Tampere University of Applied Sciences

Automated Attendance Management System Using Face Recognition (CNN)

ABU ABIR

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ABSTRACT

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Automated Attendance Management System Using Face Recognition (CNN)

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This thesis explores the development and evaluation of an automated attendance system using Face Recognition powered by Convolutional Neural Networks (CNN). The system aims to enhance accuracy and efficiency in attendance marking by recognizing and verifying individuals in real time. Trained on a diverse dataset, the CNN model demonstrated high accuracy, precision, and recall in testing, showing robustness in various lighting conditions and angles. Real-world testing confirmed the system's efficiency with rapid recognition times and low error rates. Compared to traditional methods, the system significantly improved accuracy and reduced manual errors. The findings suggest that the CNN-based attendance system is a reliable and effective solution with the potential for widespread adoption, with future improvements aimed at further enhancing adaptability and reducing error rates.

Keywords: face recognition, convolution neural network, accuracy, precision, and recall.

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ABBREVIATIONS AND TERMS

CNN	Convolutional Neural Network
Dlib	A C++ toolkit that includes machine learning algorithms and tools for developing sophisticated software in C++ to address real-world challenges.
OpenCV	Open-Source Computer Vision Library
Haar Cascades	A machine learning object detection method used to identify objects in images or videos.
ReLU	Rectified Linear Unit - An activation function used in neural networks, which outputs the input directly if it is positive, otherwise, it outputs zero, introducing non-linearity to the model.
Adam	Adaptive Moment Estimation - an optimization algorithm designed for gradient descent. It is highly efficient, especially when dealing with large-scale problems that involve extensive data or numerous parameters. Adam requires less memory and operates efficiently, making it a preferred choice for such tasks.
TP	True Positives - Instances where the model correctly predicts the positive class.
FP	False Positives - Instances where the model incorrectly predicts the positive class when it is actually negative.
TN	True Negatives - Instances where the model correctly predicts the negative class.

FN	False Negatives - Instances where the model incorrectly predicts the negative class when it is actually positive.
SVM	Support Vector Machine - A supervised learning model used for classification and regression tasks, which finds the hyperplane that best separates the classes in the feature space.
PCA	Principal Component Analysis - A dimensionality reduction technique that transforms the data into a set of orthogonal components, maximizing variance and minimizing redundancy.
RFID	Radio Frequency Identification - A wireless technology that uses electromagnetic fields to automatically identify and track tags attached to objects, transmitting data without physical contact.

1 INTRODUCTION

In daily encounters, facial recognition technology is increasingly essential for identifying individuals. This biometric identification method captures and extracts distinctive facial features to record unique face prints, enabling precise personal identification. Due to its wide range of applications across several industries, facial recognition technology has garnered significant interest from researchers. It is considered superior to other biometric techniques like fingerprint, palm print, and iris identification because it is non-invasive and contactless. These attributes enhance its acceptance and usability in various contexts, making it a preferred approach for secure and effective identity verification.

To attain high accuracy, this project makes use of the capabilities of Deep Neural Networks, specifically Convolutional Neural Networks (CNNs) with the dlib and OpenCV modules. In keeping with the more general use of biometric technologies, this project will explore key ideas required to make it happen. Our goal is to create a solid system that smoothly incorporates cutting-edge facial recognition technology for effective and dependable identity verification in attendance management by investigating and implementing these fundamental components.

1.1 Motivation

The impetus for this project arises from the urgent need for improved and secure identity verification systems in many institutional settings. Traditional attendance systems are prone to manipulation and often suffer from human errors, highlighting the need for more advanced and reliable alternatives. Facial recognition technology offers a viable solution that is both hygienic and non-contact. By automating the attendance process, this technology aims to increase operational efficiency, reduce errors, and enhance security. This project aims to develop a reliable solution that integrates cutting-edge neural network approaches with precise image-processing techniques to modernize and improve the reliability of attendance management.

1.2 Privacy Concerns and Global Perspectives

While facial recognition technology offers significant benefits, it also raises concerns about privacy and the ethical implications of storing facial images in databases. These concerns vary across different countries and cultures:

- **European Union:** The EU has stringent data privacy regulations under the General Data Protection Regulation (GDPR). Citizens are generally more aware and concerned about their privacy rights, with a strong emphasis on obtaining explicit consent before collecting biometric data. The GDPR mandates that any use of facial recognition technology must be transparent, have a clear legal basis, and ensure robust data protection measures.
- **United States:** In the US, attitudes toward facial recognition technology are mixed. While there is significant adoption in both public and private sectors, growing concerns about privacy and civil liberties exist. Several cities and states have enacted laws to regulate or ban the use of facial recognition technology by government agencies, reflecting a cautious approach toward its deployment.
- **China:** China leads in the large-scale implementation of facial recognition technology, particularly in public security and surveillance. The government's stance is more accepting, and the technology is widely used with relatively less public resistance. However, this extensive use has sparked global debates about privacy and surveillance.
- **India:** India is rapidly adopting facial recognition technology for various applications, including law enforcement and airport security. While there is enthusiasm for its potential to enhance security and efficiency, concerns exist about the lack of comprehensive data protection laws to safeguard citizens' privacy.

These varying perspectives highlight the need for a careful and context-sensitive approach to deploying facial recognition technology. Addressing privacy concerns through strong legal frameworks and ensuring transparency and consent is crucial for the technology's acceptance and ethical use.

1.3 Objectives

The primary objectives of this project are:

1. To design and implement an automated attendance management system using facial recognition technology.
2. To develop a Convolutional Neural Network (CNN) model that can accurately recognize and verify individuals based on their facial features.
3. To ensure the system operates efficiently in real-time, providing quick and accurate attendance marking.
4. To evaluate the system's performance in various conditions and ensure robustness against different lighting, angles, and facial expressions.

1.4 Significance

The significance of this project lies in its potential to revolutionize attendance management systems across various sectors, including education, corporate environments, and events. By leveraging facial recognition technology, the system provides:

1. Enhanced accuracy in attendance marking, reducing manual errors.
2. Increased efficiency by automating the attendance process.
3. A non-invasive and hygienic method for identity verification.
4. Improved security and fraud prevention through reliable biometric authentication.

1.5 Challenges of Traditional Systems

Traditional attendance systems, such as manual roll calls or card-based systems, face several challenges:

1. **Human Errors:** Manual attendance marking is prone to errors, such as missed entries or incorrect markings.
2. **Fraud:** Card-based systems can be easily manipulated, with individuals clocking in for others.
3. **Time-Consuming:** Manual systems are time-consuming, especially in large settings.
4. **Hygiene Concerns:** Physical contact with cards or biometric devices can raise hygiene issues, particularly in the context of public health concerns.

1.6 Organization of the Report

- **Introduction**

  This chapter outlines the motivation, significance, and goals of the research. It gives a summary of the difficulties linked to conventional attendance management techniques and emphasizes the potential advantages of using face recognition technology.

- **Literature Review**

  The literature on facial recognition technologies and attendance management systems is reviewed in this chapter. This thesis seeks to fill in the gaps and take advantage of the chances for improvement found in the many techniques, procedures, and technologies that have been employed in comparable systems in the past. A discussion of the most recent developments and patterns in facial recognition research, including CNN, is also included in the review.

- **Methodology**

  The project methodology and the automated attendance system's framework are discussed in detail in this chapter. It describes the methodical process that was used to develop the system, including the selection of algorithms, techniques for acquiring data, and system architecture. There are also in-depth explanations of the model architecture and its associated parts.

- **Results and Analysis**

  The results of the automatic attendance system's installation and assessment are shown in this chapter. It lists several performance indicators, points out any shortcomings, and suggests possible areas for development.

- **Discussion**

  This chapter summarizes the thesis's main conclusions and significant contributions. The discussion section explores the broader implications of the

research, its potential impact on educational institutions, and future research directions. Recommendations for further improvements and potential extensions of the system are also provided.

- **References**

  All the academic books, papers, and other sources that the thesis references are listed in this section.

2 LITERATURE REVIEW

2.1 Introduction to Attendance Systems

2.1.1 Historical Context

Attendance tracking has become a vital responsibility in various industries, most notably in educational institutions and the workplace. Roll calls and sign-in sheets were the traditional manual methods used to record attendance; these methods were labor-intensive, prone to human error, and inefficient. Maintaining accurate records was challenging due to the frequent inaccuracies that this manual method produced.

2.1.2 Evolution to Automated Systems

The demand for more precise and effective at-attendance tracking systems arose with technological improvements. Manual techniques began to give way to automated technologies like punch cards, RFID (Radio Frequency Identification) tags, and biometric systems like iris and fingerprint identification. These technologies reduced the administrative load associated with attendance tracking while improving accuracy and efficiency.

2.1.3 Importance of Accurate Attendance Tracking

Precise monitoring of attendance is essential for multiple reasons. Ensuring students meet attendance requirements in educational institutions can have a significant impact on their academic achievement and eligibility for exams. It supports the monitoring of worker productivity and timeliness in the workplace, both of which are essential for operational effectiveness. Maintaining accurate records is also essential for adhering to labor rules and regulations.

2.2 Face Recognition Technology

2.2.1 Overview of Face Recognition Technology

Face recognition technology utilizes the analysis of facial features to identify or verify individuals. The procedure usually entails capturing a photograph, extracting features, comparing the results to a database that has been recorded, and confirming or authenticating the person. This technology makes use of distinctive facial characteristics, which makes it a trustworthy biometric technique for a range of uses.

2.2.2 Comparison with Other Biometric Systems

Compared to other biometric systems like fingerprint and iris recognition, face recognition has several advantages. It can function in a variety of settings without requiring physical contact and is non-intrusive and simple to use. But it also presents difficulties including sensitivity to occlusions, facial expressions, and illumination.

2.3 Techniques and Algorithms in Face Recognition

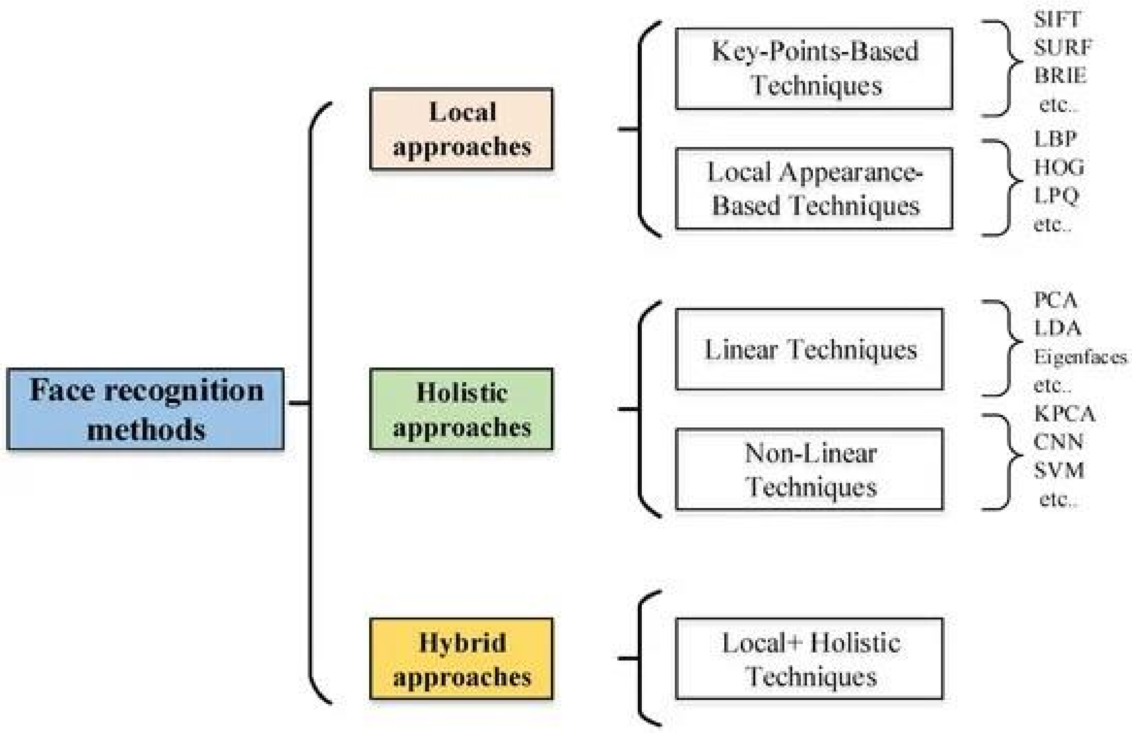


FIGURE 1. Different methods of face recognition (ResearchGate, Oct, 2022)

FIGURE 1 depicts the various techniques employed in face recognition. It contrasts traditional methods with contemporary deep learning techniques. This figure aids in comprehending the progression and efficiency of different face recognition technologies.

2.3.1 Commonly Used Algorithms

Local Binary Patterns (LBP), Eigenfaces, and Fisherfaces are examples of traditional face recognition algorithms. By concentrating on the primary components of facial photographs, Eigenfaces decrease dimensionality, whilst Fisherfaces increase class separability. By analyzing an image's local texture, LBP makes it resistant to variations in illumination.

2.3.2 Modern Deep Learning Approaches

The application of CNNs and other cutting-edge architectures in deep learning has revolutionized face recognition. In terms of accuracy and efficiency, models such as VGG-Face, FaceNet, and DeepFace have set new standards. These models work incredibly well under a variety of circumstances because they can learn intricate representations of facial features.

2.3.3 Advantages and Limitations of Different Techniques

Conventional methods are less computationally demanding but frequently less precise when compared to deep learning approaches. Deep learning methods provide exceptional results, but they necessitate substantial computer power and extensive datasets for training.

2.4 Applications of Face Recognition in Attendance Systems

2.4.1 Case Studies and Examples

Face recognition-based attendance systems have been successfully implemented in various settings. For instance, Ara et al. (2017) developed a vision-based student recognition system using CNNs. Their study combined CNNs with Support Vector Machines (SVM) to enhance recognition accuracy, demonstrating the effectiveness of hybrid models in attendance systems.

Winarno et al. (2019) implemented an attendance system using a combination of CNN and Principal Component Analysis (PCA). Their approach enhanced feature extraction, leading to improved real-time face recognition accuracy.

Rai et al. (2019) developed an end-to-end real-time attendance system with face detection using CNNs. Their system demonstrated high accuracy and efficiency, making it suitable for practical deployment in educational institutions.

Chowdhury et al. (2020) created an automated system for class attendance using CNN-based facial recognition. Their system demonstrated high accuracy in classroom environments, reducing the manual effort required for attendance tracking.

2.4.2 Implementation in Different Domains

Various industries derive distinct advantages from the implementation of facial recognition technologies. It facilitates monitoring student involvement and participation in the classroom. Within business settings, it guarantees employee responsibility and optimizes payroll procedures. In the healthcare industry, it can be utilized to track patient appointments and staff presence.

2.4.3 Comparative Analysis

Face recognition provides a contactless and more hygienic option compared to RFID and fingerprint-based systems, which is particularly crucial in post-pandemic situations. It obviates the necessity for tangible tokens or devices, hence diminishing the likelihood of loss or theft.

2.5 Challenges and Issues in Face Recognition

2.5.1 Technical Challenges

Face recognition systems encounter technological obstacles such as fluctuations in lighting conditions, different facial orientations, various facial expressions, and obstructions. These parameters might have a substantial influence on the precision and dependability of the system.

2.5.2 Ethical and Privacy Concerns

Concerns about privacy and ethics come up when face recognition technology is used. People are worried about personal data being misused, collected without permission, and being watched by a lot of people. To address these concerns and keep the public's trust, we tried to ensure data protection and got informed consent.

2.6 Evaluation and Performance Metrics

Several metrics are utilized to assess face recognition systems, including accuracy, precision, recall, and F1 score. These metrics aid in the identification of areas that require improvement and offer valuable insights into the performance of the system. Accuracy denotes the comprehensive correctness of the system, whereas precision and recall evaluate its capability to accurately identify and retrieve pertinent faces.

3 METHODOLOGY

3.1 Introduction

The face recognition-based attendance system aims to automate the attendance tracking process using facial recognition technology. This system uses a Convolutional Neural Network (CNN) model to identify and verify individuals based on their facial features.

3.2 Data Collection and Preprocessing

Our systems’ performance depends mostly on the quality of the training dataset. We need to feed the model with a sophisticated dataset. To achieve this, we need to collect good-quality images from different angles and environments. After collecting the dataset, we also need to pre-process the dataset to extract the most useful result from it. That’s why data collection and preprocessing play a vital role in our system's performance.

3.2.1 Data Collection

Dataset: A comprehensive dataset of facial images was collected. The dataset includes multiple images of each participant to account for variations in lighting, facial expressions, and angles. Permissions were obtained from all participants involved in the dataset collection process.

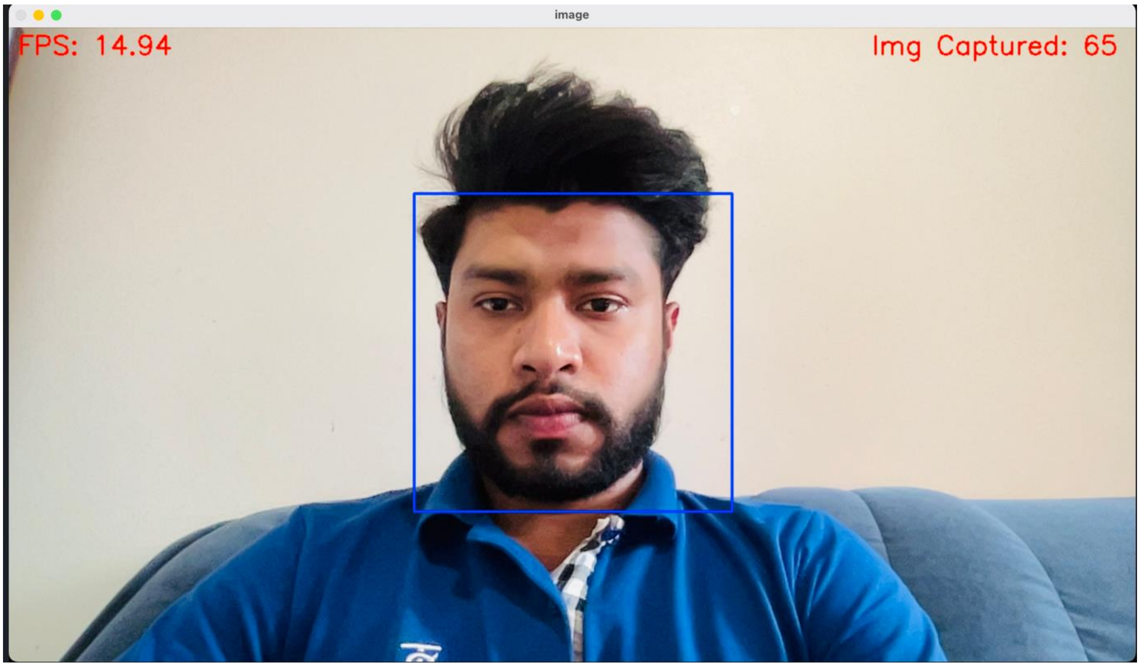
PICTURE 1: Dataset Collection

PICTURE 1 demonstrates a sample dataset collection where labels and images are stored. The data collection process involved capturing high-quality facial images from various angles and under different lighting conditions to ensure the robustness of the model.

Image Acquisition: Images were captured using an existing personal device's web camera while rotating the face to capture different angles.

3.2.2 Data Preprocessing

Face Extraction: To identify and crop faces from the photos, Haar Cascades were employed. As Haar Cascade can easily detect faces from real-time video. It generally uses edge detection or line detection features to identify a face in a frame.



PICTURE 2: Face Detection Using Haar Cascade.

PICTURE 2 demonstrates the practical application of the Haar cascade classifier. It shows a face detected within an image using the Haar Cascade method. The bounding box around the face highlights the area identified as a face by the classifier.

Image Resizing: All facial images are resized to a standard dimension of 32x32 pixels. This resizing step ensures that all input images have the same dimensions, which is essential for consistent processing by the CNN model.

Image Resizing

```
img = img.resize((32,32))
```

PICTURE 3: Image Resizing Code Snippet.

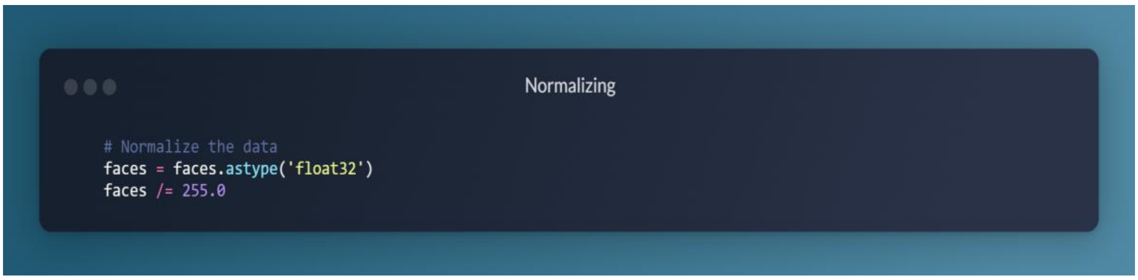
In PICTURE 3, we used the resize function to limit the shape of our input image to 32x32 resolution.

Conversion to Grayscale: Images are also converted to grayscale to optimize hardware resource usage. Grayscale images require less computational power compared to RGB images, as they contain only intensity information rather than color information in three channels.

PICTURE 4: A 32x32 Resized Grayscale Image.

PICTURE 4, above illustrates a facial image that has been resized to 32x32 pixels and converted to grayscale. This preprocessing step is crucial for standardizing the input data, making it suitable for input into the Convolutional Neural Network (CNN) model.

Normalization: To enhance the performance of the model, pixel values were normalized to the interval [0, 1].



PICTURE 5: Data Normalization Code Snippet.

In PICTURE 5, we are showcasing our normalization process. Normalization is applied to stabilize and accelerate the training process by standardizing the inputs to have a consistent scale.

3.3 Model Summary

We used a CNN model for our face recognition system. Which has a complex architecture. Usually, CNN models have three layers: **The input layer, the Hidden layer,** and **the Output layer**. Where the hidden layer consists of several layers. We have discussed all these layers and the architecture in the following sections.

3.3.1 Our CNN Model

Input Layer: The input layer accepts facial images of fixed size (32x32). This image size is sufficient to provide enough information for the model.

Convolutional Layers: Spatial characteristics were extracted from the images using multiple convolutional layers with ReLU activation functions. To lower dimensionality, either a max-pooling layer or a convolutional layer was placed after it.

Max pooling layer: In this layer, take the maximum value of a pixel from an area of the image that the kernel covers. Furthermore, max pooling acts as a noise reducer. Apart from reducing the dimensionality, it also performs de-noising and gets rid of all noisy activations.

Batch Normalization: It normalizes the inputs of each layer to reduce internal covariate shifts, improving training stability and speed. It standardizes the input using mini-batch statistics and then scales and shifts it.

Dropout layers: Dropout layers were used to prevent overfitting. It randomly sets a fraction of input units to zero during training to prevent overfitting.

Flatten Layer: This layer reshapes a multi-dimensional input into a single vector, facilitating its use in fully connected layers. It's commonly used to transition from convolutional layers to dense layers.

Dense Layer: Also known as Fully Connected layer. Here, Flattened feature maps were fed into fully connected layers to perform high-level reasoning.

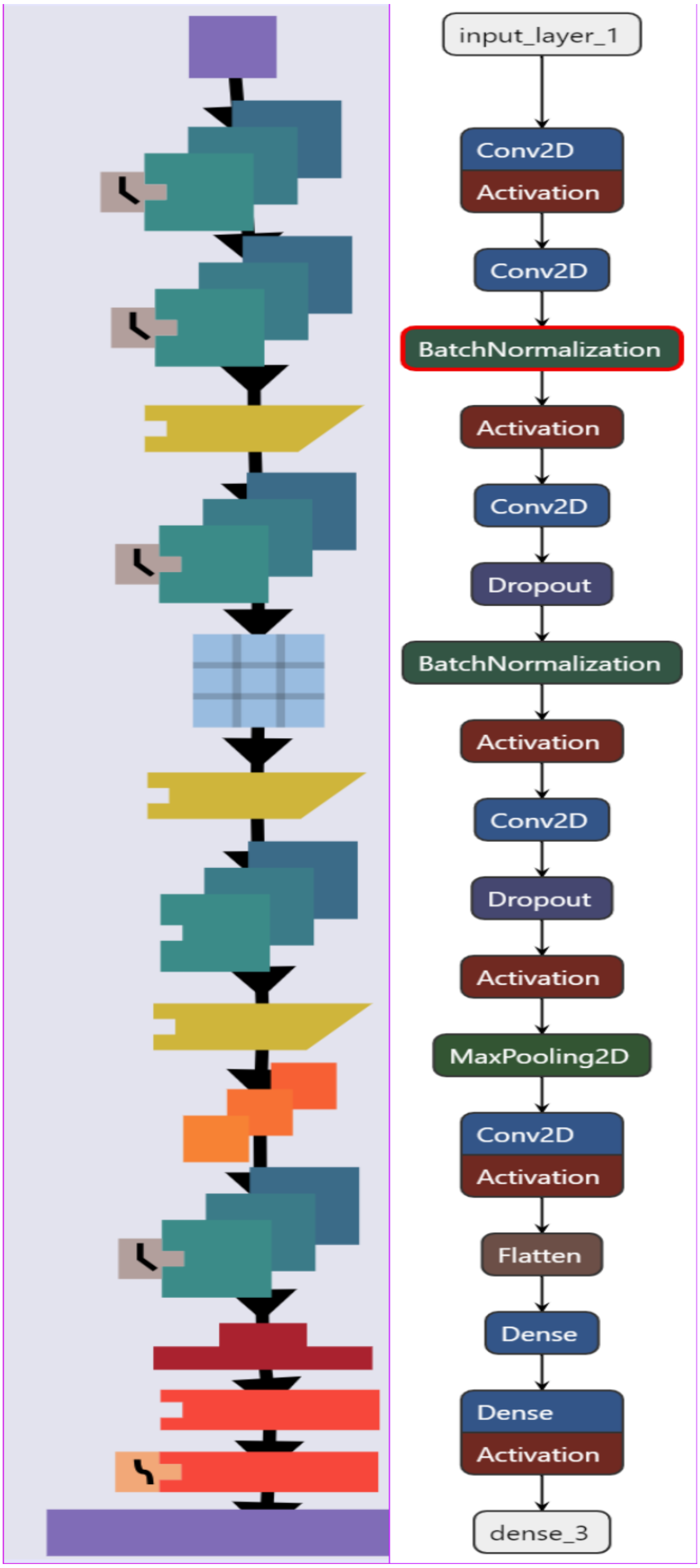


FIGURE 2. Our Model Architecture.

FIGURE 2 presents the model architecture, detailing each layer, its type, output shape, and the number of parameters. That provides a clear and concise overview of the layer sequence and parameter counts, aiding in understanding the model's structure. The architecture includes convolutional, activation, dropout, batch normalization, max pooling, flatten, and dense layers.

Output Layer: An activation function Softmax was used in the output layer to classify images into distinct classes.

3.4 Training and Validation

The training and Validation process includes the steps of compiling the model with different kinds of loss functions, optimizers, and evaluation metrics. Data splitting and epochs are also a vital part of the training process. Here, An epoch in machine learning refers to one complete pass through the entire training dataset during the training process of a model.

3.4.1 Loss Function

Categorical Cross-Entropy loss was employed to gauge the model's effectiveness. This loss function is used for multiclass classification. So, using this we can get probability for N classes of faces.

model training

```
final_model.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])
final_model.fit(x_train, y_train, batch_size=32, epochs=10, validation_data=(x_test, y_test), shuffle=True)
```

PICTURE 7: Model Compile and Training.

PICTURE 7 shows the code for compiling the model with a specific optimizer, loss function, and accuracy metrics. It also shows the batch size and epochs used to train the model.

3.4.2 Optimizer

The **Adam** (Adaptive Moment Estimation) optimizer was used to update the model's weights and minimize the loss function. Adam keeps adaptive learning rates for every parameter and modifies them with the gradients’ first and second moments.

PICTURE 8: Dataset Splitting for Model Training.

PICTURE 8 shows the dataset split process. Where we are splitting the dataset into training data and validation datasets.

3.4.3 Training

Training and validation sets (e.g., 80% training, 20% validation) were created from the dataset. To avoid overfitting, the model was trained for a predetermined number of epochs with early stopping. The data are shuffled randomly before splitting. Also, the batch size was 32 which defines the number of samples used to train the model.

3.5 System Overview

The proposed attendance management system leverages camera access and facial recognition technology to streamline the process of tracking and managing student attendance. This system is designed to automate attendance recording, reduce manual errors, and provide real-time data access. The following sections provide a detailed description of the system's components, functionalities, and workflow.

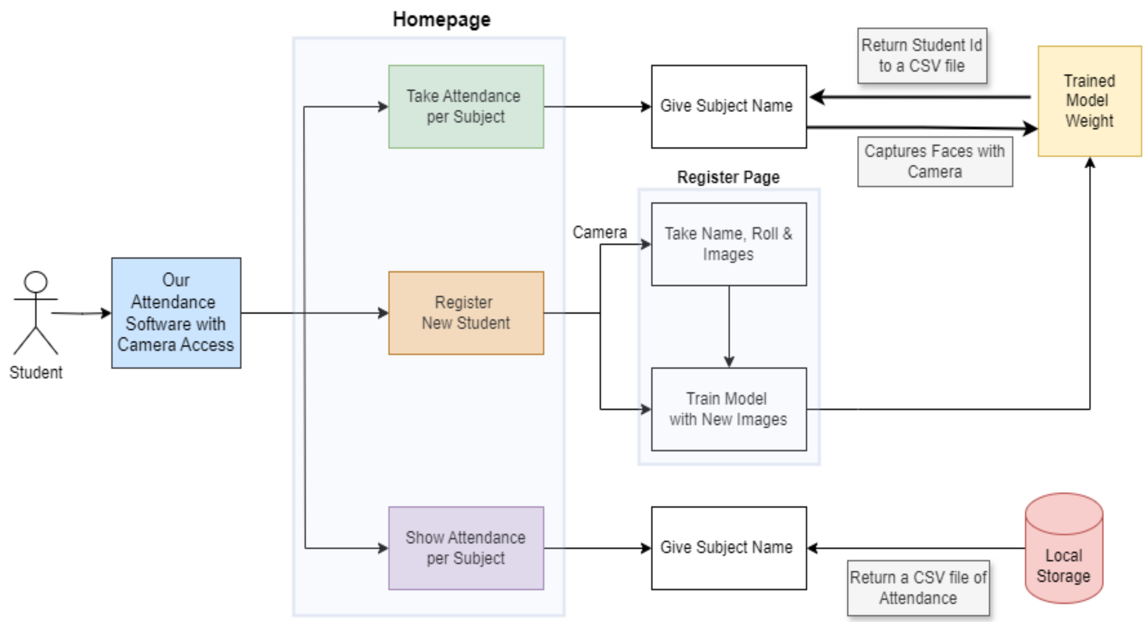


FIGURE 3. System Overview of Our Attendance System.

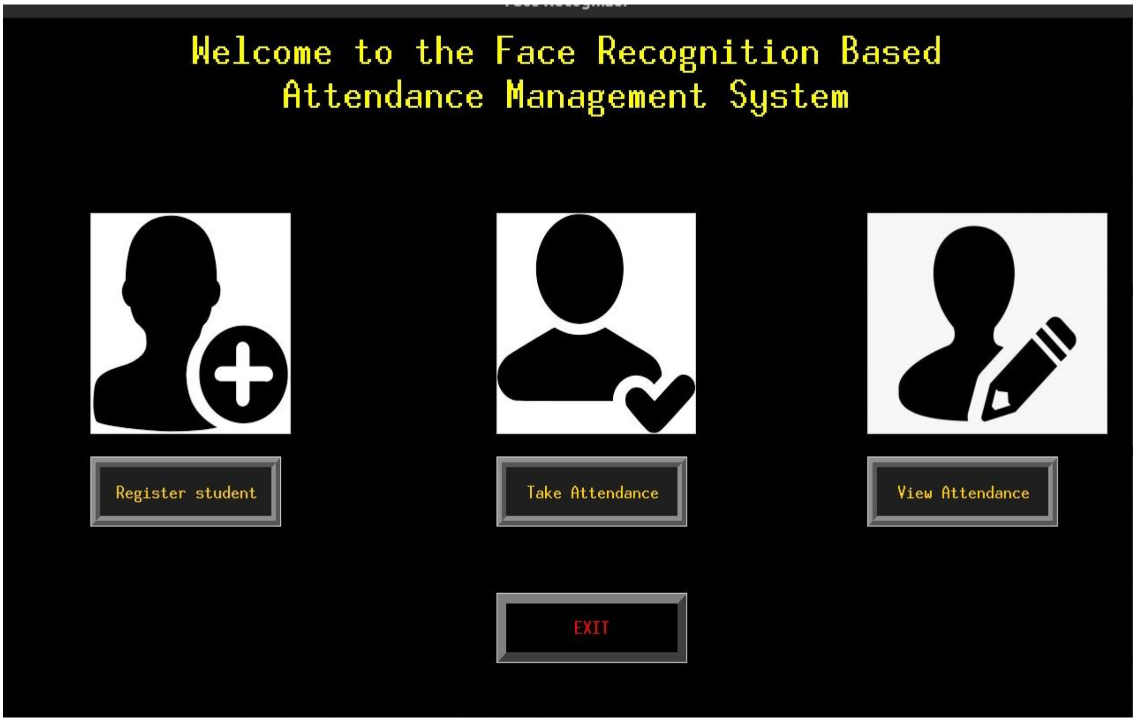
FIGURE 3. depicts a flowchart of an attendance system with camera access. It shows the process from registering new students and training a model with their images to taking attendance per subject, capturing faces, and recording attendance in a CSV file.

3.5.1 System Components

1. **Student**: The end user who interacts with the system to mark their attendance and register their details.

2. **Our Attendance Software with Camera Access**: The primary interface for students and administrators, enabling the capture and processing of attendance data.
   Homepage:

- **Take Attendance per Subject**: This functionality allows students to mark their attendance for a specific subject.
- **Register New Student**: This feature facilitates the registration of new students into the system.
- **Show Attendance per Subject**: This feature enables administrators and students to view attendance records for a specific subject.



PICTURE 9. Home Page

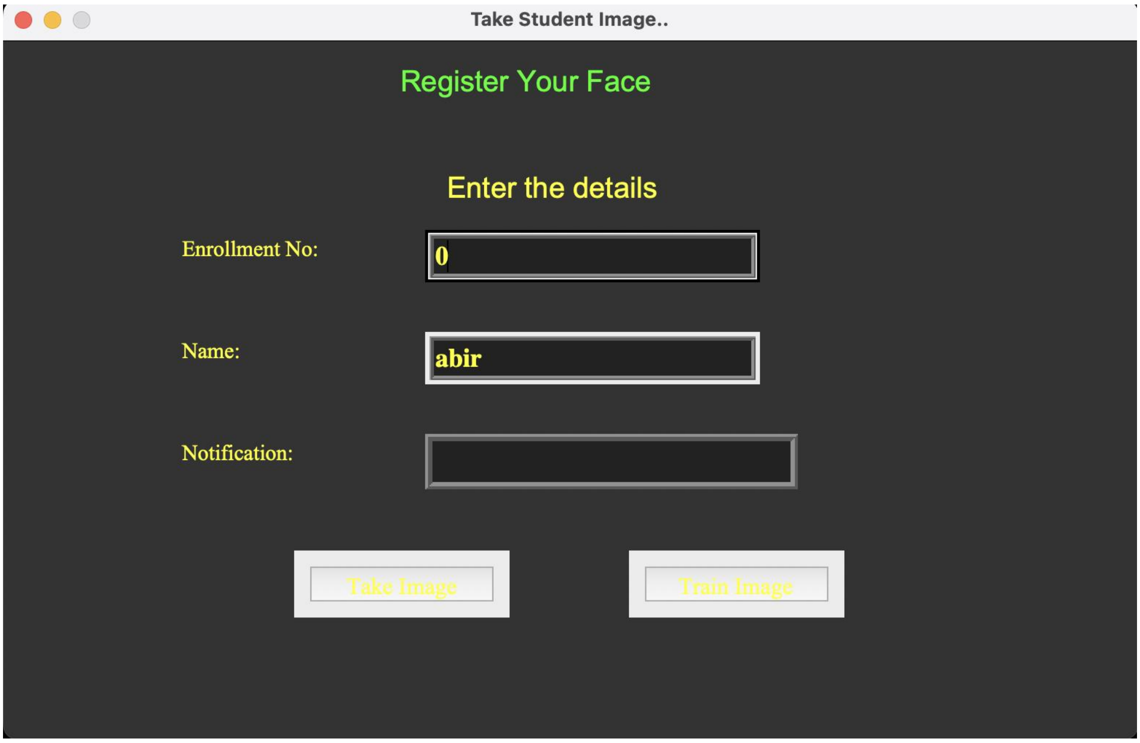
In PICTURE 9, there are three main options available: "**Student Registration**, "**Take Attendance**" and "**View Attendance**."

3.5.2 Workflow Description

The system's workflow is designed to ensure seamless interaction between students and the attendance management system, providing efficient and accurate attendance tracking. The workflow is divided into three main processes: taking attendance, registering new students, and displaying attendance records.

Registering New Students:

- **Navigation**: The user accesses the registration page.
- **Input**: The system collects the student's name, roll number, and facial images.
- **Process**: These inputs are used to train the facial recognition model with new images, updating the model weights.
- **Output**: Updated trained model weights are stored for future recognition tasks.

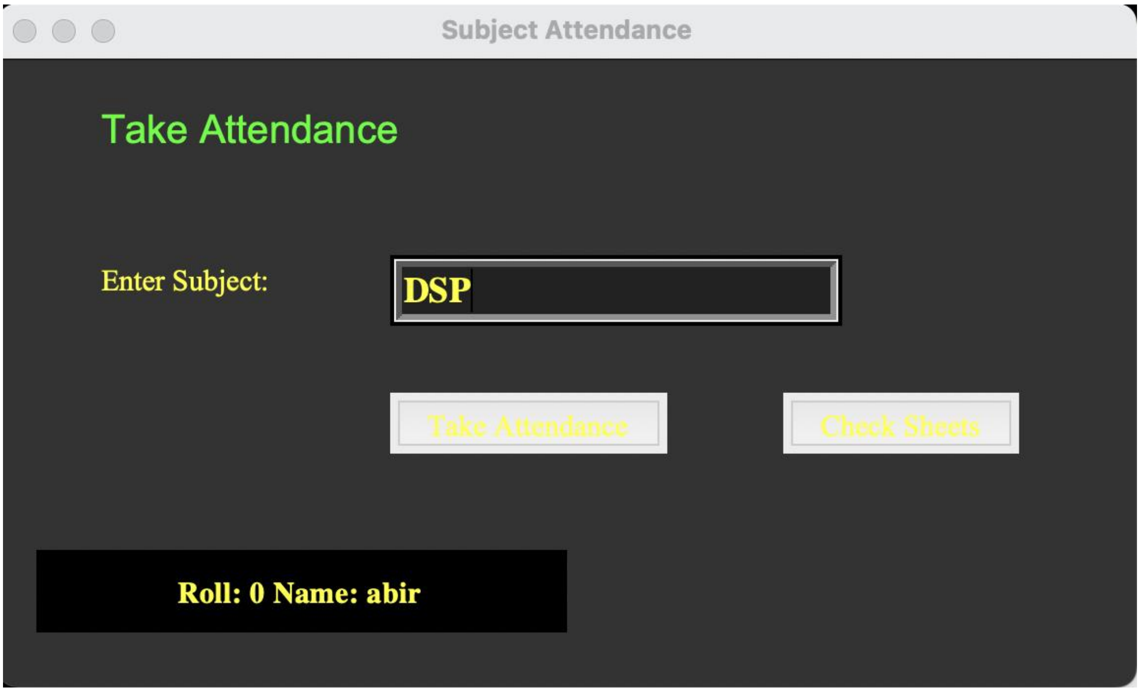


PICTURE 10. Registration Page

In PICTURE 10, Under the "**Student Registration,**" a new student can be enrolled by providing their roll number and name, along with a specified number of input images. Once these images are captured, the new dataset can be trained.

Taking Attendance per Subject:

- **Input**: The user provides the subject name.
- **Process**: The system captures faces using the camera and utilizes pre-trained model weights for facial recognition.
- **Output**: Identified student IDs are returned and stored in a CSV file



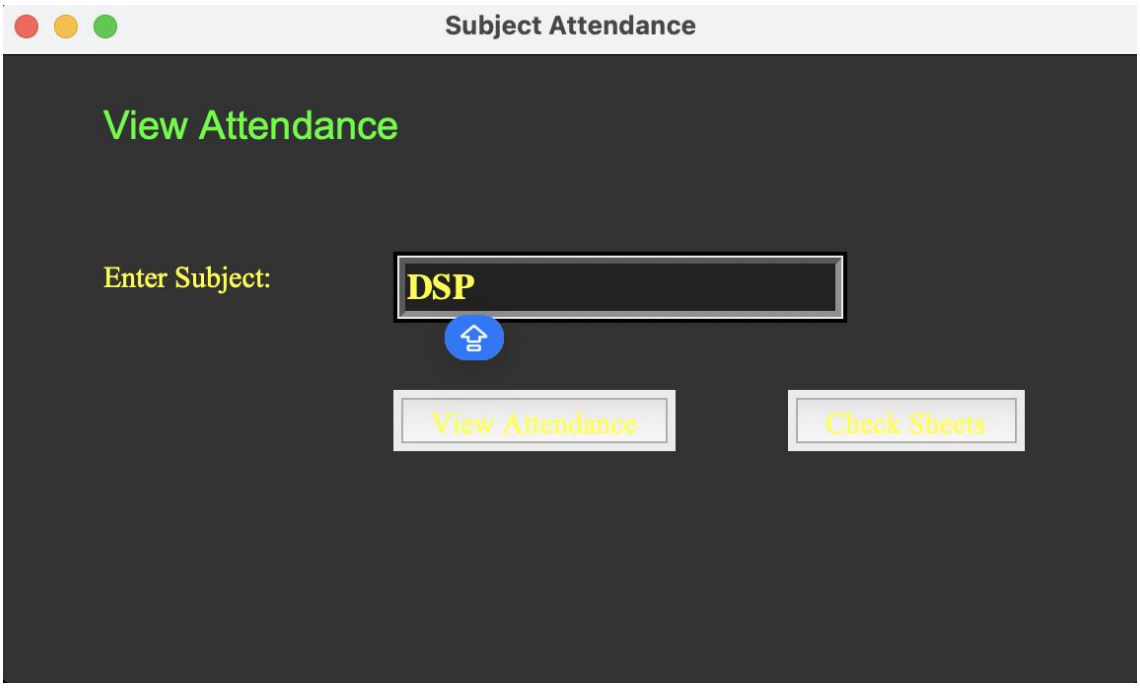
PICTURE 11. Take Attendance

In PICTURE 11, Following the training of the dataset, attendance can be recorded by specifying the subject. Here, the system will turn on the camera to capture the student's face and use the model to identify the student. After the identification, it will update the attendance sheet for the student in that subject.

Showing Attendance per Subject:

- **Input**: The user provides the subject name.
- **Process**: The system retrieves the relevant attendance records from local storage.

- **Output**: A CSV file containing the attendance records is generated and presented to the user.



PICTURE 12. View Attendance

In PICTURE 12, After recording the attendance in the previous step, the "**View Attendance**" allows for reviewing the attendance records for a specific subject. Here we will show the attendance for that subject in a pop-up window. And can check the sheet from the "**Check Sheets**" option.

3.5.3 Data Flow

The data flow within the system is critical to ensuring accurate attendance tracking and model updates:

Trained Model Weight: The facial recognition model is continuously updated with new student data to improve accuracy. These weights are crucial for identifying students during attendance taking.

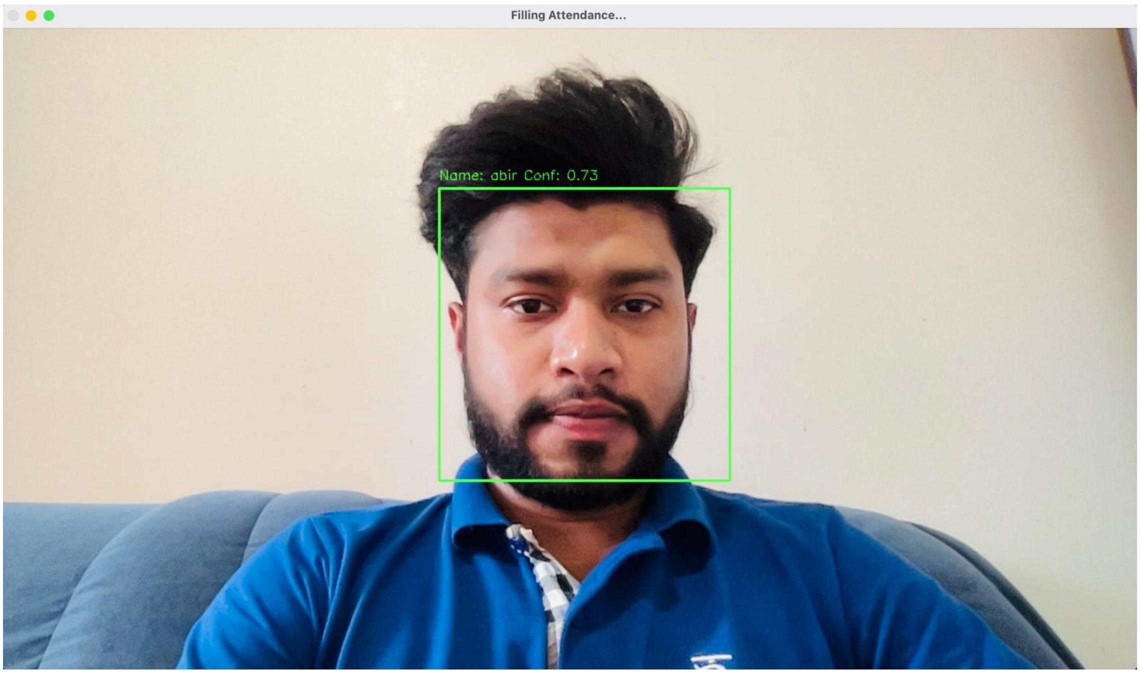
Local Storage: This component stores CSV files of attendance records and the trained model weights. It ensures that attendance data is securely saved and easily retrievable for administrative purposes.

3.6 System Operations

In summary, our system mainly performs two operations. Recognize the faces and fulfill attendance for specific dates.

3.6.1 Face Identification

During attendance, the system captures a real-time image, detects, and encodes the face, and compares it with stored feature vectors using distance metrics.



PICTURE 13: Face Matching.

In PICTURE 13, the detected face is compared to the model weights to recognize the student.

3.6.2 Attendance Marking

Identity Verification: If the face is matched with a stored feature vector within a certain threshold, the individual's identity is verified as shown in the previous section.

Attendance Log: The verified individual's attendance is recorded in the system's database with a timestamp.

Attendance CSV

```
Enrollment,Name,2024-05-17
1,Abir,1
```

PICTURE 14: Attendance Logs.

In PICTURE 14, we can see a CSV file that contains the attendance information, where the attendance of a student is stored on the basis of a particular date.

4 RESULTS AND ANALYSIS

4.1 Introduction

To assess performance, we evaluated the F1-score, Accuracy, Precision, and Recall metrics. Classification accuracy is calculated as the proportion of correct predictions to the total number of predictions made by the model. Precision is determined as the proportion of true positive predictions to the total number of true and false positive predictions. Recall, also known as sensitivity, measures the proportion of true positives to the total number of true positives and false negatives. The F1-score, or F-measure, is a single metric that balances Precision and Recall.

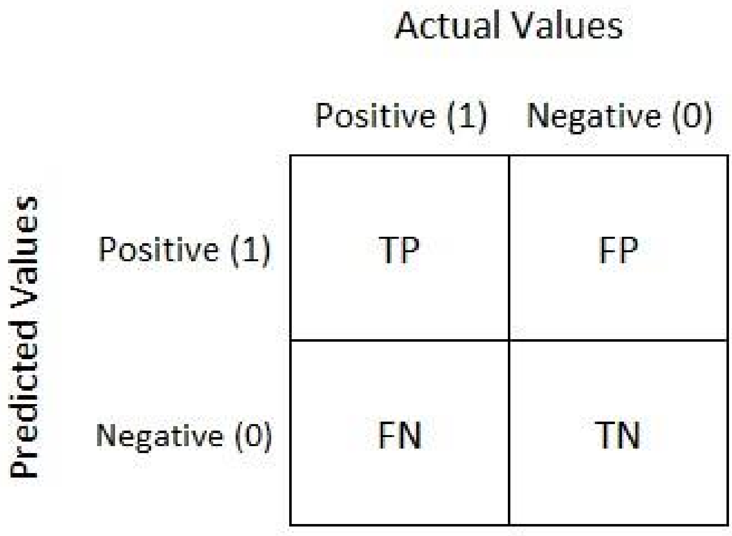


FIGURE 4. Confusion Matrix.

Figure 4 presents a confusion matrix utilized in classification tasks. It compares the predicted values with the actual values, where True Positives (TP) and True Negatives (TN) indicate correct predictions, and False Positives (FP) and False Negatives (FN) denote incorrect predictions. This matrix is instrumental in assessing the performance of a classification model.

4.2 Model Performance

The CNN model achieved the respective performance metrics on the test set:

- **Accuracy:** High accuracy, indicating the models can correctly identify individuals.
- **Precision:** High precision, reflecting the model's effectiveness in reducing false positives.
- **Recall:** High recall, showing the model's success in capturing true positives.
- **F1 Score:** Balanced F1 score, demonstrating overall model performance.

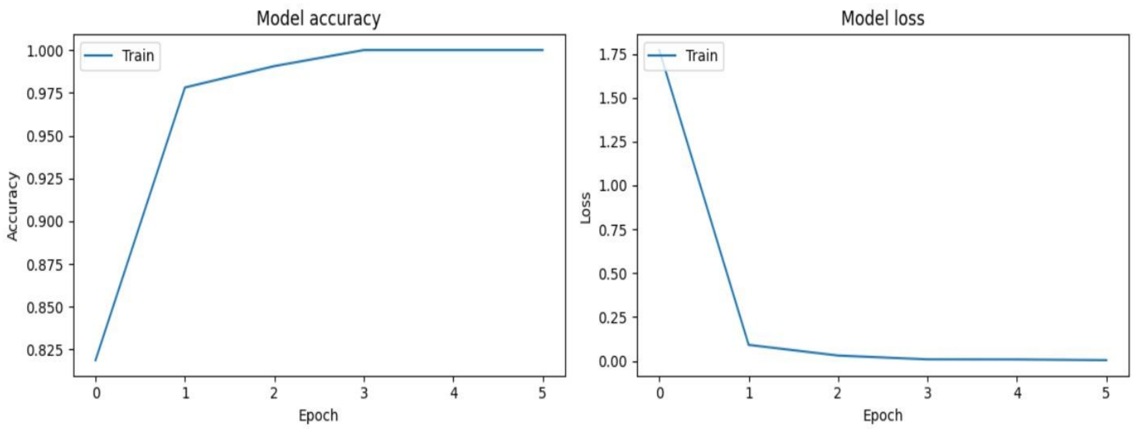


FIGURE 5. Training Data Accuracy.

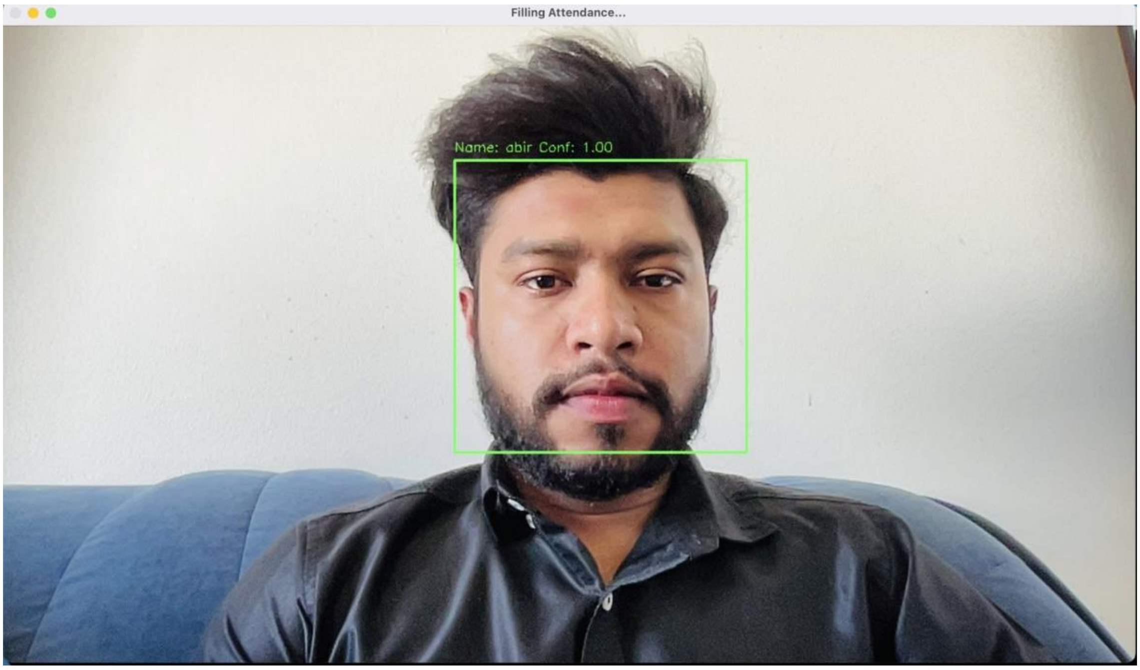
In FIGURE 5 These results indicate that the model is highly effective at correctly identifying individuals from the dataset, with balanced performance across precision and recall.

4.3 Real-Time Face Detection

When the system was tested in an actual setting, it showed the following qualities:

- **Detection Time:** The average time to detect and recognize a face was quick and efficient.
- **False Positives/Negatives:** The system recorded low false positive and false negative rates during real-time testing.

- **Environmental Robustness:** The system maintained high accuracy in various lighting conditions and angles, proving its robustness in different real-world scenarios.



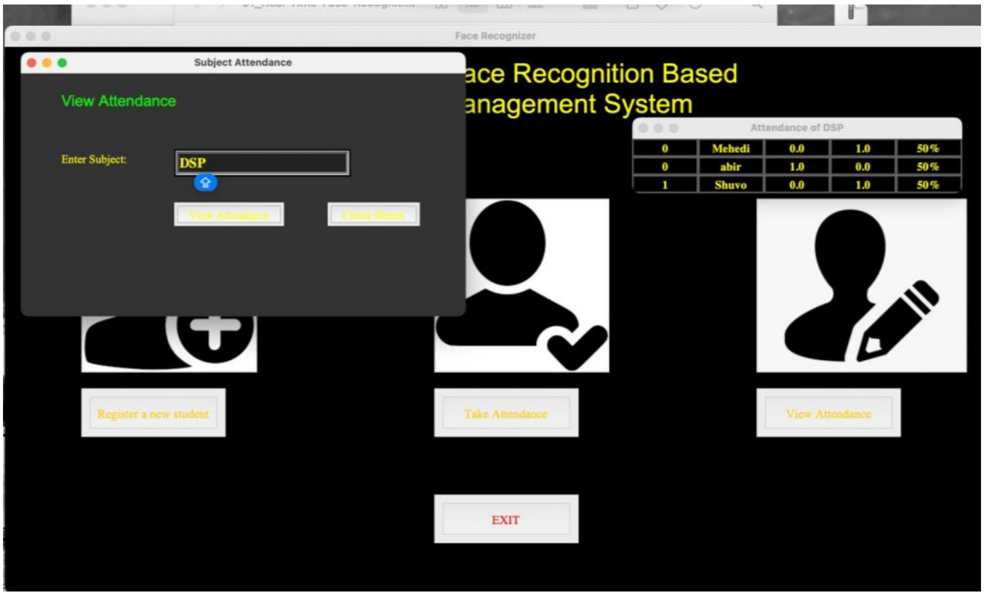
PICTURE 15. Real-time Face Detection

PICTURE 15 demonstrates a real-time face detection system. The system successfully identifies the individual, labeled as "abir" with a confidence level of 1.00. The green bounding box indicates the detected face region, showcasing the effectiveness of the face recognition algorithm in identifying and localizing the face accurately.

4.4 Attendance Accuracy

The primary goal of the system is to accurately mark attendance. The following metrics were observed:

- **Attendance Marking Accuracy:** High accuracy in marking attendance.
- **Missed Attendances:** Low number of missed attendances, indicating high reliability.
- **Duplicate Entries**: No duplicate entries, confirming the system’s ability to handle multiple recognitions of the same individual effectively.



PICTURE 16. Showing View Attendance in GUI

PICTURE 16 showcases the "**View Attendance**" functionality in a graphical user interface (GUI) of a face recognition-based automatic attendance management system. The interface allows the user to enter a subject code (e.g., DSP) to view or check attendance records. The GUI includes options for registering new students, taking attendance, and viewing attendance records, facilitating efficient attendance management.

5 DISCUSSION

5.1 Conclusions

This project effectively created an attendance system by recognizing faces using convolutional neural networks. The technology provides improved security, efficiency, and accuracy for tracking attendance. Its usefulness in a variety of settings has been rigorously tested, confirming that it is a dependable solution for companies, events, and educational institutions.

5.2 Future Work

1. **Model Performance:** Optimize the CNN architecture and explore advanced techniques like transfer learning to improve accuracy.

2. **Dataset Enlargement:** Gather a more extensive and varied dataset to improve the model's generalization to other demographics.

3. **Real-Time Processing**: Adapt the system for real-time use to provide immediate and accurate attendance tracking.

4. **Multimodal Authentication:** Incorporate additional biometric methods, such as fingerprint or iris recognition, to enhance security.

5. **Scalability**: Make sure the system is suited for large institutions by ensuring that it can manage enormous volumes of data and users.

6. **User Experience:** Enhance the user interface to make the system more intuitive for both administrators and users.

Addressing these areas will further improve the system's robustness and versatility, making it an even more effective solution for attendance management.

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6 APPENDICES

Code. GitHub repository. https://github.com/AH-ABIR/Real-Time-Face-Recognition-Using-CNN.git