20	87.70	87.19	89.99	85.34	88.58	58.63	59.18	58.54	79.63	59.11	74.37

Table 17: Performance Results of Model 17 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	6.82	5.16	74.55	83.50	50.86	83.85	63.25	90.99	41.53	29.27	41.41	69.38	29.00	89.62
Yes	2	5.16	4.77	82.13	81.82	72.24	86.01	81.31	82.01	40.96	77.98	40.78	79.95	78.18	35.79
Yes	3	4.86	4.52	83.07	82.22	79.74	84.38	86.14	80.78	47.21	48.37	47.08	76.34	48.24	76.11
No	4	4.61	4.75	83.56	85.44	82.72	83.89	75.29	89.20	53.81	53.57	53.72	72.93	53.48	72.84
No	5	4.70	4.21	83.20	85.88	83.00	83.28	76.52	89.34	56.51	50.53	56.45	71.03	50.41	76.92
No	6	4.28	4.29	84.93	86.39	82.36	85.94	68.90	92.87	57.14	50.78	57.08	71.39	50.67	75.90
Yes	7	4.28	4.10	84.63	83.88	81.26	85.96	83.95	83.86	55.88	66.41	55.80	72.65	66.44	60.25
No	8	4.30	4.27	84.09	78.95	82.56	84.68	91.41	74.34	57.88	60.55	57.82	70.69	60.51	67.46
No	9	4.21	4.18	84.34	83.77	83.34	84.73	86.42	82.79	59.03	59.29	58.98	70.19	59.25	69.24
Yes	10	4.30	4.22	84.14	84.32	83.76	84.28	84.56	84.23	57.21	61.46	57.14	72.36	61.43	67.34
No	11	4.14	4.01	84.84	83.53	84.16	85.11	86.65	82.38	57.86	57.12	57.80	71.72	57.05	71.61
No	12	4.14	3.89	84.72	86.96	82.88	85.44	77.35	90.51	56.78	56.15	56.71	73.02	56.07	72.56
No	13	4.11	3.99	85.36	83.50	83.15	86.22	87.66	81.97	57.00	66.03	56.93	73.38	66.05	62.20
Yes	14	3.97	3.87	85.94	86.03	82.90	87.13	83.49	86.97	56.28	54.36	56.20	74.38	54.26	75.16
Yes	15	3.98	3.83	85.75	86.41	83.94	86.45	82.66	87.80	57.09	51.98	57.01	73.73	51.86	77.67
No	16	3.90	4.13	86.71	83.93	82.34	88.42	86.43	83.01	57.16	61.36	57.09	73.81	61.34	67.68
No	17	4.01	3.84	86.10	85.23	83.55	87.10	86.50	84.76	56.30	55.02	56.22	75.46	54.93	75.54
Yes	18	3.84	3.67	86.27	86.71	84.25	87.06	82.44	88.29	56.74	59.10	56.66	75.01	59.04	71.31
Yes	19	3.71	3.72	87.00	87.11	84.09	88.14	81.08	89.34	56.58	53.99	56.50	75.58	53.89	75.53
No	20	3.85	3.88	86.70	87.91	84.90	87.41	73.49	93.25	56.44	48.33	56.35	75.54	48.19	80.23
No	21	3.75	3.72	87.17	85.10	83.56	88.60	86.90	84.44	56.35	61.48	56.26	75.79	61.44	68.80
No	22	3.69	3.66	87.09	85.74	84.31	88.18	85.12	85.97	56.32	59.94	56.24	76.08	59.90	70.76
Yes	23	3.66	3.62	87.35	87.63	84.54	88.46	80.44	90.30	57.20	52.99	57.12	75.63	52.88	78.00
No	24	3.65	3.83	87.37	87.15	85.16	88.24	80.39	89.65	57.38	54.64	57.30	75.72	54.54	75.96
No	25	3.69	3.85	87.32	85.96	84.99	88.24	85.14	86.26	56.97	61.00	56.88	76.16	60.95	70.25
No	26	3.76	3.59	87.19	84.96	84.90	88.09	86.51	84.39	57.64	60.31	57.56	75.39	60.26	70.80
No	27	3.63	4.22	87.09	84.04	85.90	87.56	88.07	82.55	56.95	58.64	56.86	76.07	58.58	72.84
No	28	3.54	3.52	87.70	86.85	85.96	88.38	85.27	87.44	58.26	58.93	58.19	75.42	58.87	72.75
No	29	3.46	3.59	87.95	86.43	85.64	88.86	86.04	86.57	57.08	58.56	57.00	77.11	58.50	72.60
No	30	3.48	3.50	88.07	86.45	85.04	89.26	86.14	86.56	56.54	55.90	56.45	77.72	55.81	75.90
No	31	3.46	3.61	88.24	86.42	84.70	89.63	82.36	87.92	56.50	52.24	56.41	77.94	52.12	78.99

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	32	3.45	3.47	87.75	87.24	86.43	88.27	84.03	88.43	57.49	57.23	57.40	76.79	57.15	75.20
Yes	33	3.39	3.42	88.19	88.31	85.77	89.14	81.50	90.82	57.53	53.05	57.45	77.04	52.93	79.46
No	34	3.47	3.58	88.32	86.75	85.38	89.47	86.32	86.90	55.32	54.84	55.21	78.89	54.74	77.10
No	35	3.51	3.68	88.08	88.44	85.92	88.93	78.44	92.14	57.64	51.61	57.56	76.24	51.49	80.06
No	36	3.53	3.41	87.81	87.01	85.70	88.64	85.50	87.58	56.09	57.96	55.99	78.12	57.89	74.52
No	37	3.41	3.61	88.33	85.80	85.29	89.52	87.75	85.07	56.68	58.37	56.59	77.96	58.30	73.27
No	38	3.39	3.46	88.34	87.16	85.81	89.34	85.24	87.88	57.04	56.89	56.95	77.37	56.80	75.06
No	39	3.38	3.49	88.40	87.83	86.12	89.29	82.93	89.64	57.46	58.46	57.38	77.19	58.39	73.17
Yes	40	3.39	3.39	88.53	88.33	85.73	89.63	82.31	90.55	57.45	49.63	57.36	77.47	49.48	82.74
No	41	3.39	3.49	88.25	87.50	86.11	89.09	84.44	88.64	57.14	56.78	57.05	77.41	56.69	76.04
No	42	3.42	3.54	88.51	87.79	85.65	89.63	80.65	90.43	57.53	51.01	57.44	77.73	50.87	81.13
No	43	3.44	3.49	88.45	86.78	85.80	89.49	85.81	87.15	56.37	50.36	56.27	78.21	50.22	80.16
No	44	3.45	3.56	88.24	85.36	85.79	89.21	87.68	84.50	57.04	57.37	56.95	77.52	57.29	75.10
No	45	3.29	3.38	88.80	86.91	86.40	89.74	86.04	87.24	56.92	59.86	56.82	78.76	59.80	72.56
No	46	3.23	3.36	88.90	87.62	86.77	89.74	85.61	88.37	57.40	57.05	57.30	78.83	56.96	76.22
No	47	3.33	3.46	88.91	85.62	86.28	89.95	88.54	84.53	57.44	59.47	57.34	78.78	59.41	73.69
No	48	3.27	3.42	89.13	85.94	86.75	90.06	87.75	85.27	57.83	60.64	57.74	78.64	60.59	72.42
No	49	3.30	3.35	88.96	86.41	86.87	89.78	86.70	86.30	57.04	60.08	56.94	79.46	60.02	72.69
No	50	3.26	3.39	89.20	88.16	86.29	90.34	84.16	89.63	57.65	53.63	57.56	78.96	53.51	79.62
No	51	3.17	3.30	89.28	87.24	86.75	90.27	86.46	87.53	56.84	57.29	56.73	80.18	57.20	76.34
No	52	3.12	3.31	89.30	87.72	87.34	90.07	85.72	88.46	57.74	57.85	57.64	79.64	57.77	75.41
No	53	3.14	3.35	89.30	86.90	87.06	90.18	87.20	86.79	57.10	57.07	57.00	80.17	56.98	76.63
No	54	3.13	3.29	89.37	86.78	86.99	90.31	87.28	86.59	57.55	59.23	57.45	80.00	59.16	74.51
No	55	3.11	3.30	89.37	86.82	87.41	90.14	86.86	86.80	57.65	57.86	57.55	80.15	57.78	75.63
No	56	3.06	3.27	89.51	87.30	87.30	90.37	86.49	87.60	57.36	59.12	57.26	80.64	59.05	74.41
No	57	3.06	3.29	89.63	87.91	87.19	90.58	85.51	88.80	57.53	56.36	57.43	80.60	56.26	77.27
No	58	3.09	3.30	89.53	87.80	87.35	90.39	85.69	88.58	57.56	57.27	57.46	80.54	57.19	76.57
Yes	59	3.05	3.31	89.59	88.41	87.33	90.47	83.92	90.08	57.56	58.33	57.45	80.73	58.25	75.11
No	60	3.22	3.36	89.16	87.30	86.92	90.04	85.80	87.86	56.45	58.36	56.34	80.60	58.29	74.03
No	61	3.22	3.37	89.09	86.17	86.76	90.01	87.34	85.74	56.72	54.92	56.62	80.06	54.81	78.36
No	62	3.20	3.53	89.08	85.08	87.08	89.87	85.33	84.99	57.23	58.62	57.13	79.76	58.55	74.16
No	63	3.35	3.38	88.01	88.17	85.69	88.92	82.23	90.37	57.74	55.79	57.64	78.57	55.70	75.79
No	64	3.22	3.31	89.05	87.95	86.55	90.04	84.82	89.11	57.79	56.06	57.69	79.11	55.97	77.08
No	65	3.13	3.34	89.41	87.24	87.37	90.21	85.24	87.99	57.53	59.19	57.43	80.54	59.13	73.89
Yes	66	3.10	3.34	89.42	88.68	87.40	90.21	81.74	91.25	57.29	55.39	57.18	80.84	55.29	77.88
No	67	3.25	3.53	89.18	84.95	86.54	90.21	89.25	83.35	56.89	63.32	56.79	80.24	63.29	69.31
No	68	3.16	3.31	89.20	86.70	87.60	89.83	87.18	86.52	57.72	57.03	57.62	80.22	56.94	75.86

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	69	3.10	3.30	89.35	87.16	87.38	90.13	84.69	88.07	57.50	58.69	57.40	80.87	58.62	74.36
No	70	3.08	3.36	89.46	87.61	87.40	90.27	85.74	88.31	57.26	57.74	57.16	81.24	57.66	75.57
No	71	3.07	3.47	89.34	88.29	87.55	90.05	83.72	89.98	57.69	56.07	57.58	81.26	55.98	76.30
No	72	3.08	3.26	89.73	87.55	87.51	90.60	86.19	88.06	57.64	57.19	57.53	81.65	57.10	76.26
No	73	2.99	3.26	89.73	87.75	87.91	90.44	85.32	88.64	57.77	57.12	57.66	81.95	57.03	76.76
No	74	3.03	3.31	89.95	87.51	87.41	90.94	86.07	88.04	57.71	58.16	57.61	82.17	58.08	75.43
No	75	3.00	3.25	89.95	87.48	87.59	90.88	86.31	87.91	57.02	60.62	56.90	82.88	60.57	72.82
No	76	2.96	3.23	89.94	88.13	88.18	90.63	84.88	89.34	58.31	57.21	58.20	82.10	57.12	76.51
No	77	2.95	3.22	90.03	87.30	87.80	90.91	86.81	87.49	57.94	59.64	57.83	82.57	59.57	74.21
No	78	2.96	3.24	90.04	88.21	88.00	90.84	85.00	89.39	57.76	57.94	57.65	82.95	57.86	75.76
No	79	2.96	3.24	90.12	88.32	87.79	91.04	84.19	89.85	57.93	57.26	57.82	82.87	57.17	76.43
No	80	2.94	3.23	90.19	88.46	87.82	91.12	84.36	89.98	57.98	57.73	57.87	83.05	57.65	75.79
No	81	2.93	3.22	90.20	88.42	87.76	91.15	84.48	89.88	58.07	57.21	57.96	83.08	57.12	76.50
No	82	2.92	3.22	90.20	87.84	87.95	91.09	85.67	88.64	57.85	57.91	57.73	83.41	57.83	75.78
No	83	2.93	3.21	90.18	87.69	87.97	91.05	86.10	88.28	57.88	58.17	57.76	83.36	58.09	75.69
No	84	2.93	3.21	90.18	87.93	88.11	90.99	85.51	88.83	58.26	58.22	58.15	83.11	58.14	75.57
No	85	2.91	3.21	90.29	87.58	87.91	91.22	86.34	88.04	57.84	59.24	57.72	83.57	59.17	74.55
No	86	2.91	3.21	90.22	87.98	88.10	91.05	85.34	88.95	58.00	58.66	57.88	83.49	58.58	75.16
No	87	2.91	3.21	90.19	87.95	88.12	91.01	85.55	88.83	58.36	58.06	58.25	83.09	57.98	75.72
No	88	2.90	3.21	90.31	87.90	88.00	91.22	85.57	88.77	58.03	58.39	57.92	83.46	58.31	75.38
No	89	2.90	3.21	90.23	87.91	88.13	91.05	85.54	88.79	58.01	58.48	57.90	83.51	58.41	75.34
No	90	2.90	3.21	90.30	87.83	87.94	91.22	85.78	88.60	58.11	58.48	58.00	83.39	58.40	75.28
No	91	2.90	3.21	90.27	87.79	88.11	91.12	85.83	88.51	58.08	58.70	57.97	83.61	58.63	75.07
No	92	2.90	3.20	90.29	87.92	88.04	91.17	85.55	88.79	58.16	58.32	58.04	83.42	58.24	75.46
No	93	2.90	3.21	90.28	87.81	88.12	91.13	85.80	88.55	58.01	58.50	57.90	83.69	58.42	75.29
No	94	2.90	3.21	90.32	87.84	87.99	91.23	85.71	88.63	58.04	58.42	57.92	83.67	58.34	75.37
No	95	2.90	3.21	90.27	87.84	88.18	91.09	85.72	88.62	58.22	58.55	58.10	83.50	58.47	75.20
No	96	2.90	3.21	90.27	87.89	88.13	91.10	85.64	88.72	58.14	58.45	58.03	83.50	58.38	75.31

Table 18: Performance Results of Model 18 Over Epochs

saved_model	Epoch	Train Regression Loss	Validation Regression Loss	Train Classification Accuracy	Validation Classification Accuracy	Train Class 0 Accuracy	Train Class 1 Accuracy	Validation Class 0 Accuracy	Validation Class 1 Accuracy	Train Centroid Accuracy	Validation Centroid Accuracy	Train Centroid Class 0 Accuracy	Train Centroid Class 1 Accuracy	Validation Centroid Class 0 Accuracy	Validation Centroid Class 1 Accuracy
No	1	7.41		68.40	67.13	69.20	68.09	82.64	61.40	59.00	87.30	58.96	68.29	87.53	37.32
No	2	5.86		80.21	73.82	66.70	85.52	20.20	93.65	72.23	75.81	72.25	68.22	75.84	70.32
No	3	4.66	4.75	82.51	78.70	78.15	84.23	84.54	76.54	78.78	78.32	78.82	69.40	78.36	70.39
No	4	4.44	5.80	83.69	85.73	79.66	85.28	57.92	96.02	78.53	77.37	78.57	70.31	77.40	70.80
No	5	4.23	4.07	84.18	84.32	83.26	84.54	73.45	88.35	79.25	77.16	79.29	69.74	77.18	72.25
No	6	4.06	4.05	85.23	86.59	82.21	86.42	74.40	91.09	78.49	79.92	78.53	70.90	79.97	69.90
No	7	4.00	3.82	84.43	87.88	84.02	84.59	69.68	94.61	79.75	79.88	79.80	69.61	79.93	70.09
No	8	4.12	4.33	85.66	71.73	78.46	88.48	91.04	64.59	78.47	83.85	78.51	70.75	83.95	62.22
No	9	3.88	3.97	84.94	86.56	84.33	85.18	79.65	89.11	78.45	77.22	78.48	70.96	77.25	72.09
No	10	4.04	3.96	85.25	87.77	84.00	85.74	68.67	94.83	78.86	78.24	78.90	70.60	78.27	70.67
Yes	11	3.68	3.70	87.10	84.51	83.27	88.60	84.96	84.35	78.44	78.76	78.47	71.85	78.79	71.69
No	12	4.05	4.19	85.69	87.97	81.65	87.28	68.40	95.21	78.25	77.24	78.28	71.60	77.27	72.23
Yes	13	3.92	3.95	85.96	86.73	81.95	87.53	81.32	88.73	77.83	80.84	77.85	72.27	80.90	67.94
No	14	3.74	3.62	86.49	85.15	84.09	87.44	88.42	83.95	78.08	76.97	78.10	72.17	76.99	72.95
No	15	3.70	3.78	86.61	88.41	83.55	87.81	72.19	94.41	78.22	77.03	78.25	72.00	77.05	72.69
No	16	3.65	3.75	86.82	88.25	84.35	87.79	77.22	92.33	78.17	75.72	78.19	72.33	75.73	74.66
Yes	17	3.46	3.50	87.77	88.30	84.55	89.03	83.45	90.09	78.50	76.10	78.52	72.33	76.11	74.40
No	18	3.56	4.09	87.64	88.94	85.22	88.59	73.51	94.65	78.35	77.13	78.38	72.62	77.15	73.51
No	19	3.68	4.06	86.39	81.58	83.62	87.48	88.10	79.16	78.60	75.79	78.63	71.49	75.80	74.23
No	20	3.49	3.74	86.96	87.62	86.26	87.24	77.64	91.32	78.08	79.32	78.10	72.60	79.36	70.53
No	21	3.51	6.37	86.72	58.57	84.35	87.65	95.58	44.88	77.54	87.11	77.56	73.00	87.27	51.70
No	22	3.50	3.44	87.87	86.93	83.18	89.72	86.44	87.11	77.75	75.69	77.77	73.21	75.69	74.97
No	23	3.41	3.82	87.85	80.56	84.74	89.07	91.30	76.58	78.06	80.96	78.09	73.21	81.02	68.76
No	24	3.36	3.39	88.14	86.07	85.38	89.23	87.93	85.38	78.32	80.57	78.34	73.13	80.62	70.07
No	25	3.37	3.57	87.77	83.00	85.53	88.65	89.70	80.52	78.03	82.62	78.05	73.35	82.69	67.24
No	26	3.32	3.32	88.59	88.55	85.37	89.85	79.13	92.03	77.53	77.93	77.55	74.01	77.95	73.14
No	27	3.30	3.82	88.35	87.82	84.85	89.73	85.04	88.85	78.80	74.54	78.83	72.71	74.53	75.91
No	28	3.32	3.59	88.50	86.88	85.14	89.82	87.72	86.57	77.63	78.36	77.64	74.10	78.39	72.50
No	29	3.24	3.46	88.47	88.29	86.42	89.28	79.37	91.59	78.44	78.18	78.46	73.24	78.20	72.60
No	30	3.29	3.38	88.89	86.02	84.83	90.48	88.72	85.01	77.66	74.78	77.67	74.14	74.77	75.77
No	31	3.26	3.37	88.09	85.80	86.80	88.60	89.05	84.60	78.52	79.60	78.54	73.47	79.64	71.40
No	32	3.38	3.71	88.06	88.15	84.66	89.39	83.57	89.84	77.67	81.97	77.69	74.07	82.03	68.47

saved_model	Epoch	Train Regression Loss	Validation Regression Loss	Train Classification Accuracy	Validation Classification Accuracy	Train Class 0 Accuracy	Train Class 1 Accuracy	Validation Class 0 Accuracy	Validation Class 1 Accuracy	Train Centroid Accuracy	Validation Centroid Accuracy	Train Centroid Class 0 Accuracy	Train Centroid Class 1 Accuracy	Validation Centroid Class 0 Accuracy	Validation Centroid Class 1 Accuracy
No	33	3.23	3.57	88.29	85.12	85.95	89.21	88.86	83.73	78.25	77.67	78.28	73.41	77.69	73.05
No	34	3.22	3.18	88.34	87.78	87.38	88.72	85.03	88.79	78.02	78.93	78.04	74.10	78.96	72.38
Yes	35	3.15	3.29	88.66	88.98	86.47	89.53	82.81	91.26	78.23	75.98	78.25	73.88	75.98	75.27
No	36	3.39	3.60	88.88	86.28	85.18	90.34	87.95	85.66	77.64	78.28	77.66	74.07	78.30	72.10
No	37	3.29	3.44	88.31	85.76	85.70	89.33	86.31	85.55	78.19	80.20	78.21	73.50	80.24	70.66
No	38	3.42	3.46	88.43	87.85	83.86	90.22	85.59	88.68	77.70	77.91	77.72	73.88	77.93	73.16
No	39	3.32	3.37	88.17	89.09	86.92	88.66	79.35	92.69	78.21	77.24	78.24	73.53	77.26	73.74
Yes	40	3.13	3.60	89.09	89.20	86.65	90.04	83.18	91.43	78.28	76.33	78.29	74.06	76.34	74.87
No	41	3.41	3.85	88.22	82.97	85.09	89.45	88.02	81.09	77.65	83.27	77.67	73.88	83.35	65.03
No	42	3.33	4.26	88.54	89.23	85.61	89.69	74.33	94.74	78.00	77.94	78.02	73.84	77.96	72.70
No	43	3.19	3.30	89.31	86.30	85.96	90.62	89.16	85.23	78.44	77.52	78.46	73.78	77.54	73.63
No	44	3.14	3.24	89.34	87.15	86.43	90.49	88.04	86.82	77.72	79.82	77.73	74.81	79.86	70.91
No	45	3.11	3.33	88.92	86.35	87.39	89.52	89.01	85.36	77.81	81.23	77.82	74.67	81.28	69.67
No	46	3.05	3.39	89.53	84.91	86.86	90.58	90.16	82.96	78.00	83.36	78.02	74.54	83.44	66.71
No	47	2.98	3.13	89.95	87.88	87.13	91.06	87.73	87.93	78.32	79.21	78.34	74.64	79.24	72.23
No	48	3.07	3.44	89.32	85.89	87.11	90.18	89.86	84.42	78.05	78.49	78.06	74.75	78.52	72.28
No	49	2.99	3.20	89.87	86.76	86.85	91.05	88.95	85.95	78.05	79.33	78.06	75.04	79.37	71.55
No	50	3.01	3.15	89.74	89.04	87.83	90.49	84.49	90.73	78.00	76.49	78.01	74.91	76.49	74.92
No	51	2.92	3.10	90.02	88.35	87.37	91.06	86.34	89.09	78.08	76.19	78.10	75.13	76.19	75.17
No	52	2.87	3.12	89.83	88.10	88.34	90.41	86.43	88.71	78.13	76.60	78.15	75.16	76.61	74.90
No	53	2.90	3.14	90.34	86.95	87.38	91.51	88.42	86.40	77.84	79.01	77.86	75.43	79.04	72.22
No	54	2.87	3.15	90.11	87.92	88.01	90.93	87.08	88.23	77.92	77.36	77.94	75.37	77.38	73.99
No	55	2.89	3.14	90.30	88.67	87.91	91.25	85.40	89.88	78.14	77.12	78.16	75.33	77.14	74.22
No	56	2.83	3.10	90.21	88.73	88.34	90.94	85.66	89.87	77.80	78.80	77.80	75.76	78.83	72.73
No	57	2.82	3.11	90.27	89.02	88.29	91.05	84.88	90.55	77.75	77.64	77.75	75.92	77.66	73.83
No	58	2.81	3.12	90.49	88.78	88.21	91.39	85.49	90.00	78.29	77.56	78.30	75.31	77.58	73.89
No	59	2.80	3.08	90.60	88.47	88.43	91.45	86.46	89.22	77.87	77.44	77.88	75.86	77.45	74.02
No	60	2.78	3.09	90.73	88.53	88.09	91.77	86.04	89.45	78.23	77.88	78.24	75.55	77.90	73.54
No	61	2.74	3.10	90.78	88.54	88.32	91.75	85.97	89.49	77.70	77.97	77.70	76.12	77.99	73.49
No	62	2.74	3.09	90.62	88.73	88.84	91.32	85.58	89.90	78.09	77.95	78.10	75.79	77.97	73.53
No	63	2.76	3.09	90.77	88.21	88.19	91.78	86.75	88.75	78.01	78.33	78.02	75.95	78.35	73.01
No	64	2.76	3.09	90.65	88.49	88.81	91.37	86.06	89.40	77.88	77.55	77.89	76.01	77.56	73.88
No	65	2.73	3.10	90.99	88.51	87.89	92.21	85.99	89.44	77.92	77.83	77.93	76.06	77.85	73.49
No	66	2.71	3.10	90.69	88.45	88.99	91.35	85.83	89.42	77.88	78.08	77.89	76.16	78.10	73.35
No	67	2.72	3.10	90.77	88.59	88.49	91.67	85.80	89.62	78.00	77.53	78.01	76.08	77.54	73.85
No	68	2.72	3.09	90.92	88.51	88.56	91.85	85.98	89.45	77.95	77.96	77.96	76.10	77.98	73.39
No	69	2.75	3.09	90.77	88.40	88.48	91.67	86.04	89.27	78.02	77.86	78.03	76.01	77.88	73.55
No	70	2.73	3.10	90.88	88.62	88.50	91.82	85.51	89.78	77.77	77.70	77.78	76.28	77.72	73.71

Table 19: Performance Results of Model 19 Over Epochs

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	1	6.93		75.42	27.04	49.53	85.59	99.35	0.29	55.91	99.35	55.86	67.39	99.80	0.18
No	2	5.25		81.17	78.94	72.59	84.53	60.71	85.69	76.10	77.63	76.13	69.81	77.68	67.12
No	3	4.83	4.28	82.46	84.78	79.45	83.64	78.59	87.07	75.25	81.48	75.27	70.94	81.55	66.73
No	4	4.41	5.82	83.98	63.72	81.22	85.07	92.49	53.08	80.40	82.96	80.46	67.93	83.05	62.49
No	5	4.28	4.29	83.80	86.78	83.79	83.81	71.85	92.30	79.67	78.57	79.72	69.24	78.61	70.42
Yes	6	4.10	3.94	85.40	83.14	83.05	86.33	88.60	81.12	78.20	79.76	78.24	71.06	79.81	68.94
Yes	7	4.08	4.18	84.71	83.38	83.56	85.16	87.84	81.73	78.86	80.52	78.90	70.37	80.57	69.50
No	8	4.03	4.18	85.85	86.87	82.96	86.98	78.54	89.95	78.25	79.47	78.28	71.21	79.51	70.25
No	9	3.90	5.99	84.01	87.19	85.53	83.42	68.96	93.93	79.17	71.70	79.21	70.25	71.68	76.54
Yes	10	4.24	3.92	86.06	83.89	80.14	88.39	86.68	82.86	79.36	81.06	79.40	70.31	81.12	67.42
No	11	4.02	4.75	85.70	78.48	84.27	86.27	88.39	74.81	78.21	82.52	78.24	71.58	82.60	62.99
No	12	3.84	4.02	86.70	79.17	83.31	88.04	91.67	74.54	77.98	76.95	78.01	71.91	76.97	71.27
Yes	13	3.86	3.79	85.69	87.68	84.81	86.04	82.69	89.52	78.78	74.02	78.81	71.12	74.01	75.77
No	14	3.75	3.99	86.52	83.61	84.77	87.20	83.86	83.52	78.11	80.18	78.13	72.29	80.23	69.88
No	15	3.66	4.01	86.64	80.88	85.07	87.26	83.48	79.91	78.63	80.38	78.66	71.96	80.43	69.49
No	16	3.62	3.82	87.38	87.63	83.64	88.85	79.43	90.66	78.57	79.54	78.60	72.03	79.58	70.92
No	17	3.59	3.67	87.44	82.19	84.31	88.67	90.27	79.19	78.16	79.84	78.19	72.51	79.89	70.47
Yes	18	3.54	3.52	87.59	87.74	84.72	88.72	85.44	88.60	77.94	78.24	77.96	72.99	78.27	72.61
No	19	3.60	4.43	87.03	74.05	82.50	88.80	88.85	68.57	78.44	84.67	78.47	72.25	84.78	59.97
No	20	3.69	3.67	87.61	85.77	82.34	89.68	86.08	85.66	78.11	78.98	78.13	72.64	79.01	71.42
Yes	21	3.54	3.66	87.53	88.02	85.10	88.48	83.62	89.66	78.43	78.60	78.45	72.70	78.63	72.18
No	22	3.52	3.89	87.91	84.89	84.76	89.15	87.48	83.94	78.49	79.20	78.52	72.65	79.24	71.62
No	23	3.39	3.55	88.34	87.60	85.04	89.64	85.87	88.25	78.35	76.61	78.37	73.25	76.62	74.16
No	24	3.37	3.34	88.51	86.52	85.52	89.68	88.46	85.80	77.90	78.48	77.92	73.83	78.51	72.51
No	25	3.31	3.71	88.25	84.06	86.01	89.13	89.48	82.06	78.54	80.52	78.56	73.25	80.57	70.01
No	26	3.24	3.39	89.02	85.33	85.87	90.26	88.98	83.98	78.23	78.62	78.25	73.85	78.65	72.17
Yes	27	3.36	4.23	88.66	89.14	85.89	89.75	80.49	92.34	78.60	71.95	78.62	73.37	71.93	78.22
No	28	3.33	3.32	88.51	87.44	85.45	89.71	84.38	88.57	77.85	78.61	77.87	73.81	78.64	72.44
No	29	3.28	3.54	88.72	87.40	86.38	89.64	85.86	87.97	78.33	77.05	78.35	73.56	77.06	73.75
No	30	3.29	4.29	88.44	77.00	85.71	89.52	92.02	71.44	77.94	83.64	77.96	74.02	83.73	63.66
No	31	3.41	3.59	88.23	86.37	85.40	89.34	85.23	86.79	78.42	76.91	78.45	73.18	76.92	73.12

saved_model	Epoch	Train Regression Loss (m)	Validation Regression Loss (m)	Train Classification Accuracy (%)	Validation Classification Accuracy (%)	Train Class 0 Accuracy (%)	Train Class 1 Accuracy (%)	Validation Class 0 Accuracy (%)	Validation Class 1 Accuracy (%)	Train Centroid Accuracy (%)	Validation Centroid Accuracy (%)	Train Centroid Class 0 Accuracy (%)	Train Centroid Class 1 Accuracy (%)	Validation Centroid Class 0 Accuracy (%)	Validation Centroid Class 1 Accuracy (%)
No	32	3.41	4.07	88.28	88.15	85.51	89.36	84.82	89.38	78.28	75.65	78.30	73.30	75.66	74.64
No	33	3.34	3.31	88.78	85.27	86.06	89.85	88.86	83.94	77.78	79.89	77.79	74.19	79.94	70.72
No	34	3.24	3.67	88.59	86.16	87.62	88.97	89.01	85.11	78.74	74.99	78.77	73.43	74.99	75.58
No	35	3.15	3.41	89.48	84.22	85.72	90.96	90.46	81.92	77.95	81.68	77.96	74.43	81.74	68.27
No	36	3.14	3.36	89.06	89.07	87.45	89.70	81.65	91.81	77.93	73.39	77.95	74.39	73.37	77.49
No	37	3.05	3.33	89.95	87.77	86.78	91.19	87.26	87.96	78.37	78.30	78.39	74.41	78.32	72.85
No	38	3.02	3.25	89.80	88.91	87.57	90.68	84.26	90.62	78.11	78.46	78.12	74.83	78.48	72.81
No	39	3.02	3.22	90.00	88.41	86.46	91.40	85.18	89.60	78.51	77.95	78.53	74.40	77.97	73.43
No	40	3.00	3.19	90.00	86.97	86.70	91.29	88.20	86.52	78.42	77.20	78.43	74.60	77.22	73.84
No	41	2.95	3.19	89.78	88.97	87.70	90.60	84.22	90.73	78.09	78.08	78.10	75.01	78.10	73.22
No	42	2.99	3.14	90.52	88.36	86.98	91.91	85.89	89.28	78.18	78.01	78.20	75.02	78.03	73.34
No	43	2.92	3.14	90.14	87.92	87.80	91.06	86.63	88.41	78.38	77.35	78.39	74.96	77.37	74.01
No	44	2.89	3.14	90.41	88.83	87.58	91.52	84.20	90.54	78.38	77.80	78.40	74.94	77.81	73.58
No	45	2.86	3.13	90.38	88.18	88.04	91.31	86.43	88.82	78.13	79.36	78.14	75.31	79.40	71.86
No	46	2.84	3.15	90.58	88.60	87.97	91.60	84.58	90.09	78.39	77.60	78.40	75.17	77.62	73.67
No	47	2.88	3.15	90.80	88.36	87.70	92.01	85.72	89.34	78.31	77.82	78.32	75.30	77.84	73.29
No	48	2.82	3.15	90.72	88.27	87.99	91.79	85.12	89.44	78.04	78.77	78.05	75.68	78.80	72.46
No	49	2.79	3.16	90.90	88.75	87.78	92.13	84.11	90.46	78.41	77.90	78.43	75.40	77.92	73.35
No	50	2.81	3.16	90.93	88.51	88.27	91.97	84.77	89.90	78.31	77.78	78.32	75.55	77.80	73.45
No	51	2.79	3.16	90.88	88.34	88.28	91.91	84.88	89.62	78.31	77.99	78.32	75.60	78.01	73.11
No	52	2.79	3.16	91.08	88.13	87.80	92.37	85.91	88.96	78.10	78.31	78.11	75.83	78.33	72.74
No	53	2.76	3.15	90.98	88.41	88.33	92.02	85.05	89.65	78.23	78.40	78.24	75.73	78.42	72.76
No	54	2.80	3.16	90.98	88.31	88.33	92.02	84.87	89.58	78.34	77.88	78.36	75.54	77.91	73.17
No	55	2.80	3.16	91.06	88.31	88.02	92.25	85.07	89.50	78.19	78.16	78.20	75.77	78.19	72.95
No	56	2.74	3.16	91.14	88.47	88.23	92.28	84.71	89.86	78.22	78.25	78.23	75.78	78.28	72.88
No	57	2.74	3.16	91.15	88.37	88.46	92.20	85.03	89.60	78.31	78.18	78.32	75.74	78.21	72.90

