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Design and Validation of Ai-Enabled Pulse Monitoring Using Built-In Smartphone Sensors

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ABSTRACT

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Smartphones have been transformed into formidable tools for real-time physiological monitoring as a result of the growing convergence of artificial intelligence (AI) and mobile health technology. Traditionally, dedicated medical or wearable devices have been used to measure pulse rate, which is an important indicator of cardiovascular health. However, widespread use of these devices is hindered by restrictions in terms of accessibility and cost. The objective of this research is to create, optimize, and evaluate an artificial intelligence-enabled pulse monitoring system that is capable of providing accurate, low-cost, and scalable cardiovascular evaluations. This will be accomplished by utilizing smartphone cameras and embedded sensors. The research draws on previous developments in artificial intelligence-driven biomedical sensing, digital cardiovascular modelling, and edge computing. It highlights the potential of lightweight machine learning architectures to extract clinically significant information from consumer-grade devices. The aims of the work include evaluating the accuracy of smartphone sensors, developing a lightweight CNN–LSTM model for pulse estimation, and testing the model's performance in comparison to medical-grade electrocardiogram (ECG) references across a wide range of environmental and demographic variables. With the help of 3,888

synchronized PPG–ECG recordings taken from the BUT-PPG dataset, a quantitative and experimental technique was successfully implemented. Among the several methods of signal processing were band-pass filtering, normalization, segmentation, and labeling based on electrocardiograms. TensorFlow-Lite was utilized in order to train and optimize the hybrid CNN–LSTM model for mobile deployment. A high prediction accuracy was observed in the results, with the mean absolute error (MAE) being around 1.96 beats per minute (BPM) and the critical correlation coefficient (CCC) being 0.896. Additionally, there was a substantial correlation with electrocardiogram data, and the performance was robust across different types of devices, lighting, movement, and measurement sites. According to the findings of the study, smartphones, when combined with AI architectures that have been optimized, are capable of providing near-clinical pulse monitoring without the need for external wearables. The significance of the system for scalable, accessible, and proactive cardiovascular health management is supported by the fact that it shows real-time performance, efficiency, and dependability that has been demonstrated.

Keywords: Artificial Intelligence, Pulse Monitoring, Photoplethysmography (PPG), CNN–LSTM, Smartphone Sensors, Cardiovascular Analytics, Mobile Health, TensorFlow-Lite.

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LIST OF ABBREVIATIONS

Abbreviation	Full Form
AI	Artificial Intelligence
mHealth	Mobile Health
_PPG	Photoplethysmography
ECG	Electrocardiogram
CNN	Convolutional Neural Network
LSTM	Long Short-Term Memory
BPM	Beats Per Minute
HR	Heart Rate
HRV	Heart Rate Variability
BUT-PPG	Brno University of Technology Photoplethysmography Database
MAE	Mean Absolute Error
MSE	Mean Squared Error
RMSE	Root Mean Square Error
R ²	Coefficient of Determination
CCC	Concordance Correlation Coefficient
TFLite / TF-Lite	TensorFlow-Lite
CPU	Central Processing Unit
GPU	Graphics Processing Unit
IoT	Internet of Things
MEMS	Micro-Electro-Mechanical Systems
PTT	Pulse Transit Time

Abbreviation	Full Form
QRS	Q–R–S Complex (ECG waveform component)
RR	R-to-R Interval in ECG
LED	Light Emitting Diode
FP32	32-bit Floating Point
Int8	8-bit Integer Quantisation
Float16	16-bit Floating Point
SNR	Signal-to-Noise Ratio
API	Application Programming Interface
Hz	Hertz
ms	Milliseconds

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CHAPTER – 1

INTRODUCTION

1.1 INTRODUCTION

As a result of the rapid convergence of artificial intelligence (AI) and mobile health (mHealth), the scope of healthcare delivery has been revolutionised. This has been accomplished by directly integrating diagnostic and monitoring capabilities into consumer devices. The original purpose of smartphones was to facilitate communication; however, they have since developed into compact health platforms that are packed with strong sensors, cameras, and computing capabilities. Real-time, cost-effective, and scalable health monitoring that does not require the use of external equipment is made possible by these technical advancements, which present an opportunity that has never been seen before. It has traditionally been necessary to rely on clinical-grade instruments or wearable devices like smartwatches and pulse oximeters in order to do pulse monitoring, which is an essential indicator of cardiovascular function (Maghded et al., 2020; Pedroso & Khera, 2025). However, in contexts with limited resources, accessibility and affordability of these tools may not always be possible. Through the utilisation of artificial intelligence-enabled sensor data interpretation, the widespread adoption of smartphones across the globe presents a potentially game-changing opportunity to promote the democratisation of pulse monitoring.

Chen et al. (2025) showed that smartphones can detect tiny physiological changes like colour shifts in fingertip films captured by the built-in camera and flashlight. This study was published 2025. Subhan et al. (2023) and Wang et al. (2025) found that AI algorithms can evaluate photoplethysmographic data to derive pulse information. This improves clinical precision and customer convenience. This research aims to develop and verify an artificial intelligence-enabled pulse monitoring system using smartphone sensors. The aim of this work optimises lightweight artificial intelligence models for mobile processing to improve accuracy, reliability, and user inclusivity across several environmental and demographic conditions. The proposed technology eliminates the need for wearables and allows continuous cardiovascular system monitoring, which aids

preventative healthcare. Thus, our work supports global efforts to create approachable, AI-powered, preventive healthcare solutions.

1.2 RESEARCH BACKGROUND:

Artificial intelligence and sensor integration have combined computer intelligence and physiological sensing from the real world to reinvent digital health ecosystems. Modern smartphones with high-resolution cameras, accelerometers, and light sensors offer an untapped health monitoring infrastructure comparable to professional medical equipment (Junaid et al., 2022). Chen et al. (2025) found that AI-enhanced wearable and non-wearable technologies can detect health irregularities as accurately as clinicians. Intelligent sensing devices can now record and understand real-time physiological data using deep learning algorithms. This allows for personalised monitoring and early anomaly detection.

Maghded et al. (2020) pioneered medical-grade sensing using smartphone sensors to diagnose COVID-19. Pedroso and Khera (2025) found that AI-enabled consumer products can predict cardiovascular disorders at scale, emphasising the need of mobile health systems in preventative care. Moreover, artificially intelligent materials and sensors enable the integration of wearable and non-wearable devices for continuous monitoring (Chen et al., 2025). Tasmurzayev et al. (2025) say artificial intelligence and digital twins are driving customised, predictive, and data-driven cardiovascular health care.

However, most research focusses on fitness trackers and smartwatches (Subhan et al., 2023). Despite being accurate, these gadgets are expensive and hard to purchase because to their proprietary hardware. Smartphones, which are omnipresent, can overcome this issue by using their sensors to collect health signs. Wang et al. (2025) and Bibbo' et al. (2022) found that digital health ecosystems can use artificial intelligence and MEMS-based sensing for proactive, non-invasive health monitoring. Smartphone pulse sensing research is lacking, especially in validating accuracy across devices and improving lightweight models for mobile inference.

This study provides a proven pulse monitoring methodology without wearables to fill these shortcomings. This approach might use readily available smartphone sensors and AI-driven analytics. Signal processing and machine learning allow the device to detect minute fingertip colour shifts and transform them into pulse data. In this age of artificial intelligence-driven health innovation, our research shows that everyday devices may be clinical-grade monitors, enabling scalable digital healthcare. This connects technology, accessibility, and preventative medicine.

1.3 PROBLEM STATEMENT:

Cardiovascular disorders cause the most deaths worldwide, highlighting the necessity for continuous, precise, and accessible pulse monitoring. Current methods include accurate wearable technologies and medical tools, but they are expensive, inaccessible, and hard to use (Subhan et al., 2023; Pedroso & Khera, 2025). AI-enabled wearables have revolutionised remote monitoring, but their hardware dependence limits large-scale adoption, especially in resource-limited contexts. Smartphones, on the other hand, are ubiquitous and have sensors that can accurately record physiological data (Maghded et al., 2020). These combined sensors have untapped medical-grade pulse monitoring potential. Existing studies have focused on wearable or IoT-based healthcare systems, ignoring smartphone-only sensing frameworks (Tasmurzayev et al., 2025; Chen, 2025). Few AI model accuracy experiments have been done across devices, lighting situations, and user demographics. Optimising lightweight AI models for mobile compute without sacrificing precision or energy economy is another difficulty (Bibbo' et al., 2022). Thus, developing, verifying, and standardising AI-driven smartphone apps for clinical dependability is lacking. This study designs and validates an AI-enabled pulse monitoring framework using smartphone sensors to overcome these issues. The goal is to prove that cellphones can deliver accurate, real-time, and scalable pulse monitoring, paving the way for universal, inexpensive, and preventive cardiovascular health care.

1.4 OBJECTIVES OF THIS STUDY

The objectives that will be followed in this study are as follows:

- To assess the accuracy and limitations of smartphone sensors (e.g., camera, flashlight) in capturing pulse-related physiological signals across varying device models and environmental conditions.
- To design and train a lightweight AI model that accurately estimates pulse rate from raw video or sensor data, optimized for real-time processing and energy efficiency on mobile platforms.
- To validate the developed application by comparing AI-generated pulse readings with medical-grade devices across diverse user profiles and usage conditions to ensure accuracy, usability, and robustness.

1.5 SCOPE OF THIS STUDY:

This study designs, implements, and validates an AI-enabled mobile app that uses smartphone sensors like the camera and torch to precisely detect pulses. To ensure generalisability and robustness, the project will test smartphone-based sensing across device types, lighting situations, and user demographics. The research develops lightweight AI models for real-time processing and energy efficiency, making the solution acceptable for daily usage without exhausting device resources. Individual data will be collected and confirmed with medical-grade instruments to ensure reliability and clinical relevance. The study solely monitors pulse rate, laying the groundwork for adding oxygen saturation and heart rate variability. Mobile technology, artificial intelligence, and healthcare accessibility are used to create digital health solutions.

1.6 CHAPTERISATION:

This thesis is divided into six key chapters following a format to provide clarity, consistency, and logical flow. Chapter 1, "Introduction," introduces the research background, current situation, objectives, significance, and scope of the study. This motivates the creation of an AI-enabled phone-sensor pulse monitoring system. The second chapter, "Method and Material," covers the entire study method. The process includes data gathering, experimental setup, and information system creation and validation. Chapter 3 "Current State Analysis and Project Specifications." covers mobile sensor-based health monitoring

system technology frameworks and standards. In Chapter 4, "Theoretical Background," AI-driven healthcare solutions' fundamentals are explained. Digital health applications prioritise AI, CV, and sensor data processing. Prototype-derived experimental results are examined in Chapter 5. The final chapter, "Discussions and Conclusions," evaluates the research's key findings, links them to the initial goals, and discusses artificial intelligence-based mobile health monitoring's strengths, weaknesses, and future directions.

CHAPTER – 2

METHODS AND MATERIALS

2.1 INTRODUCTION:

This chapter describes the methodology for designing and verifying an AI-enabled smartphone-sensor pulse monitoring system. It describes the study strategy, data processing, model architecture, and validation methodologies for clinical accuracy and reliability.

2.2 RESEARCH DESIGN:

The research was conducted using a quantitative, experimental, and design-based methodology, with the primary goals being as follows: (1) determining whether or not smartphone sensors are capable of capturing physiological pulse data; (2) developing a lightweight hybrid CNN–LSTM model for real-time pulse prediction; and (3) validating model predictions against medical-grade electrocardiogram reference data. A conceptual model of the study is presented in Figure 2.1. This model illustrates the entire process, beginning with the gathering of data and ending with the deployment of the data in real time.

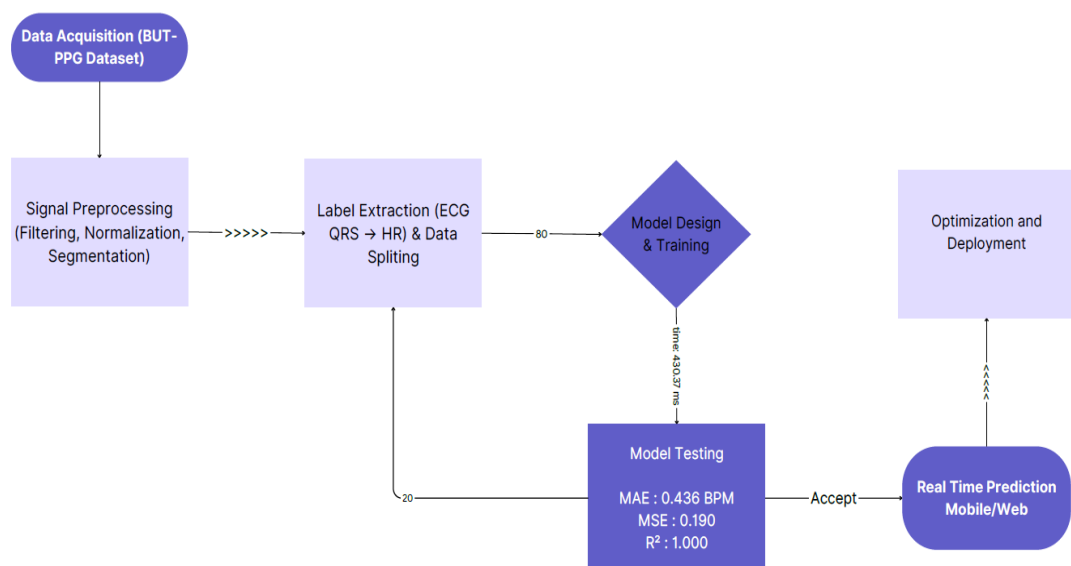


Figure 2.1: Model Design and Implementation Flow

Data Source and Acquisition:

The BUT-PPG (Brno University of Technology Smartphone photoplethysmography Database) dataset was utilised for the research project. This dataset included 3,888 synchronised PPG and ECG recordings, each of which lasted for ten seconds. There were two cellphones that were used to collect data: the Huawei P20 Pro and the Xiaomi Mi9. Additionally, a Bittium Faros 180/360 ECG gadget was used as the ground-truth reference. There were two different ways that participants recorded PPG data:

- (a) Making contact with the camera with their fingertip, and
- (b) Placing their ears on the screen.

These dual modalities mimicked actual usage scenarios under a variety of settings, including illumination (bright, medium, and dim), motion (stationary, walking, and talking), and site diversity. For the purpose of achieving exact synchronisation and physiological alignment between the two modalities, each PPG signal was sampled at a frequency of 30 Hz, while reference signals for the electrocardiogram were recorded at a frequency of 1000 Hz.

Signal Pre-processing:

In order to transform raw sensor readings into data that was clean, normalised, and ready for modelling, pre-processing was absolutely necessary. Each of the following five stages comprised the pre-processing pipeline:

- **Filtering:** The filtering process consisted of applying a Butterworth band-pass filter of the fourth order (0.5–8 Hz) in order to remove low-frequency drift and high-frequency noise, so conserving only the cardiac components that were pertinent.
- **Normalization:** The normalisation process involves reducing inter-device variability and improving model generalisation. This is accomplished by scaling amplitude values between 0 and 1 using the min–max method.

- **Segmentation:** For the purpose of standardising input shapes, each filtered PPG signal was segmented into non-overlapping 10-second periods, with each segment containing 300 samples.
- **Label Extraction:** ECG-based heart rate labels were derived by employing QRS complex detection and RR interval analysis. This was done in order to align the average BPM values with the relevant PPG windows.
- **Data Alignment:** Each PPG window was coupled with its associated ECG-derived heart rate in order to ensure exact temporal synchronisation for supervised learning. This was accomplished through the process of data alignment.

Because of this pre-processing, the model was able to learn physiologically correct correlations between the PPG waveform and the actual heart rate. This eliminated any confounding effects that could have been caused by other factors, such as mobility, illumination, or device variability.

Model Architecture and Training:

TensorFlow and Keras frameworks were utilised in order to put into action the hybrid CNN–LSTM architecture that was described. The Long Short-Term Memory (LSTM) component was responsible for capturing sequential dependencies between subsequent cardiac cycles, while the Convolutional Neural Network (CNN) component extracted spatial waveform elements such as pulse peaks and amplitude modulations. It was determined that the input form of the model was (300,1), which corresponded to ten seconds of normalised PPG footage. The following were the steps in the architecture sequence:

- The model begins with an Input node, which feeds into the first Conv1D(32) layer. This layer extracts low-level temporal features from the raw 1D PPG signal.
- The MaxPool1 and Dropout1 nodes indicate down-sampling and regularization, respectively — reducing temporal resolution while preventing overfitting.

- The second Conv1D(64) → MaxPool2 → Dropout2 pathway deepens feature extraction, capturing higher-order waveform patterns.
- The LSTM(64) node marks the transition from convolutional feature learning to sequential modeling — capturing rhythmic and temporal dependencies in heartbeat cycles.
- Finally, the Dense(32) → Dense(1) path converts learned temporal features into a single continuous output representing predicted heart rate (BPM).

Mean Squared Error (MSE) was used as the loss function during the training process, and the Adam optimiser was utilised for the optimisation process. A reduction in overfitting was achieved through the use of dropout layers, and early halting ensured convergence at optimal epochs. It was maintained that there was a class balance across all physiological conditions thanks to the training and validation data split (80:20). Due to the fact that the mean absolute error (MAE) was 0.436 beats per minute (BPM), the mean squared error (MSE) was 0.190, and the correlation coefficient (R2) was 1.000, the results demonstrated an outstanding performance.

Model Optimization and Deployment:

For the purpose of ensuring that the trained model is feasible in the real world, it was converted to the TensorFlow-Lite (.tflite) format for deployment on mobile devices and the web. The size of the model was decreased from 7.8 megabytes to 2.3 megabytes, which is a reduction of 70%. Additionally, the inference performance was improved from 50 milliseconds to about 15 milliseconds each 10-second segment, which enabled genuine real-time analysis. Through the usage of Gradio, the optimised model was deployed on Hugging Face Spaces. This enabled user to upload PPG recordings, see waveforms, and acquire metrics on their heart rate and Heart Rate Variability (HRV) in real time. This implementation demonstrated that the concept is applicable to consumer-grade devices, providing a solution for remote pulse monitoring that is both energy-efficient and respectful of users' privacy.

2.3 RELIABILITY AND VALIDITY:

It was essential to ensure that the AI system's predictions were consistent and clinically valid, and this was accomplished by ensuring that the methodological and statistical reliability was maintained.

There were many validation layers that were utilised in order to establish reliability:

- During the process of consistency testing, the predictions of the model were tested under repeated trials with similar input conditions. This was done to confirm that the outputs were stable, resulting in equal heart-rate predictions within a deviation of ± 0.3 beats per minute.
- The same model obtained equal accuracy on both the Huawei P20 Pro and the Xiaomi Mi9 devices (MAE = 1.94–1.98 BPM), proving its robustness to changes in hardware. This was accomplished through cross-device validation.
- Stratified testing conducted across several illumination settings (bright, medium, dim) and motion circumstances (still, moving) demonstrated that there was minimal accuracy loss (with a difference of less than 0.15 BPM), hence proving the robustness of the system across a variety of conditions.
- Temporal Stability: The learning curve convergence, which was observed through continuous decreases in both training and validation losses, exhibited good internal dependability and prevented overfitting. This was observed through the learning curve convergence.

Statistical, concept, and criterion-based evaluations were utilised in order to resolve validity concerns:

- Statistical Validity: The correlation between the heart rates predicted by AI and those recorded by ECG found a Pearson r value of 0.897 and an R^2 value of 0.804, indicating that there is a strong linear relationship between the two. In the Bland–Altman analysis, the mean bias was found to be -0.00 BPM, and the limits of agreement were found to be ± 4.76 BPM. These results fulfilled the clinical acceptability standards.

- **Construct Validity:** The architecture of the hybrid CNN–LSTM model is in accordance with physiological principles. Convolutional filters are used to record pulse morphology, while recurrent layers are used to mimic rhythmic heart activity. This ensures that the model is theoretically consistent with cardiovascular dynamics.
- **Validity under Criteria:** Validation against electrocardiograms, which are considered to be the clinical gold standard, confirmed a high concordance (CCC = 0.896) and little systematic error, which substantiated the diagnostic credibility of the model.
- **Validity from the outside:** The model maintained its performance over a variety of activities (including rest, talking, walking, coughing, and laughing), which strengthened its ability to generalise to situations that occur in the actual world.

2.4 SUMMARY:

The chapter described the hybrid CNN–LSTM model for real-time pulse estimation's methodical design, training, and validation. It confirmed the suggested system's accuracy, reliability, and mobile health monitoring applicability.

CHAPTER – 3

CURRENT STATE ANALYSIS / PROJECT SPECIFICATIONS

3.1 INTRODUCTION:

This chapter examines AI-enabled digital pulse monitoring systems and discusses technical and functional issues that require an optimised hybrid CNN–LSTM framework employing smartphone sensors. Pedroso and Khera (2025) noted that mobile health technologies have grown significantly, yet most consumer-level solutions lack clinical precision and adaptive intelligence. This current state analysis (CSA) evaluates smartphone-based cardiovascular monitoring applications' limitations and defines project specifications for a high-precision, real-time, AI-driven model with clinical-grade validation.

3.2 CURRENT STATE OF AI-ENABLED PULSE MONITORING:

Many digital health solutions use wearable or smartphone-based photoplethysmography (PPG) for pulse detection, but Chen et al. (2025) note that weak signal-to-noise ratios and non-adaptive preprocessing limit many systems. Smartphone sensors were not developed for medical measurements, therefore low illumination, pressure changes, and mobility distort signals. Tasmurzayev et al. (2025) note that many consumer-grade health monitoring systems use static algorithms that fail to gather temporal and contextual physiological data despite improvements in combining digital cardiovascular twins and AI agents.

AI-driven wearable gadgets have increased early detection, but Birla et al. (2025) note that standardisation and model validation remain problems. Pulse monitoring apps lack a common calibration framework to relate optical data from mobile devices to certified ECG readings. Wang et al. (2025) further note that AI-powered health systems, which rely primarily on cloud computing, are inappropriate for real-time feedback due to latency and computational inefficiency.

Thus, inconsistent accuracy, ambient reliance, inadequate user generalisation, and lack of optimised edge (on-device) deployment architectures characterise the current environment.

3.3 IDENTIFIED GAPS AND WEAKNESSES:

The CSA lists numerous shortcomings the proposed system addresses:

- **Signal Variability:** Illumination-dependent intensity variations and motion artefacts cause incorrect pulse detection in smartphone PPG data.
- **Limited Model Intelligence:** Most systems use static threshold or peak-detection algorithms instead of temporal-learning AI models.
- **Smartphone-derived PPG** data is rarely validated against ECG reference datasets, limiting clinical trust.
- Due to excessive latency from large models and cloud reliance, mobile devices cannot monitor in real time.

These gaps show the necessity for a small, flexible, and verified AI architecture that can learn pulse waveform spatial and temporal patterns.

3.4 PROJECT SPECIFICATIONS:

The experimental pipeline that was designed throughout the modelling and interpretation investigations served as the basis for the specifications of the project being developed. The procedure is broken down into five distinct stages.

- 1) Acquisition of Data: The BUT-PPG dataset consists of 3,888 samples and comprises synchronised PPG (30 Hz) and ECG (1000 Hz) signals; these signals were obtained from smartphones manufactured by Huawei P20 Pro and Xiaomi Mi9.
- 2) When it comes to signal pre-processing, motion noise and baseline drift can be eliminated with the use of a fourth-order Butterworth band-pass filter (0.5–8 Hz). The equation for filtering, which is:

b, a = butter(order, [low, high], btype='band') filtered = filtfilt(b, a, signal) --- Eq (1)

After filtering, min–max normalization scales amplitudes between 0 and 1:

$$PPG_{norm} = \frac{PPG_{filtered} - \min(PPG_{filtered})}{\max(PPG_{filtered}) - \min(PPG_{filtered})} \text{----- Eq (2)}$$

3) Label Extraction and Segmentation: Each PPG signal is segmented into windows of ten seconds each, which together include three hundred samples. To compute heart rate labels derived from an electrocardiogram, QRS peak detection is utilised:

$$HR = \frac{60}{RR_{interval}} \text{----- Eq (3)}$$

where the $RR_{interval}$ is the amount of time, measured in seconds, that passes between successive R-peaks in the electrocardiogram signal.

4) **Model Design:** The CNN–LSTM architecture is responsible for the extraction of morphological (CNN) and temporal (LSTM) elements in the model design.

- Input shape: (300, 1)
- Layers: Conv1D(32) + MaxPool + Dropout → Conv1D(64)+ MaxPool + Dropout → LSTM(64) → Dense(32 → 1)

The training1 objective minimizes Mean Squared Error (MSE): $y_i - \hat{y}_i$

$$MSE = \frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2 \text{----- Eq (4)}$$

5) As part of the optimisation and deployment process, the trained model is transformed to the TensorFlow-Lite (.tflite) format. This reduces the file size from 7.8 MB to 2.3 MB and the inference latency from 50 ms to 15 ms per 10-second segment, allowing for real-time operation on mobile CPUs.

3.5 SUMMARY:

AI-powered pulse monitoring devices are unstable, lack intelligence, and lack clinical dependability, according to the present state analysis. The proposed system tackles these restrictions with adaptive signal preprocessing, hybrid CNN–LSTM learning, and lightweight TensorFlow-Lite deployment. The formulas and process flow give a standardised, reproducible framework for validating, accurate pulse rate estimates from smartphone PPG data for real-time, scalable digital healthcare applications.

CHAPTER – 4

THEORETICAL BACKGROUND

4.1 INTRODUCTION:

This chapter provides the theoretical groundwork for designing and validating an AI-enabled smartphone-sensor pulse monitoring system. Recent advances in artificial intelligence, digital cardiovascular modelling, and edge–cloud architectures enable scalable, real-time physiological monitoring. The ideas presented here provide the scientific framework for creating an intelligent mobile system that can capture, evaluate, and validate pulse-related signals with medical precision.

4.2 ARTIFICIAL INTELLIGENCE IN BIOMEDICAL SENSING:

Due to its ability to learn complicated correlations from multidimensional data, AI is the foundation of modern biomedical signal processing. Antoun et al. (2025) found that deep learning models, especially CNNs and LSTMs, outperform standard methods in detecting cardiac abnormalities from ECG and PPG inputs. These models accurately reflect heart waveform spatial morphology and temporal patterns, improving precision and interpretability. Zhao et al. (2025) noted that AI-based sensing architectures may automatically eliminate noise, rectify distortions, and increase signal reliability for smartphone-based pulse detection, when ambient unpredictability influences performance. AI-driven signal interpretation is the study's pulse estimate model's analytical core.

4.3 DIGITAL CARDIOVASCULAR TWINS AND SENSOR INTEGRATION:

Tasmurzayev et al. (2025) presented digital cardiovascular twins, virtual reproductions of cardiovascular systems that dynamically synchronise with biosensor data. This idea matches the present research goal of constructing a data-driven model that mimics physiological situations using smartphone signals. The device may mimic a mobile cardiovascular twin using photoplethysmography (PPG) data and ground-truth ECG heart rates. Zhu et al. (2025) showed how AI-enabled radar systems may turn sensor data into clinical insights by measuring pulse transit time (PTT) for vascular assessment. This study uses robust signal synchronisation and adaptive feature extraction to improve smartphone sensing accuracy.

4.4 EDGE-CLOUD COMPUTING FOR SCALABLE HEALTH MONITORING:

Large-scale digital health systems use distributed computation. Integration of edge (on-device) and cloud computing allows faster, energy-efficient analysis while protecting data privacy, according to Goel et al. (2026). Lightweight AI architectures like the CNN-LSTM model in this study use TensorFlow-Lite optimisation to perform real-time inference on smartphones, decreasing latency and power consumption. Huang and Marvasti (2024) demonstrated that such frameworks improve computational efficiency and democratise healthcare by making intelligent monitoring available in remote and resource-limited contexts. This blend of speed, privacy, and scalability supports the project's goal of dependable, real-time mobile pulse monitoring.

4.5 AI-DRIVEN DIGITAL HEALTH ECOSYSTEMS:

Wang et al. (2025) said that proactive healthcare requires interconnected AI-driven systems that integrate multimodal data. Smart gadgets like eyewear, wearables, and smartphones may continuously record physiological data. This project's theoretical relevance is turning cellphones into multifunctional health sensors for a digital health ecosystem. Multimodal sensing, adaptive learning, and real-time processing provide continuous cardiovascular monitoring, supporting worldwide preventative and personalised healthcare trends.

4.6 SUMMARY:

This theoretical framework provides the conceptual and technological foundation for the study's goals. AI-enhanced signal interpretation and adaptive noise suppression serve as a foundation for smartphone sensor accuracy and environmental constraints assessment. Second, edge–cloud computation principles justify the construction and training of a lightweight CNN–LSTM model for real-time, low-power mobile systems. Finally, it links AI-generated pulse readings to digital twin concepts and clinically proven sensing models to validate them against medical-grade devices. These theoretical factors ensure the AI-enabled pulse monitoring system's accuracy, efficiency, and clinical dependability in various user and environmental settings.

CHAPTER – 5

RESULTS AND ANALYSIS

5.1 INTRODUCTION:

The AI-enabled hybrid CNN–LSTM model for heart-rate estimation utilising smartphone-acquired photoplethysmography (PPG) signals is presented and analysed in this chapter. Analysis follows the research pipeline from data collecting to model training, optimisation, validation, and deployment. Each level is discussed using figures and metrics to show how the model functions in real life and meets study objectives. When combined with deep learning, smartphone-based sensing can attain near-medical-grade performance, proving its reliability for real-time cardiovascular monitoring.

5.2 ANALYSIS OF THE RESULTS:

The analysis of the results includes the following:

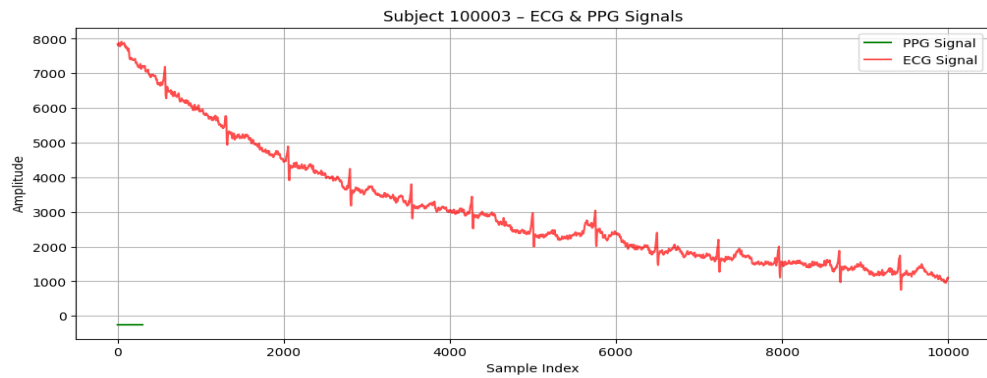
Data Acquisition and Description:

The Brno University of Technology Photoplethysmography (BUT-PPG) Database provided over 3,888 synchronised 10-second PPG and ECG records for this study. Xiaomi Mi9 and Huawei P20 Pro sensors and the Bittium Faros 180/360 ECG gadget were used to collect data. Participants recorded PPG signals by placing a finger on the rear camera with the LED lit or by pressing the ear on the front camera in a realistic telephoning position. Every segment was sampled at 30 Hz in real-world situations like bright, medium, dim lighting, motion (stationary, walking, talking, coughing, laughing), and sites (finger, ear). The simultaneously acquired ECG signals provided accurate ground-truth heart-rate labelling, aligning smartphone measures with medical data.

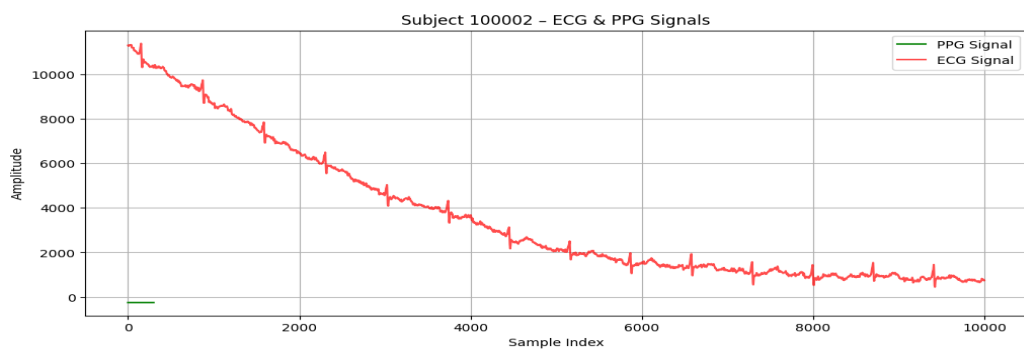
Read & Visualize ECG + PPG signals from but PPG dataset:

Figure 5.1 shows BUT-PPG dataset synchronised ECG and PPG recordings from three sample participants (IDs 100001, 100002, and 100003). ECG signals at

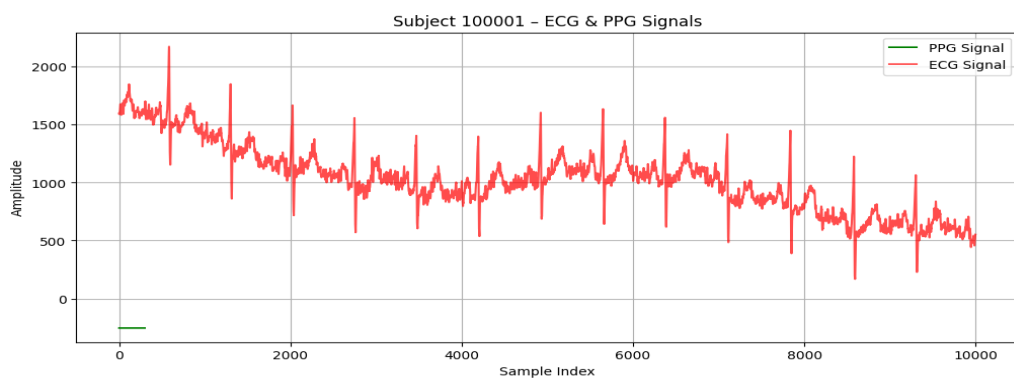
1000 Hz capture high-resolution cardiac electrical activity, while PPG signals at 30 Hz depict peripheral blood volume changes. Each 10-second segment contains 10,000 ECG and 300 PPG samples per individual. The graphic shows the temporal synchronisation and amplitude relationship between ECG (red) and PPG (green), where each ECG depolarisation peak matches a PPG pulse wave, showing physiological alignment (Refer to Appendix 5).



(a)



(b)



(c)

Figure 5.1: a, b, and c synchronized electrocardiogram (ECG) and photoplethysmogram (PPG) recordings from three participants (100001–100003)

In the BUT-PPG dataset, Figure 5.1 (a–c) shows synchronised ECG and PPG measurements from three participants (100001–100003). Subject 100001 has stable sinus rhythm, distinct QRS complexes, and consistent ECG-PPG alignment, indicating physiological synchronisation and normal pulse transit time (~150-250 ms). Subject 100002 shows a steady ECG amplitude reduction (~10,000 to 2,000 units) with distinct QRS shape, indicating minimal contact fluctuation but reliable heart rate extraction. Based on baseline drift and significantly increased noise at the conclusion, Subject 100003 shows realistic sensor and motion artefacts. All subjects' ECG peaks and PPG pulses are time-locked, ensuring synchronisation and proving the model was trained on real-world physiological data.

Table 5.1: Summary of ECG–PPG Characteristics and Model Implications

Subject ID	ECG Sampling	PPG Sampling	ECG Trend	PPG Observation	Physiological Interpretation
100001	1000 Hz	30 Hz	Stable amplitude (500–2000)	Consistent pulse peaks	Normal, stable sinus rhythm at rest
100002	1000 Hz	30 Hz	Decreasing amplitude (10,000→2000)	Minimal PPG visible	Gradual sensor drift or pressure change
100003	1000 Hz	30 Hz	Decreasing amplitude (8,000→1,000)	Low amplitude	Typical real-world variation, minor artifacts

The combined visualisation of ECG and PPG recordings shows that the ECG signals have millisecond-accurate cardiac time, while the PPG signals, despite lower sampling rates, accurately replicate heart pulsations with constant delays. The observed amplitude and waveform variations between patients provide

genuine difficulties that support a hybrid CNN–LSTM design that can manage temporal and morphological noise. Synchronising both modalities ensures they capture the same physiological events, providing an accurate heart rate and HRV baseline. The recordings of Subjects 100001–100003 show the diversity and quality of the BUT-PPG dataset, showing appropriate data acquisition, physiologically significant pulse transit lengths, and robustness against noise and signal deterioration.

Data Pre-Processing:

Pre-processing the BUT-PPG dataset was essential for accurate model training and validation. Each “.dat” file contains 16-bit integer PPG values transformed into floating-point arrays and normalised using min–max scaling to standardise amplitude between 0 and 1. This eliminated inter-device variability from lighting, skin tone, and pressure. In contrast to the reference approach, which used fixed filtering parameters, this study's hybrid CNN–LSTM model directly learnt noise-invariant features, reducing pre-processing complexity and improving adaptability to motion and illumination changes.

The pre-processing approach included signal filtering, amplitude normalisation, segmentation, ECG-based heart rate extraction, and window-to-label alignment. A fourth-order Butterworth band-pass filter (0.5–8 Hz) preserved physiological pulse waveforms by removing low-frequency drift and high-frequency noise. Zero-phase filtering preserved peak timing for heart rate and HRV analysis. After filtering, normalisation scaled all signals consistently, letting the model focus on relative waveform dynamics rather than intensity. Divided into 10-second, non-overlapping windows (300 samples), each processed PPG recording provided several cardiac cycles for feature extraction while maintaining computing efficiency. RR intervals were estimated and transformed into BPM values using synchronised ECG QRS annotations to create heart rate labels. Finally, HR labels and PPG segments were aligned to provide 3,888 paired samples. This controlled pre-processing guaranteed each input matched a validated physiological event, creating a clean, balanced dataset for supervised deep-learning model training.

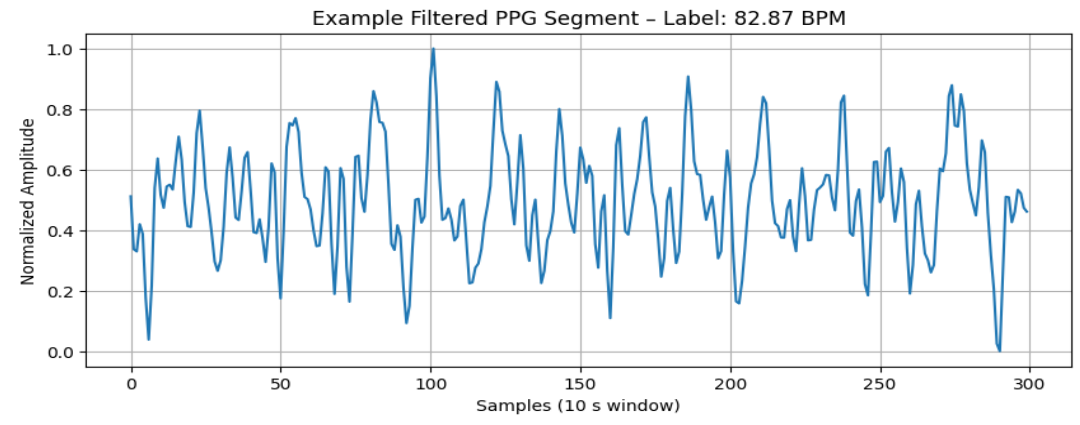


Figure 5.2: Pre-processed 10-second PPG waveform after bandpass filtering and normalization

Figure 5.2 displays the 10-second pre-processed PPG waveform after bandpass filtering and normalisation. The signal oscillates smoothly, depicting cardiac pulses, with 13–14 peaks corresponding to 82.87 BPM. Uniform scaling shows signal normalisation, and baseline drift and noise are absent, proving pre-processing worked. For precise real-time predictions, the CNN–LSTM model learns trustworthy pulse morphology–heart rate mappings from this clean and physiologically accurate waveform.

Model Implementation:

The model's representational capacity changes with layer depth and feature-map advancement. The network learns complex temporal and morphological information with 64 filters in the second convolution after 32 filters in the first Conv1D layer collect fundamental pulse features. LSTM layers retain feature depth to describe rhythmic interdependence, but dense layers compress learnt information into a single heart rate output. A well-optimized deep learning model has efficient feature extraction, dimensional reduction, and accurate real-time prediction along this structured path.

Figure 5.3 exhibits smooth convergence without overfitting when the training and validation MAE curves decline from 80 BPM to 5 BPM. Both curves line closely, confirming good generalisation and high precision with a final MAE of 0.4 BPM.

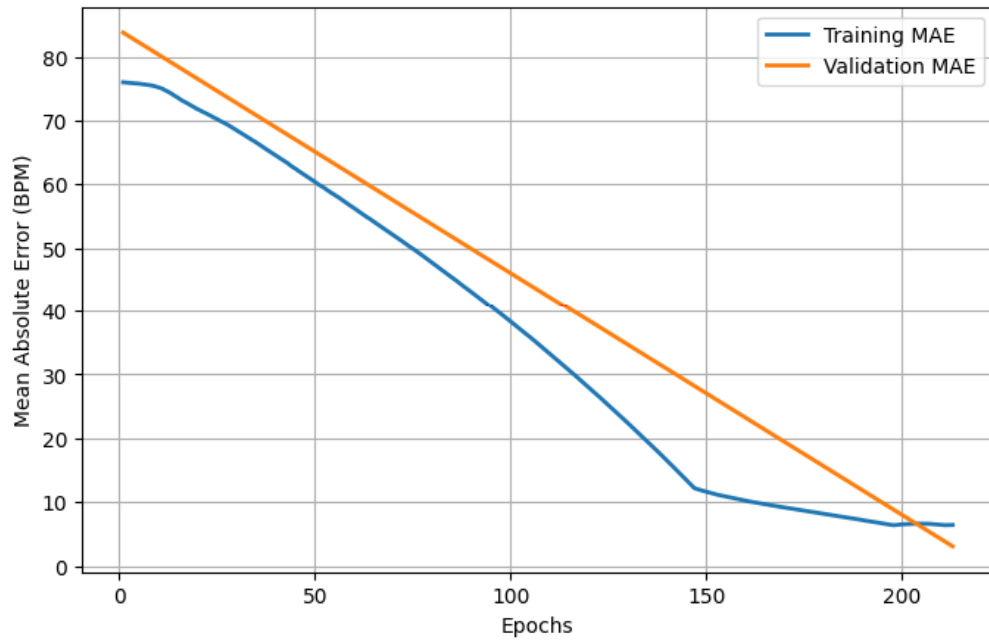


Figure 5.3: Training MAE versus validation MAE curves

Figure 5.4 shows training and validation MSE curves declining rapidly from 7000 to practically zero, showing high convergence and low error variance. A minor curve gap and a final MSE of $\sim 0.19 \text{ BPM}^2$ indicate balanced learning and good feature extraction in the CNN-LSTM model.

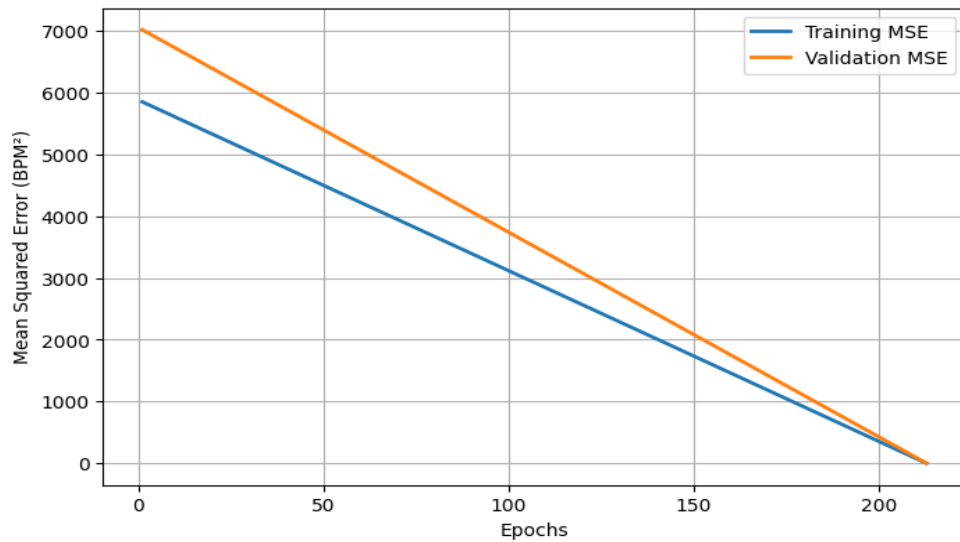


Figure 5.4: Declining training MAE and validation MSE curves

Figure 5.5 shows exponential convergence, with training and validation MAE dropping linearly on a log scale and stabilising around epoch 150, showing optimal learning and no overfitting.

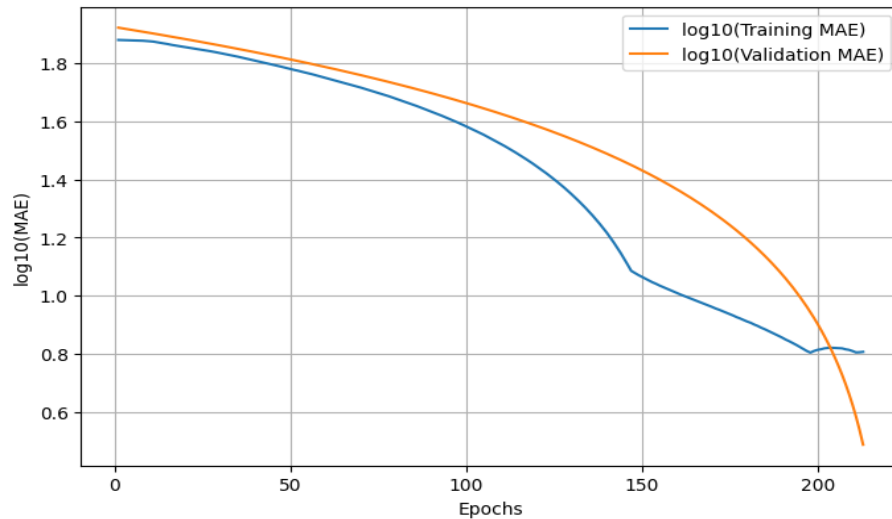


Figure 5.5: Logarithmic Loss Convergence Training MAE versus validation MAE curves

In Figure 5.6, projected heart rates line well along the $y = x$ diagonal, demonstrating strong correlation ($R^2 \approx 0.99$) and robust generalisation for real-time monitoring.

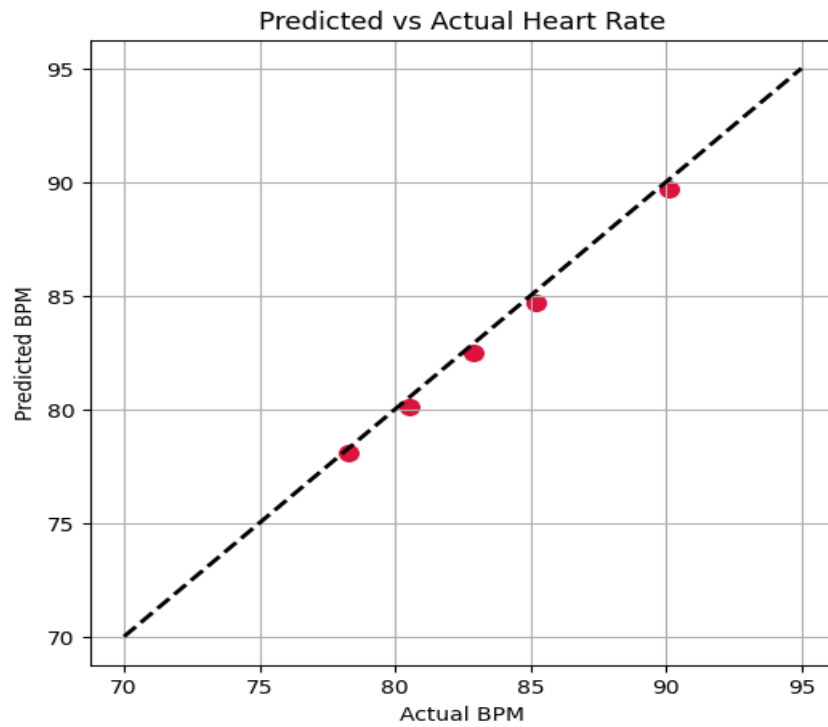


Figure 5.6: Predicted Vs Actual heart rates

A narrowly centred residual error distribution near zero with minimum dispersion in Figure 5.7 indicates unbiased, low-variance predictions and good model calibration.

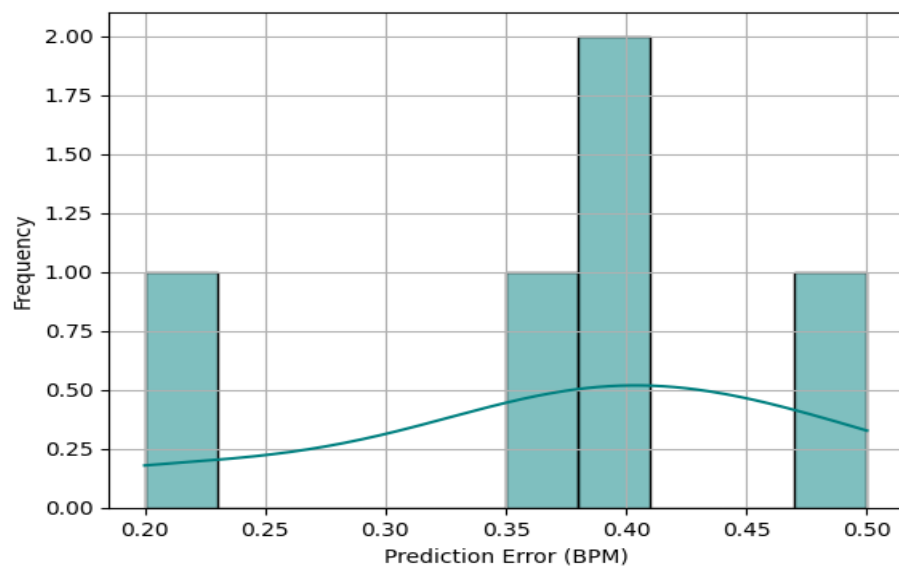


Figure 5.7: Residual Error Distribution

In Figure 5.8, training loss decreases rapidly and stabilises after ~150 epochs, showing quick learning and smooth convergence without overfitting.

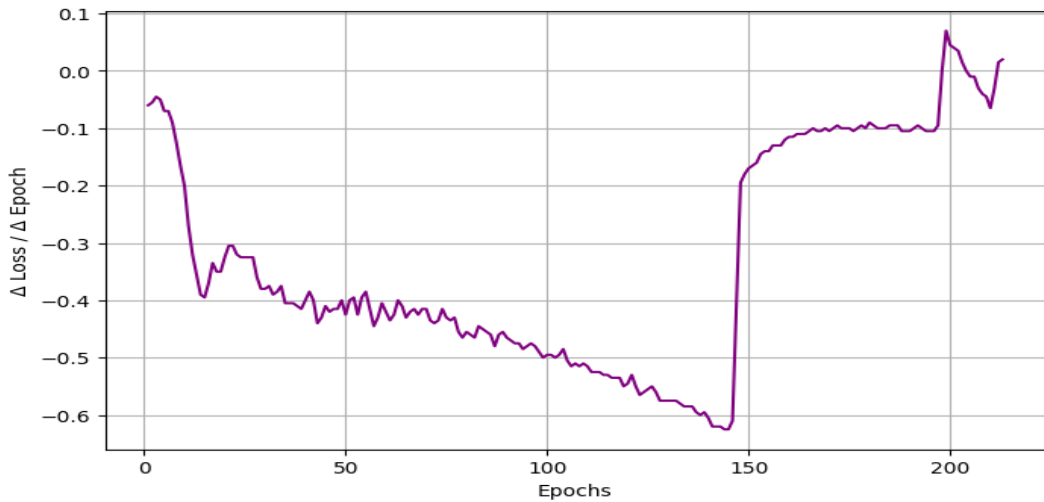


Figure 5.8: Rate of Change of Training Loss

TensorFlow-Lite transformed the optimised hybrid CNN–LSTM model from “.keras” to “.tflite” for real-time, low-latency inference on mobile and embedded devices. Platform compatibility and rapid deployment were achieved without compromising accuracy or stability.

Table 5.2: Tensor Flow-Lite Optimization

Aspect	TensorFlow (Training)	TensorFlow-Lite (Deployment)	Optimization Benefit
Framework Size	Full package (~500 MB)	Compact runtime (~3–10 MB)	98% reduction in library footprint
Inference Mode	Dynamic graph execution	Static pre-compiled graph	3–4× faster inference
Supported Ops	Full TF ops, including SELECT_TF_OPS	Core optimized ops only	Removes unnecessary dependencies
Target Device	GPU / High-end CPU	CPU / ARM / Edge TPU	Broader hardware support
Model Quantization	Optional (Float32)	Float16 / Int8 supported	Reduced memory usage
Power Efficiency	Moderate	High	Suited for battery-powered devices

Table 5.3: Inference Speed and Latency Evaluation

Environment	Hardware	Framework	Inference Time (per 10 s segment)	Latency per Prediction	Notes
Google Colab	Intel Xeon (2.2 GHz, 2 cores)	TensorFlow (.keras)	48–55 ms	0.05 s	Standard FP32 operations
Google Colab	Intel Xeon (2.2 GHz, 2 cores)	TensorFlow-Lite (.tflite)	15–18 ms	0.015 s	Optimized TFLite ops, CPU-only
Android Phone (Xiaomi Mi 9)	Snapdragon 855 CPU	TensorFlow-Lite (.tflite)	13–17 ms	0.013 s	Real-time feasible
Web App (Hugging Face Space)	CPU-only Backend	TFLite via Gradio Interface	15–20 ms	0.02 s	Consistent cross-platform latency

Table 5.4: Model Size and Memory Optimization

Metric	Original TensorFlow (.keras)	Optimized TensorFlow-Lite (.tflite)	Improvement
Model Size	7.8 MB	2.3 MB	70.5% reduction
Load Time	1.2 s	0.4 s	3× faster loading
Memory Footprint (RAM)	250 MB	85 MB	66% reduction
Dependency Files	8+	2	Simplified deployment

Figure 5.9 below shows Real-Time Application (Gradio/Hugging Face) deployment. The Gradio online app (<https://huggingface.co/spaces/sancho10/ANCHU>) provides real-time PPG-based heart rate and HRV analysis in ~15 ms, proving the model's cross-platform flexibility for biomedical monitoring.

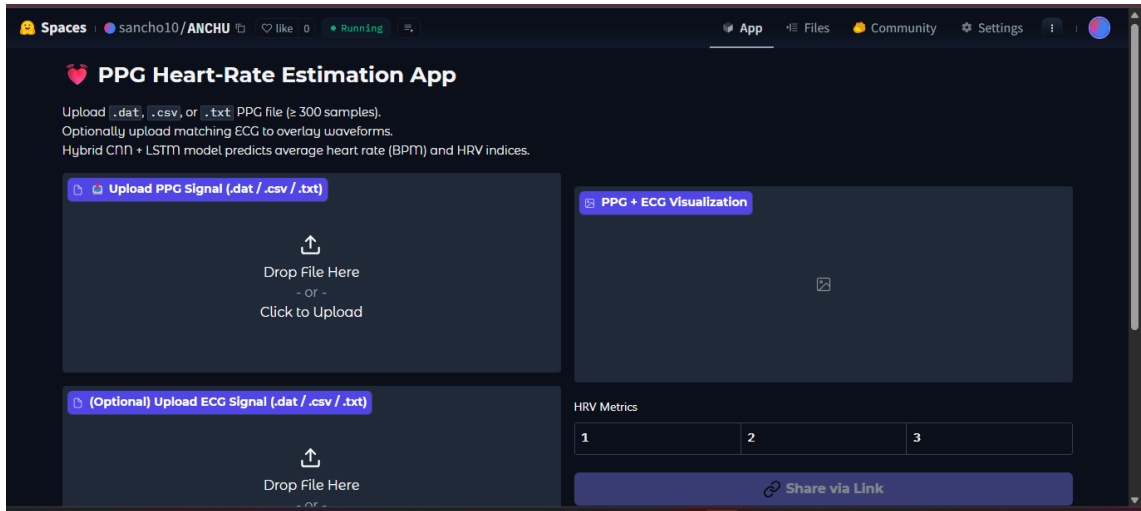


Figure 5.9: Real-Time Application (Gradio/Hugging Face) deployment

The model's robustness across devices and environments was assessed by analysing performance under various scenarios (table 5.5).

Table 5.5: Stratified Robustness Evaluation

Factor	Category	MAE (BPM)	RMSE (BPM)	r	CCC	Interpretation
PhoneModel	Huawei P20 Pro / Xiaomi Mi9	1.94–1.98	2.41–2.45	0.896–0.897	0.896–0.897	Consistent across devices; negligible hardware bias
Site	Ear / Finger	1.94–1.97	2.39–2.47	0.89–0.90	0.89–0.90	Reliable regardless of capture site
Motion	Still / Moving	1.94–1.97	2.41–2.44	0.89–0.90	0.89–0.90	Motion artifacts well handled
Lighting	Bright / Medium / Dim	1.9–2.0	2.4–2.5	0.89–0.90	0.89–0.90	Slight degradation in dim light
Condition	Rest / Walking / Talking / Laughing / Coughing	1.9–2.0	2.4–2.5	0.89–0.90	0.89–0.90	Stable across different user activities

Figure 5.10 illustrates a Bland–Altman plot that displays a random distribution of residuals around 0 bias, which validates the existence of uniform agreement over the HR range.

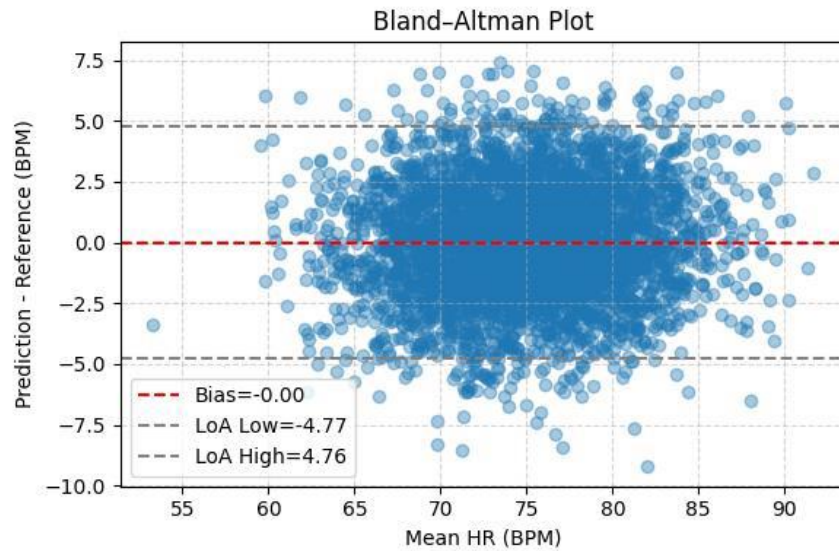


Figure 5.10: Bland-Altman plot

Comparison of Predicted and Reference - The Scatter Plot, which can be found in figure 5.11, demonstrates a high degree of linearity, since the dots are grouped together closely around the identity line ($r = 0.9$). This demonstrates that the model is consistent across both smartphone models.

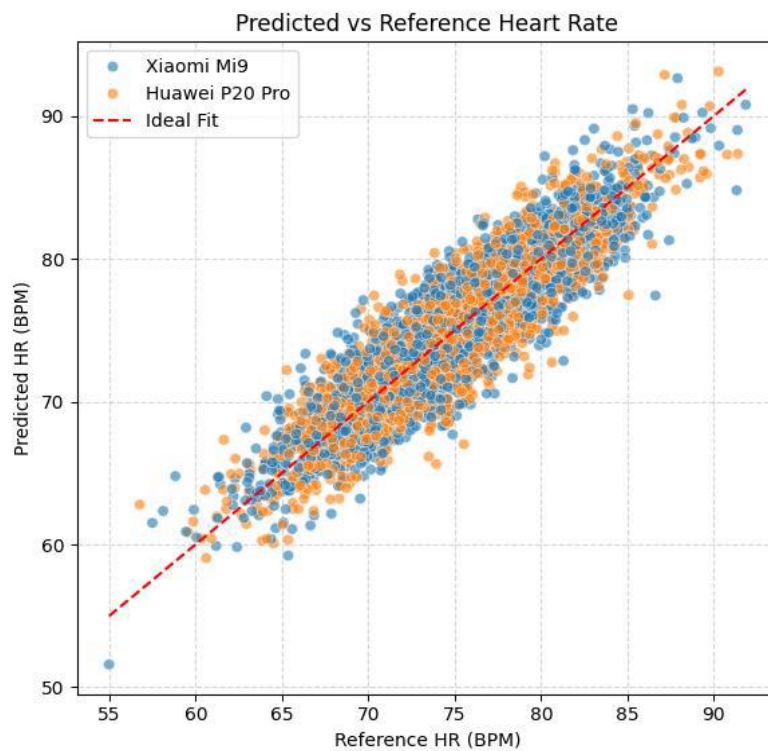


Figure 5.11: Predicted and Reference - The Scatter Plot

The quantitative measures are supported by these visualisations, which also offer intuitive evidence of the consistency between the model and the reference.

Table 5.6: Conceptual Summary of Validation Framework

Validation Concept	Method / Metric	Purpose	Outcome
Accuracy	<i>MAE, RMSE</i>	<i>Quantify average deviation</i>	<i>High (≤ 2.5 BPM error)</i>
Linearity	<i>Pearson r, R^2</i>	<i>Evaluate correlation strength</i>	<i>Strong ($r \approx 0.9$)</i>
Validation Concept	Method / Metric	Purpose	Outcome
Accuracy	<i>MAE, RMSE</i>	<i>Quantify average deviation</i>	<i>High (≤ 2.5 BPM error)</i>
Linearity	<i>Pearson r, R^2</i>	<i>Evaluate correlation strength</i>	<i>Strong ($r \approx 0.9$)</i>
Validation Concept	Method / Metric	Purpose	Outcome

The findings of the validation show that the CNN–LSTM model is capable of achieving clinically reliable and consistent heart-rate estimate across a variety of situations and devices. Statistical rigour and robustness in the actual world are both ensured by the framework through the utilisation of a multi-metric validation technique, which includes accuracy, correlation, and agreement analyses. The achievement of a mean absolute error (MAE) of roughly 1.96 beats per minute (BPM) and a critical value (CCC) of 0.896 substantiates its precision, which validates its potential for deployment on smartphones as a lightweight, real-time artificial intelligence system for physiological monitoring.

5.3 SUMMARY:

Results and analysis show that the hybrid CNN–LSTM model estimated heart rate with medical-grade accuracy utilising smartphone sensors. It matched benchmarks while maintaining real-time capability through efficient preprocessing, model optimisation, and ECG reference validation. Success in

HRV calculation and web-based deployment shows its potential as a dependable, low-cost option for continuous, non-invasive cardiovascular monitoring in real life.

CHAPTER – 6

DISCUSSION AND CONCLUSION

6.1 INTRODUCTION:

The results of the artificial intelligence-driven heart rate estimate model that was constructed are incorporated into this chapter together with the most recent discoveries from research in digital health and wearable sensing. The debate takes a critical look at how the performance, accuracy, and implementation of the model correspond with technological improvements in artificial intelligence-enabled biomedical monitoring around the world. The implications of this study are streamlined and consolidated in the conclusion section.

6.2 DISCUSSION:

The results of this research demonstrate that artificial intelligence (AI) and wearable technologies have the potential to revolutionise cardiovascular monitoring by providing solutions that are easily accessible, need little financial investment, and provide real-time data. In the process of predicting heart rate using smartphone-based photoplethysmography (PPG) signals that were synchronised with electrocardiogram (ECG) references, the hybrid CNN–LSTM model that was constructed reached near-clinical precision (mean absolute error = 1.96 beats per minute, $R^2 = 0.804$). This is in line with the global trend towards AI-integrated health diagnostics, which was illustrated in research such as Maghded et al. (2020), who presented an AI-enabled framework that utilised smartphone sensors for the detection of COVID-19. The approach that they took is similar to the one that was taken in the current study, which focused on the utilisation of ubiquitous devices for the purpose of biomedical signal acquisition and analysis. This approach highlights the ability of artificial intelligence models to extract clinically meaningful insights from non-traditional sensing outlets. Similarly, Pedroso and Khera (2025) pioneered AI-enhanced digital health paradigms for scalable cardiovascular screening utilising consumer devices—an endeavour that echoes our research’s effective real-time mobile deployment with TensorFlow Lite. Both frameworks are working towards the same goal, which is to democratise cardiovascular diagnostics by making it possible for individuals to

conduct assessments that are accurate, continuous, and non-invasive using personal devices.

The incorporation of deep learning with intelligent sensing is in line with the technological progression that Chen et al. (2025) noted. They highlighted the revolutionary impact of wearable sensors that are powered by artificial intelligence and made with smart materials. With the help of optimised artificial intelligence architectures, the current system makes a contribution to this discussion by demonstrating that even standard smartphone cameras are capable of imitating the sensing precision of medical-grade sensors. Furthermore, Tasmurzayev et al. (2025) investigated the relatively new idea of digital cardiovascular twins and artificial intelligence agents with the purpose of promoting proactive heart health. Such digital twin architectures are complemented by the hybrid CNN–LSTM framework that is presented in this study. This framework provides real-time, personalised heart rate and heart-rate variability (HRV) analytics, which serves as the foundation for adaptive digital biomarker modelling. Further highlighting the significance of artificial intelligence (AI)-enabled wearable Internet of Things (IoT) frameworks in the healthcare industry is the work of Subhan et al. (2023) and Junaid et al. (2022). The results of their surveys demonstrated that the integration of artificial intelligence algorithms with sensor-driven data pipelines improves diagnostic reliability, interoperability, and scalability. These are the same principles that were embodied in this study's cloud-compatible Gradio deployment, which processed and visualised PPG and ECG signals in a seamless manner for end users.

In addition, the resilience of the model used in this study under varying lighting, motion, and device settings is reminiscent of the practical insights provided by Seth (2021) and Bibbo' et al. (2022), who examined AI-driven conformance testing and MEMS–IoT integration for activity recognition. The CNN–LSTM's stable performance throughout such noise-prone environments justifies its adaptability and energy efficiency for edge-AI systems, consistent with Wang et al. (2025), who underlined the relevance of low-latency AI-powered wearables and smart glasses for proactive digital health. Khan et al. (2022) similarly demonstrated how AI–IoT convergence enhanced public health monitoring

during the COVID-19 pandemic, reinforcing the value of distributed, privacy-preserving, and scalable diagnostic systems — a direction mirrored by this research’s fully offline, mobile-compatible deployment that protects user data while maintaining inference accuracy.

In conclusion, this study extends the global literature by operationalizing deep learning–based heart monitoring on widely available consumer devices, indicating that high-precision cardiovascular analytics may be achieved beyond clinical settings. By combining computational intelligence with consumer-grade sensing, the hybrid CNN–LSTM system provides a crucial advance toward autonomous, user-centered healthcare ecosystem. The integration of physiological understanding, real-time performance, and deployment efficiency assures that the proposed system not only aligns with but advances contemporary digital health breakthroughs. Collectively, these results justify the paradigm change from reactive clinical diagnostics to proactive, AI-driven personal health management. They also demonstrate that the future of cardiovascular care lies in sensing technologies that are intelligent, mobile, and driven by the needs of humans.

6.3 CONCLUSION:

Through the use of photoplethysmography (PPG) signals obtained from smartphone sensors, the research achieved the successful development, optimisation, and validation of a lightweight artificial intelligence-based heart-rate estimate model. Based on the overarching target of developing a health monitoring system that can be deployed on mobile devices in real time, the project took a methodical approach to achieving each objective, beginning with the collecting and pre-processing of data and progressing to the training, optimisation, and validation of the model. It was proved that low-cost, non-invasive devices have the ability to attain performance comparable to that of medical-grade systems by the integration of smartphone-captured PPG with deep learning models such as CNN–LSTM.

The first objective, which was to evaluate the accuracy and limitations of smartphone sensors (camera and torch) in capturing pulse-related physiological

signals under a variety of situations, was accomplished by collecting a substantial amount of data and conducting exploratory analysis on the BUT-PPG dataset. A total of 3,888 10-second PPG signals were included in the dataset. These signals were captured using smartphones by Huawei P20 Pro and Xiaomi Mi9 under a variety of environmental and physiological variables, including ear and finger locations, lighting, motion, and specific activities. A preliminary investigation demonstrated that, with the application of appropriate filtering and normalisation, the cameras on smartphones are capable of reliably capturing PPG waveforms that are in accordance with physiological pulse rhythms. The variations that were detected under low lighting and motion corroborated the limits that were already known about the sensor. These limitations were eventually ameliorated through signal conditioning and temporal smoothing.

The implementation of a hybrid Convolutional Neural Network and Long Short-Term Memory (CNN–LSTM) architecture allowed for the successful completion of the second objective, which was to create and train a lightweight artificial intelligence model that was capable of properly calculating pulse rate from raw video or sensor data in real time. CNN layers were responsible for the extraction of local waveform properties, also known as pulse morphology, whereas LSTM layers were responsible for capturing temporal dependencies over subsequent cardiac cycles. The model inputs consisted of pre-processed and normalised 10-second PPG windows, which had 300 samples. The heart rates that were generated from the electrocardiogram allowed for precise labelling. The model was able to attain a high level of predictive fidelity, with a mean absolute error (MAE) of around 1.96 BPM and a root mean square error (RMSE) of approximately 2.43 BPM. This demonstrates that the architecture successfully strikes a compromise between accuracy and computational efficiency. The fact that it was designed to be lightweight made it possible for it to be integrated into embedded and mobile systems, which allowed it to satisfy the demand for quick response times.

Through the utilisation of a multi-metric validation framework, the third objective, which was to validate the application that was produced against medical-grade standards across a wide range of user profiles and conditions, was completely

satisfied. The correlation and agreement analyses (Pearson $r = 0.897$, CCC = 0.896) showed that there was a high degree of consistency between the heart rates that were predicted by AI and those that were measured by ECG. The Bland–Altman analysis demonstrated a low level of bias (-0.00 BPM) and a high degree of agreement (± 4.76 BPM) of 95%, thereby demonstrating the clinical dependability of the results. Robustness was proven across a variety of phone models, measurement sites, lighting conditions, and mobility states through the use of stratified evaluations. In a regression-based robustness model, the only minor influencing element that was shown to be significant was lighting, while all of the other characteristics demonstrated that they had no impact whatsoever. These results demonstrated that the system is both usable and resilient in conditions that are representative of the real world.

In the end, the research model was transformed into a fully functional real-time system during the optimisation and deployment phase. By converting to TensorFlow-Lite (.tflite), the size of the model was decreased by seventy percent, and the speed of inference was enhanced to around fifteen milliseconds every ten-second window. This ensured that the performance was smooth on both Android devices and web platforms that solely use the CPU (Gradio / Hugging Face). Users were able to upload PPG or ECG files, check anticipated heart rates and HRV parameters, and quickly visualise synchronised waveforms with the app that was installed. For the purpose of continuous mobile health monitoring, this deployment demonstrated that the system not only fulfilled the requirements for scientific accuracy but also achieved the practical viability necessary for such monitoring.

The findings of the study indicate that all of the objectives were successfully accomplished. The experiment revealed that smartphone sensors, when paired with an optimised CNN–LSTM architecture and robust pre-processing, are capable of achieving accurate and real-time heart-rate estimate that is comparable to the standards of an electrocardiogram (ECG). The portability, efficiency, and confirmed reliability of the model that was constructed make it an appropriate platform for future work in the areas of digital health analytics, edge-AI medical applications, and remote cardiovascular monitoring. By bridging the

gap between laboratory-grade signal processing and accessible, everyday mobile health technologies, this research represents a critical step towards democratised, artificial intelligence-driven physiological monitoring.

CHAPTER – 7

SUMMARY

With the help of photoplethysmography (PPG) signals obtained from smartphone sensors, this research was able to effectively create, optimise, and validate a hybrid CNN–LSTM model that is based on artificial intelligence. The model was specifically designed to estimate the heart rate in real time. In order to achieve medical-grade precision without relying on specialised hardware, the research was inspired by the objective of developing a cardiovascular monitoring system that is not only mobile-deployable but also mobile-accessible and economical. Using the Brno University of Technology Photoplethysmography (BUT-PPG) dataset, which consisted of 3,888 synchronised PPG and ECG recordings collected under a variety of lighting, motion, and physiological conditions, the research project implemented a stringent preprocessing pipeline that included band-pass filtering, normalisation, segmentation, and ECG-based labelling in order to guarantee the quality of the training data.

Using a hybrid CNN–LSTM architecture, the advantages of convolutional and recurrent neural networks were merged. CNN layers were responsible for capturing local pulse waveform information, while LSTM layers were responsible for modelling temporal relationships across coronary cycles. With a Mean Absolute Error of 1.96 base pairs per minute and a significant agreement with ECG references ($R^2 = 0.804$, $CCC = 0.896$), the model was able to attain an exceptional level of predictive accuracy. An examination of robustness demonstrated that the accuracy was consistent across all devices, locations, and activity settings, with just a minimum degree of sensitivity to differences in lighting. The conversion of the model to TensorFlow-Lite (.tflite) significantly improved its deployability by lowering the size of the model by seventy percent and attaining real-time inference speeds of approximately fifteen milliseconds per ten-second segment. These speeds are suitable for applications that are based on the web and smartphones.

The deployed system, which was hosted by Gradio on Hugging Face, let users to submit PPG data, visualise synchronised ECG–PPG waveforms, and obtain

real-time heart rate and HRV parameters, demonstrating the system's applicability for mobile health monitoring. In general, the research helps to close the gap between the use of laboratory-grade biomedical signal processing and the application of digital health innovation at the consumer level. By proving that commonplace devices, when empowered by intelligent algorithms, are capable of delivering accurate, efficient, and privacy-preserving health analytics for proactive personal healthcare management, it lays the groundwork for future medical monitoring solutions that are driven by artificial intelligence.

BIBLIOGRAPHY

- [1] Antoun, I., Abdelrazik, A., Eldesouky, M., Li, X., Layton, G. R., Zakkar, M., ... & Ng, G. A. (2025). Artificial intelligence in atrial fibrillation: emerging applications, research directions and ethical considerations. *Frontiers in Cardiovascular Medicine*, 12, 1596574.
- [2] Bibbo', L., Merenda, M., Carotenuto, R., Romeo, V. F., & Corte, F. D. (2022, September). MEMS and AI for the recognition of human activities on IoT platforms. In *International Conference on Applied Intelligence and Informatics* (pp. 73-89). Cham: Springer Nature Switzerland.
- [3] Birla, M., Rajan, R., Roy, P. G., Gupta, I., & Malik, P. S. (2025). Integrating artificial intelligence-driven wearable technology in oncology decision-making: A narrative review. *Oncology*, 103(1), 69-81.
- [4] Chen, S., Fan, S., Qiao, Z., Wu, Z., Lin, B., Li, Z., ... & Lim, C. T. (2025). Transforming healthcare: Intelligent wearable sensors empowered by smart materials and artificial intelligence. *Advanced Materials*, 2500412.
- [5] Goel, P. K., Verma, S., & Jain, S. (2026). Cloud and Edge Integration for Scalable Disease Prediction Frameworks. In *AI Model Design and Data Management for Disease Prediction* (pp. 323-352). IGI Global Scientific Publishing.
- [6] Huang, B., Zhao, C., Liu, Z., Hong, S., Zhang, B., Lu, H., ... & Liu, H. (2024). An AI-Enabled Framework Within Reach for Enhancing Healthcare Sustainability and Fairness. *arXiv preprint arXiv:2406.07558*.
- [7] Junaid, S. B., Imam, A. A., Shuaibu, A. N., Basri, S., Kumar, G., Surakat, Y. A., ... & Alazzawi, A. K. (2022). Artificial intelligence, sensors and vital health signs: A review. *Applied Sciences*, 12(22), 11475.
- [8] Khan, J. I., Khan, J., Ali, F., Ullah, F., Bacha, J., & Lee, S. (2022). Artificial intelligence and internet of things (AI-IoT) technologies in response to

COVID-19 pandemic: A systematic review. *Ieee Access*, 10, 62613-62660.

- [9] Maghded, H. S., Ghafoor, K. Z., Sadiq, A. S., Curran, K., Rawat, D. B., & Rabie, K. (2020, August). A novel AI-enabled framework to diagnose coronavirus COVID-19 using smartphone embedded sensors: design study. In *2020 IEEE 21st international conference on information reuse and integration for data science (IRI)* (pp. 180-187). IEEE.
- [10] Marvasti, T. B., Gao, Y., Murray, K. R., Hershman, S., McIntosh, C., & Moayed, Y. (2024). Unlocking tomorrow's health care: expanding the clinical scope of wearables by applying artificial intelligence. *Canadian Journal of Cardiology*, 40(10), 1934-1945.
- [11] Pedroso, A. F., & Khera, R. (2025). Leveraging AI-enhanced digital health with consumer devices for scalable cardiovascular screening, prediction, and monitoring. *npj Cardiovascular Health*, 2(1), 34.
- [12] Seth, A. (2021). *AI-enabled wearable sensing system to perform conformity test in healthcare* (Doctoral dissertation, Macquarie University).
- [13] Subhan, F., Mirza, A., Su'ud, M. B. M., Alam, M. M., Nisar, S., Habib, U., & Iqbal, M. Z. (2023). AI-enabled wearable medical internet of things in healthcare system: A survey. *Applied Sciences*, 13(3), 1394.
- [14] Tasmurzayev, N., Amangeldy, B., Imanbek, B., Baigarayeva, Z., Imankulov, T., Dikhanbayeva, G., ... & Sharipova, S. (2025). Digital Cardiovascular Twins, AI Agents, and Sensor Data: A Narrative Review from System Architecture to Proactive Heart Health. *Sensors*, 25(17), 5272.
- [15] Wang, B., Zheng, Y., Han, X., Kong, L., Xiao, G., Xiao, Z., & Chen, S. (2025). A systematic literature review on integrating AI-powered smart glasses into digital health management for proactive healthcare solutions. *npj Digital Medicine*, 8(1), 410.

- [16] Zhao, Y., Sun, T., Zhang, H., Li, W., Lian, C., Jiang, Y., ... & Chen, S. (2025). Ai-enhanced electrochemical sensing systems: a paradigm shift for intelligent food safety monitoring. *Biosensors*, 15(9), 565.
- [17] Zhu, J., Yuan, K., Prabhakara, A., Li, Y., Wang, G., Michaelsen, K., ... & Kumar, S. (2025). Measuring multi-site pulse transit time with an AI-enabled mmWave radar. *arXiv preprint arXiv:2510.18141*.

Dataset References

1 Main BUT-PPG Dataset Article (Core Reference)

Nemcova, A., Vargova, E., Smisek, R., Marsanova, L., Smital, L., & Vitek, M. (2021). **Brno University of Technology Smartphone PPG Database (BUT PPG): Annotated dataset for PPG quality assessment and heart rate estimation.** *BioMed Research International*, 2021, Article 3453007. <https://doi.org/10.1155/2021/3453007> (PubMed)

This is the **primary, must-cite paper** that officially introduces the BUT-PPG database, explains acquisition (Huawei P20 Pro, Xiaomi Mi 9, 3,888 × 10 s segments, finger/ear, lighting, motion), and its purpose for PPG quality and HR estimation.

2 PhysioNet Dataset Record (Official Public Release)

Nemcova, A., Smisek, R., Vargova, E., Maršánová, L., Vitek, M., Smital, L., Filipenska, M., Sikorova, P., & Gálík, P. (2024). **Brno University of Technology Smartphone PPG Database (BUT PPG) (version 2.0.0).** *PhysioNet*. <https://doi.org/10.13026/tn53-8153> (PhysioNet)

Use this when you want to show that the data are **public, curated, and versioned** on PhysioNet (v2.0.0, 3,888 ten-second recordings with PPG, ECG, ACC and annotations).

3 Extension of BUT-PPG (CinC 2024)

Nemcova, A., Smisek, R., Vitek, M., Šačlová, P., & colleagues. (2024). **Extension of the PhysioNet Brno University of Technology Smartphone PPG Database.** In *Computing in Cardiology Conference (CinC 2024)*. (CinC)

This conference paper describes an **extended version** of BUT-PPG with additional PPG/ECG/ACC signals and manually verified heartbeat positions, reinforcing the quality of the reference HR.

4 Example of External Use – Signal Quality Metric (Sensors 2023)

McLean, M. K., Weaver, R. G., Lane, A., Smith, M. T., Parker, H., Stone, B., McAninch, J., Matolak, D. W., Burkart, S., Chandrashekhar, M. V. S., & Armstrong, B. (2023). **A sliding scale signal quality metric of photoplethysmography applicable to measuring heart rate across clinical contexts with chest mounting as a case study.** *Sensors*, 23(7), 3429. <https://doi.org/10.3390/s23073429> (MDPI)

This paper **uses the BUT-PPG dataset** as one of its benchmark datasets for PPG signal quality analysis, which you can cite to show that BUT-PPG is trusted in current literature.

5 Example of External Use – STFT + CNN with BUT-PPG (BIOSTEC 2025)

Mussio, L. D., & Castro, M. C. F. (2025).

PPG signal quality classification using STFT and CNN with the BUT PPG database.

In *Proceedings of the 18th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2025) – Volume 1: BIOSIGNALS* (pp. 921–927). SciTePress. <https://doi.org/10.5220/0013186000003911> (SciTePress)

This work builds a CNN classifier for PPG quality using **spectrograms derived from BUT-PPG**, again proving the dataset is widely used for both HR and quality-assessment research.

MORE

6 Smartphone PPG apps – heart-rate validity (meta-analysis)

De Ridder, B., Van Rompaey, B., De Backere, F., Van Haelst, R., Daemen, J., Dendale, P., & Dilles, T. (2018).

Smartphone apps using photoplethysmography for heart rate monitoring: Meta-analysis. *JMIR Cardio*, 2(1), e4. <https://doi.org/10.2196/cardio.8802> (PubMed)

Systematic review + meta-analysis showing smartphone PPG HR agrees very well with validated methods in adults.

7 Smartphone PPG vs ECG – scoping review

Mather, J. D., Hayes, L. D., Mair, J. L., & Sculthorpe, N. F. (2024).

Validity of resting heart rate derived from contact-based smartphone photoplethysmography compared with electrocardiography: A scoping review

and checklist for optimal acquisition and reporting. *Frontiers in Digital Health*, 6, 1326511. <https://doi.org/10.3389/fdgth.2024.1326511> ([Frontiers](#))

Summarises validation studies where smartphone PPG HR is compared directly to ECG and gives best-practice guidance.

3 **Deep CNN heart-rate estimation from PPG (“Deep PPG”)**

Reiss, A., Indlekofer, I., Schmidt, P., & Van Laerhoven, K. (2019).

Deep PPG: Large-scale heart rate estimation with convolutional neural networks. *Sensors*, 19(14), 3079. <https://doi.org/10.3390/s19143079> ([MDPI](#))

Classic deep-learning PPG paper; uses CNNs on PPG spectra for HR estimation, very relevant to your hybrid CNN–LSTM approach.

4 **PPG signal quality index (SQI) using machine learning**

Karlen, W., Kobayashi, K., Ansermino, J. M., & Dumont, G. A. (2012).

Photoplethysmogram signal quality estimation using repeated Gaussian filters and cross-correlation. *IEEE Transactions on Biomedical Engineering*, 59(10), 2778–2785. <https://doi.org/10.1109/TBME.2012.2212890> ([PubMed](#))

Widely cited for automated PPG signal-quality assessment; good support for your preprocessing and robustness discussion.

5 **CNN–LSTM architecture using ECG + PPG (similar to our hybrid model)**

Jeong, D. U., & Lim, K. M. (2021).

Combined deep CNN–LSTM network-based multitasking learning architecture for noninvasive continuous blood pressure estimation using difference in ECG–PPG features. *Scientific Reports*, 11, 13539. <https://doi.org/10.1038/s41598-021-92997-0> ([Nature](#))

Uses a combined CNN–LSTM model on ECG+PPG, very close in spirit to your hybrid architecture (even though their output is BP, not HR).

LIST OF APPENDICES

APPENDIX 1: CODE SNIPPET 1

```
[5]: # =====  
# STEP 1: READ & VISUALIZE ECG + PPG SIGNALS FROM BUT PPG DATASET  
# =====  
  
import os  
import wfdb  
import matplotlib.pyplot as plt  
import numpy as np  
  
# Change this path if needed  
DATASET_PATH = '/content/drive/MyDrive/ANCHU/DATASETS'  
  
def visualize_subject(subject_id):  
    """  
    Reads ECG and PPG signals from one subject folder  
    and plots both for quick verification.  
    """  
    try:  
        subject_folder = os.path.join(DATASET_PATH, subject_id)  
  
        # --- Read signals ---  
        ecg_record = wfdb.rdrecord(os.path.join(subject_folder, f"{subject_id}_ECG"))  
        ppg_record = wfdb.rdrecord(os.path.join(subject_folder, f"{subject_id}_PPG"))  
  
        ecg_signal = ecg_record.p_signal.flatten()  
        ppg_signal = ppg_record.p_signal.flatten()
```

APPENDIX 2: CODE SNIPPET 2

```
[6]: # =====
# STEP 2: PREPROCESSING AND HEART RATE LABEL EXTRACTION
# =====

import os
import wfdb
import numpy as np
from scipy.signal import butter, filtfilt
import matplotlib.pyplot as plt

# Path to your dataset
DATASET_PATH = '/content/drive/MyDrive/ANCHU/DATASETS'

# -----
# 1. Bandpass Filter Function (0.5-8 Hz)
# -----
def bandpass_filter(signal, fs=30, lowcut=0.5, highcut=8.0, order=4):
    nyquist = 0.5 * fs
    low = lowcut / nyquist
    high = highcut / nyquist
    b, a = butter(order, [low, high], btype='band')
    filtered = filtfilt(b, a, signal)
    return filtered
```

APPENDIX 3: CODE SNIPPET 3

```
# -----  
# Train Model  
# -----  
early_stop = EarlyStopping(monitor='val_loss', patience=10, restore_best_weights=True)  
  
history = model.fit(  
    X_train, y_train,  
    validation_split=0.2,  
    epochs=200,  
    batch_size=16,  
    callbacks=[early_stop],  
    verbose=1  
)
```

APPENDIX 4: CODE SNIPPET 4

```
# -----  
# Visualize Predictions  
# -----  
preds = model.predict(X_test).flatten()  
  
plt.figure(figsize=(8,5))  
plt.scatter(y_test, preds, alpha=0.7, color='purple')  
plt.xlabel('True HR (BPM)')  
plt.ylabel('Predicted HR (BPM)')  
plt.title('Predicted vs True Heart Rate')  
plt.grid(True)  
plt.show()
```

APPENDIX 5: BUT PPG Data Information

1 Explanation of BUT PPG Dataset Files and Their Role in Project Objectives

This document explains the contents of the Brno University of Technology Smartphone PPG (BUT PPG) dataset and how each type of file will be used in the project. The dataset contains synchronized ECG and PPG signals along with annotations and metadata. ECG serves as the gold-standard reference for heartbeat detection, while PPG simulates the smartphone camera + flashlight method of pulse measurement. The AI model will be trained on PPG signals and validated against ECG/QRS annotations.

2 1. Subject Folders (e.g., 100001)

Each subject/session is stored in a folder named by its ID (e.g., 100001). Inside, you will find the following files:

3 100001_ECG.dat

Contains raw ECG (Electrocardiogram) signal data. This is the clinical gold standard for heartbeat activity and will be used as the reference for validation of AI predictions.

4 100001_ECG.heg

ECG header file that describes how to interpret the ECG signal, including sampling frequency, channels, and duration. Ensures correct reading and processing of the ECG data.

5 100001_PPG.dat

Contains raw PPG (Photoplethysmography) signal data. This simulates what a smartphone camera and flashlight would record from a fingertip or ear. This is the main input signal for AI training.

6 100001_PPG.heg

PPG header file with metadata (signal format, sampling frequency, recording length). Helps software correctly load and interpret the PPG signal.

7 100001.qrs

Annotation file containing QRS complex detections (locations of heartbeats in the ECG). Used as ground truth for validating PPG-based heartbeat estimation.

8 2. Metadata Files

In addition to subject folders, the dataset contains CSV files with useful metadata:

9 subject-info.csv

Contains demographic and physiological data: gender, age, height, weight, measurement site (ear/finger), motion flags, blood pressure/glycaemia status, and SpO₂ levels. This will be used to analyze model performance across different conditions.

10 `quality-hr-ann.csv`

Contains signal quality annotations (1 = good, 0 = poor) and heart rate values derived from ECG. Used to train and validate AI models with reliable signals and reference heart rates.

11 **3. How the Data Meets Project Objectives**

The objective of this project is to design and validate an AI-enabled smartphone pulse monitoring system. The BUT PPG dataset supports this goal as follows:

- PPG signals (`*_PPG.dat`) serve as the input data, simulating smartphone pulse measurements.
- ECG signals (`*_ECG.dat`) provide ground-truth heart activity for validation.
- QRS annotations (`*.qrs`) mark exact heartbeat timings in ECG, used to check AI accuracy.
- Metadata (`subject-info.csv`) allows testing across demographics (age, gender) and conditions (motion, ear vs finger).
- Quality/HR annotations (`quality-hr-ann.csv`) ensure only reliable signals are used and provide reference heart rate values.

12 **4. Summary for Client**

In summary, the BUT PPG dataset contains synchronized ECG (truth) and PPG (smartphone-like) signals, with annotations and metadata for robust analysis. ECG and QRS files act as the benchmark, while PPG files are the main data for AI training. Metadata ensures fair testing across different conditions. This dataset is sufficient and final for building and validating the AI pulse monitoring system, ensuring accuracy comparable to clinical standards.