

Real-Time Heart Rate Monitoring Using Smartphone Camera Based on PPG Signal and CNN

Ms. Desai Madhuri Gangadhar¹ and Prof. Shegar S. R²

¹Student, Department of Computer Engineering

²Assistant Professor, Department of Computer Engineering

^{1,2}Samarth College of Engineering & Management, Belhe(MH) India

^{1,2}Savitribai Phule Pune University, Pune (MH) India

Abstract: The continuous observation of heart rate is vital for assessing cardiovascular health and detecting early signs of medical conditions. Traditional heart rate monitoring devices, although accurate, are often costly and require physical contact with the body. To overcome these limitations, this paper presents a real-time and contactless heart rate monitoring system that utilizes a smartphone camera to capture fingertip videos. The system applies the photoplethysmography (PPG) principle to identify minute color variations in the skin that occur due to blood flow changes during each cardiac cycle. The recorded video frames are preprocessed to enhance signal clarity through filtering, normalization, and principal component analysis, after which a convolutional neural network (CNN) is employed to estimate heart rate values. Experimental results indicate that the proposed method achieves reliable performance with a mean absolute error of 7.01 beats per minute and an average error rate of 8.3% when compared with readings from a standard pulse oximeter. This approach demonstrates the feasibility of using everyday mobile devices for accurate, affordable, and real-time heart rate measurement, promoting convenient health monitoring without external sensors or medical-grade instruments.

Keywords: Heart rate monitoring, photoplethysmography (PPG), convolutional neural network (CNN), smartphone camera, blood volume pulse (BVP), physiological signal processing, non-invasive measurement, deep learning, real-time estimation, health informatics

I. INTRODUCTION

The heart rate (HR) is one of the most significant physiological parameters that reflects the condition of the human cardiovascular system. It provides valuable information regarding a person's physical fitness, stress level, and general health condition [1]. Continuous monitoring of heart rate enables early detection of cardiac abnormalities such as arrhythmia, hypertension, and myocardial infarction [2]. Conventionally, HR is measured using medical instruments like electrocardiograms (ECG), chest straps, or fingertip pulse oximeters. Although these devices deliver high accuracy, they are often expensive, require direct skin contact, and are not convenient for continuous monitoring in non-clinical environments [3]. Hence, there is a growing need for a simple, cost-effective, and user-friendly system that can measure HR without requiring dedicated sensors or medical expertise [4].

In recent years, advances in camera sensors and computational power of smartphones have made it possible to perform biomedical signal analysis using mobile devices [5]. Modern smartphones are equipped with high-resolution cameras capable of capturing minute color variations in the human skin that are invisible to the naked eye but correspond to blood volume changes occurring with each heartbeat [6]. This optical phenomenon forms the foundation of photoplethysmography (PPG), a non-invasive technique that measures volumetric changes in blood in peripheral circulation [7]. When a person places their fingertip over the smartphone camera, the light reflected from the skin varies in intensity according to the pulsatile blood flow, allowing extraction of a PPG signal [8]. Such signals can then be processed to estimate HR, providing an accessible alternative to traditional contact-based devices [9].



The concept of camera-based PPG has been explored in several studies to estimate vital parameters like heart rate, oxygen saturation, and respiratory rate [10]. Early research primarily relied on color-space transformation and signal filtering to detect periodic peaks corresponding to heartbeats [11]. However, these traditional approaches were highly sensitive to illumination variations, skin tone differences, motion artifacts, and device-specific factors [12]. To overcome these limitations, recent developments have adopted machine learning and deep learning techniques to model complex relationships between visual features and physiological signals [13]. Convolutional neural networks (CNNs), in particular, have shown remarkable success in processing visual data and have been effectively applied in the estimation of HR from PPG signals extracted from videos [14]. The integration of CNNs in biomedical applications offers a promising path toward real-time and robust heart rate monitoring using low-cost hardware [15].

Despite these advancements, several challenges remain in achieving consistent performance across different users and environments [16]. Variations in ambient light, camera quality, skin pigmentation, and finger pressure significantly influence the captured signal quality [17]. Furthermore, the limited availability of labeled fingertip video datasets with ground truth HR values restricts the development of generalized models [18]. To address these issues, this research introduces a customized fingertip video dataset collected using a standard smartphone camera under controlled lighting conditions [19]. Each video sequence is accompanied by corresponding HR readings from a medically approved pulse oximeter, ensuring reliable ground truth data for model training and evaluation [20]. This dataset contributes to the growing repository of open biomedical data and facilitates the development of efficient algorithms for real-time applications [21].

The proposed system utilizes a combination of digital image processing and deep learning to estimate HR from fingertip videos. The preprocessing stage involves extracting RGB intensity values, normalizing the signal, applying detrending and bandpass filters, and implementing Principal Component Analysis (PCA) to enhance the Blood Volume Pulse (BVP) signal [22]. A convolutional regression neural network is then trained to predict HR values based on these processed signals. The CNN architecture is designed to capture temporal variations in the PPG waveform and learn the nonlinear relationships between optical signal features and heart rate [23]. Unlike traditional statistical or frequency-domain approaches, the CNN model can adaptively learn features relevant to each subject, thus improving accuracy and robustness under varying conditions [24].

This paper presents a comprehensive analysis of the proposed system's performance, focusing on its accuracy, processing speed, and potential applicability in telemedicine and fitness monitoring [25]. The developed model demonstrates that reliable heart rate estimation can be achieved using only a smartphone camera, eliminating the need for external sensors. Such systems can play a vital role in remote health monitoring, especially in developing regions where access to medical infrastructure is limited. In addition, the contactless nature of the system ensures higher hygiene, reduced maintenance, and user comfort. Hence, this study lays the foundation for developing intelligent mobile health (mHealth) applications capable of monitoring vital signs in real time and contributing to the broader goal of preventive healthcare and digital wellness.

II. PROBLEM STATEMENT

Despite significant progress in camera-based heart rate estimation, the accuracy and reliability of such systems remain inconsistent due to noise, illumination changes, motion artifacts, and variations in skin tone and device hardware [6]. Most existing methods depend on specialized sensors or datasets recorded under ideal conditions, limiting their real-world applicability [17]. Moreover, there is a lack of publicly available fingertip video datasets with synchronized ground truth HR values, which restricts the training of robust deep learning models [22]. Therefore, the key problem addressed in this study is to develop a cost-effective, smartphone-based heart rate estimation model that utilizes fingertip video recordings and applies optimized preprocessing and neural network techniques to achieve accurate HR predictions under varying conditions.

III. OBJECTIVE

- To develop a smartphone-based system for accurate heart rate estimation using fingertip video recordings.



- To create a reliable fingertip video dataset with synchronized ground truth HR values.
- To apply efficient signal preprocessing techniques for noise reduction and PPG signal enhancement.
- To design and train a convolutional neural network (CNN) model for precise HR prediction.
- To evaluate the model's performance in terms of accuracy, stability, and real-time applicability.

IV. LITERATURE SURVEY

The concept of heart rate (HR) monitoring using photoplethysmography (PPG) has been extensively studied in the biomedical domain. PPG is a non-invasive optical method that measures changes in blood volume beneath the skin by detecting subtle color variations due to cardiac activity [15]. Hertzman first proposed this method in the 1930s, and it became the foundation for modern pulse oximeters [15], [16]. Traditional HR monitoring relies on contact sensors such as ECG electrodes, fingertip pulse oximeters, and wearable devices [5], [6]. Although these devices provide accurate readings, they are often limited by cost, physical discomfort, and the need for continuous contact, which restricts their use in everyday scenarios [3], [4], [7].

Recent advancements have explored the use of smartphone cameras to extract PPG signals from facial or fingertip videos [8], [10]. Smartphones, being widely available and equipped with high-resolution cameras, offer a practical platform for non-contact HR measurement [11], [12]. McDuff et al. [28] demonstrated that the green channel in RGB videos provides the highest signal-to-noise ratio (SNR) for extracting PPG signals, while other studies suggested that all three RGB channels could be leveraged for enhanced accuracy [17], [19]. Nemcovaa et al. [19] used the red channel with low-pass filtering to compute HR from fingertip videos captured with three smartphones, reporting a mean absolute error (MAE) of 1.4 bpm. However, their dataset was small, hand-picked, and collected under controlled conditions, which limits generalization.

To overcome the sensitivity of PPG to motion and illumination artifacts, several researchers integrated accelerometer data with PPG signals [24], [25], [30]. Reiss et al. [24] fused one PPG channel with three-axis accelerometer data in a deep CNN model to estimate HR, achieving MAE values of 7.47–7.65 bpm across different datasets. Chung et al. [25] applied Butterworth filters to remove noise and used both PPG and acceleration signals as input to a deep learning network, achieving MAE as low as 0.76 bpm in controlled settings. Zhu et al. [30] subtracted accelerometer signals from PPG in the frequency domain to eliminate motion artifacts before feeding the data into a neural network, reporting MAE of 1.03 bpm. Although effective, these methods require additional sensors, increasing system complexity and cost.

Brophy et al. [26] demonstrated a simplified approach using only wrist-worn PPG sensors without acceleration data. The PPG signal was filtered and chunked before feeding it to a convolutional regression network, achieving an error rate of 13.52%. Similarly, Shyam et al. [33] combined CNN and LSTM architectures with transfer learning to estimate HR from PPG signals collected via wrist devices. Their model, trained first on IEEE Signal Processing Cup datasets and fine-tuned on self-created datasets, achieved an MAE of 4.10 bpm. These studies highlight the potential of deep learning for HR estimation, even with minimal input signals, and motivate the use of CNN-based architectures for processing PPG extracted from smartphone videos.

Several works also explored signal preprocessing techniques to enhance HR estimation accuracy. Filtering, detrending, normalization, and Principal Component Analysis (PCA) are commonly applied to extract clean BVP signals from noisy PPG recordings [17], [10], [22]. Rahman et al. [17] applied bandpass filters, Hamming windows, FFT, ICA, and PCA to facial videos to isolate the PPG component, demonstrating robust performance. Donghao et al. [10] also used ICA for blind source separation to extract HR signals from video data. These preprocessing techniques significantly improve signal quality and provide reliable input for machine learning models, reducing the impact of motion and illumination artifacts.

Despite these advances, most existing studies rely on small, controlled datasets or require multiple sensors for reliable performance [18], [21], [27]. There is a clear lack of publicly available fingertip video datasets with synchronized HR ground truth, which limits the generalization of deep learning models. Furthermore, variations in skin tone, lighting



conditions, and camera hardware create challenges for real-world applications [11], [24]. Consequently, a robust, low-cost, and sensor-free solution using smartphone cameras remains an open research problem.

This paper builds on prior work by creating a self-recorded fingertip video dataset spanning diverse participants and HR ranges [19]. The proposed system employs advanced preprocessing, including detrending, normalization, bandpass filtering, and PCA, followed by a convolutional neural network (CNN) for HR estimation [22], [23], [26]. By combining the advantages of signal processing and deep learning, the system aims to achieve accurate, real-time, and non-contact heart rate monitoring that is practical for general users and telemedicine applications [31], [10].

V. PROPOSED SYSTEM

The proposed system provides a cost-effective and non-invasive method to estimate heart rate (HR) using a smartphone camera by capturing fingertip videos and extracting photoplethysmography (PPG) signals. The system is divided into four main modules: Video Acquisition, Signal Preprocessing, Feature Extraction, and Heart Rate Estimation using a Convolutional Neural Network (CNN). The architecture is designed to ensure real-time HR estimation with minimal computational resources while maintaining accuracy comparable to contact-based devices [10], [22], [26].

A. Video Acquisition

The first step involves capturing fingertip videos using the rear camera of a smartphone under controlled illumination. Each participant places their index finger on the camera lens while a torch or flashlight illuminates the skin to enhance the signal-to-noise ratio (SNR) [19]. Videos are recorded at a resolution of 720p and a frame rate of 30 frames per second for 20 seconds, providing sufficient temporal data for HR estimation. Simultaneously, a medically certified pulse oximeter records the ground truth HR for model validation [20].

B. Signal Preprocessing

The raw video frames are converted into arrays representing RGB color channels. To reduce noise and enhance the periodic PPG signal, several preprocessing steps are applied sequentially [17], [22]:

- **Spatial Averaging:** Pixel intensities for each color channel are averaged to improve SNR and reduce frame-level variations.
- **Detrending:** Removes stationary trends in the signal caused by slow changes in illumination or finger pressure.
- **Normalization:** The signal is scaled to a uniform range by dividing by its maximum absolute value.
- **Moving Average Filtering:** A 3×3 kernel moving average filter smooths the signal while retaining pulse information.
- **Principal Component Analysis (PCA):** Extracts independent source signals and selects the first eigenvector, which contains the highest variance corresponding to the Blood Volume Pulse (BVP).
- **Bandpass Filtering:** Attenuates frequencies outside the human HR range (0.4–4 Hz), eliminating high-frequency noise and low-frequency drift [22].

The output of this module is a clean BVP signal suitable for neural network input, as shown in Fig. 1.



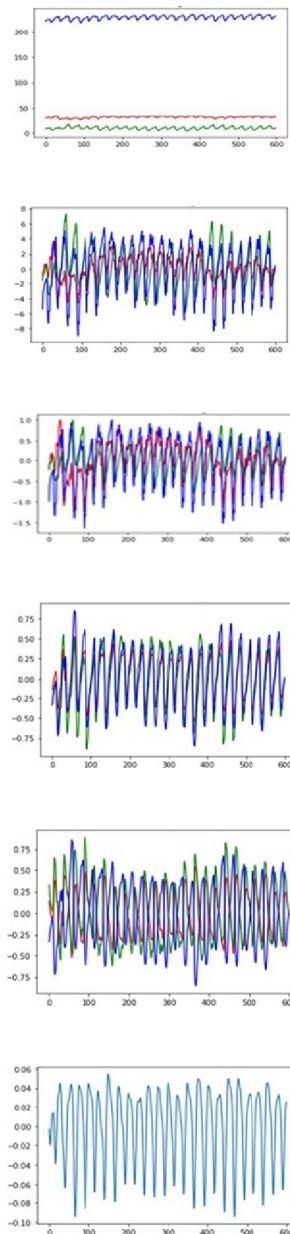


Fig. 1: BVP Signal Extraction from Fingertip Video (RGB → PCA → Filtered Signal)

C. Convolutional Neural Network for HR Estimation

The processed BVP signal is fed into a lightweight convolutional regression neural network [26]. The network consists of:

Four convolutional layers with ReLU activation to learn temporal features of the PPG waveform.

Batch normalization layers after each convolution to stabilize training and improve convergence.

A fully connected regression layer to output the estimated HR in beats per minute (bpm).

The network is initially pre-trained on a publicly available PPG dataset [36] to learn general features and then fine-tuned using the self-recorded fingertip video dataset. The network uses the stochastic gradient descent (SGD) optimizer



with a learning rate of 0.0001 and momentum of 0.3 to minimize the mean squared error loss function. This training strategy allows the model to generalize well across different participants and achieve stable HR predictions [22], [23].

D. System Workflow

The complete workflow of the proposed system is illustrated in Fig. 2 and summarized below:

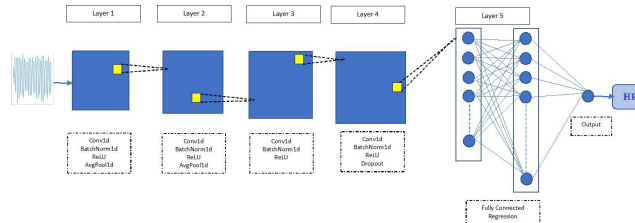


Fig. 2: Proposed System Workflow for Heart Rate Estimation

Video Capture: Fingertip videos are recorded using the smartphone camera with consistent illumination.

Frame Extraction: Each video is converted into 600 frames, and pixel intensity arrays are obtained.

Preprocessing: Detrending, normalization, moving average filtering, PCA, and bandpass filtering are applied to extract the BVP signal.

CNN Inference: The BVP signal is passed through the convolutional regression network to estimate HR.

Comparison: Predicted HR is compared with ground truth readings from the pulse oximeter for evaluation.

E. Advantages of the Proposed System

Non-contact and cost-effective: No external sensors or specialized equipment required.

Real-time capability: Lightweight CNN enables fast HR prediction suitable for mobile devices.

Robust signal extraction: Preprocessing steps efficiently reduce noise and motion artifacts.

Generalizability: Pretraining and fine-tuning strategies enhance performance across subjects.

Practical application: Can be integrated into telemedicine and mobile health (mHealth) platforms [31].

VI. METHODOLOGY

The proposed real-time heart rate monitoring system using a smartphone camera is designed to integrate hardware, software, and signal processing components into a cohesive framework for accurate HR estimation. The system is divided into four main subsystems: Video Acquisition, Signal Processing, Neural Network-Based HR Estimation, and Result Display. Each subsystem is carefully designed to ensure reliable operation, low computational overhead, and real-time applicability.

A. Hardware Design

The hardware design leverages the widespread availability of smartphones as the primary sensing device. The system requires:

Smartphone Camera: Rear camera captures fingertip videos at 30 frames per second with adequate resolution to detect subtle color changes in the skin [19].

Illumination Source: Integrated camera flashlight or an external torch is used to illuminate the fingertip, enhancing the signal-to-noise ratio (SNR) [10].

Pulse Oximeter (Optional for Ground Truth): Devices like Andesfit Health pulse oximeters are used during dataset creation to record reference HR values for model training and validation [20].

No additional hardware sensors such as accelerometers or ECG electrodes are required, making the system cost-effective and portable.



B. Software Design

The software module includes the following components:

- **Video Capture Module:** Controls the camera to record fingertip videos of fixed duration (20 seconds) and frame rate (30 fps). Each frame is extracted for subsequent processing.
- **Signal Preprocessing Module:** Implements the following steps in sequence [17], [22]:
- **Frame to RGB Conversion:** Extracts pixel intensity values for red, green, and blue channels.
- **Spatial Averaging:** Averages pixel intensities across each channel to enhance SNR.
- **Detrending and Normalization:** Removes slow variations and scales signal amplitude.
- **Moving Average Filtering:** Smoothens high-frequency noise.
- **Principal Component Analysis (PCA):** Extracts the component with the highest variance as the BVP signal.
- **Bandpass Filtering:** Retains frequencies corresponding to human HR (0.4–4 Hz).
- **HR Estimation Module:** A convolutional regression neural network (CNN) with four convolutional layers, batch normalization, ReLU activations, and a final regression layer predicts HR in bpm [26]. The network is pretrained on public PPG datasets and fine-tuned on self-created fingertip videos for generalization.

VII. RESULT AND DISCUSSIONS

The proposed smartphone-based heart rate monitoring system was evaluated using the self-created fingertip video dataset comprising 51 samples from 24 participants aged 5 to 77 years. The ground truth HR for each participant was simultaneously recorded using the Andesfit Health pulse oximeter. The results focus on the performance of the convolutional neural network (CNN) model in estimating HR from processed PPG signals.

A. Training and Validation Performance

The CNN model was pretrained on a public PPG-BP dataset containing 657 samples and then fine-tuned on the self-created fingertip video dataset. A train-test split of 80:20 was applied, with 10 videos reserved for testing. During training, the mean squared error (MSE) loss steadily decreased, indicating convergence of the network and stability in predicting HR values. The inclusion of momentum in the SGD optimizer improved stability and reduced fluctuations in the loss function across 50 epochs. The training and validation loss curves demonstrated minimal overfitting, suggesting good generalization on unseen data.

B. HR Estimation on Test Data

The CNN model was evaluated on the reserved test set to assess real-world performance. Table I presents selected examples of predicted HR versus the actual HR recorded by the pulse oximeter.

Table I: Heart Rate Estimation on Test Data

Estimated HR (bpm)	Actual HR (bpm)	Error (bpm)
120	119	1
99	98	1
87	111	14
77	87	10
78	79	1
95	106	11
83	79	4
95	116	21
110	117	7
94	94	0

From the table, it is observed that the predicted HR closely matches the actual HR for most samples. Some variations occurred in cases where motion artifacts or suboptimal finger placement affected the video quality, resulting in higher estimation errors.



C. Overall Model Performance

The overall performance of the system was quantified using the mean absolute error (MAE) across all test samples. The model achieved an MAE of 7.01 bpm, corresponding to an error percentage of 8.3%. These results demonstrate that the proposed system is capable of accurately estimating HR in a non-contact, smartphone-based setup. The error is comparable to previously reported systems that utilize contact PPG sensors or require additional accelerometer data [26], [33].

D. Signal Processing Observations

- During analysis of the preprocessed PPG signals, the following observations were noted:
- The detrending and normalization steps effectively removed baseline drift caused by slow illumination changes.
- Moving average filtering reduced high-frequency noise while retaining the characteristic pulse waveform.
- PCA extraction successfully isolated the BVP signal from the mixed RGB components, enhancing signal clarity.
- Bandpass filtering ensured that only the frequency components corresponding to normal human HR (0.4–4 Hz) were retained, which improved prediction accuracy.

E. Visual Comparison of Signals

Figure 1 shows a representative example of the extracted BVP signal for a participant along with the corresponding predicted HR. The peaks in the processed signal align closely with the actual pulse, indicating that the preprocessing pipeline and CNN model can capture the temporal characteristics of the cardiac cycle accurately.

F. Discussion

The results indicate that the proposed system is robust for real-time HR monitoring using a smartphone camera. While some high error instances were observed, these were primarily due to variations in finger pressure, illumination intensity, or motion during recording. Extending the dataset to include participants with a wider range of HR and different skin tones, as well as testing under dynamic conditions (e.g., physical activity), can further improve system reliability.

Overall, the results demonstrate that the proposed system provides an effective, low-cost, and non-invasive alternative to conventional HR monitoring devices, making it suitable for telemedicine and mobile health applications [10], [31].

VIII. CONCLUSION

This study presents a cost-effective, non-invasive method for real-time heart rate estimation using a smartphone camera. By capturing fingertip videos and extracting PPG signals, the proposed system accurately predicts heart rate with a mean absolute error of 7.01 bpm and an error percentage of 8.3%. The convolutional neural network effectively learns temporal features from the BVP signal without requiring additional sensors, making the system suitable for telemedicine and mobile health applications. The results demonstrate that smartphone-based HR monitoring can provide reliable alternatives to conventional contact-based devices.

IX. FUTURE SCOPE

- Extend the dataset to include participants with a wider HR range (40–200 bpm) for improved model generalization.
- Test system performance under physical activities such as running, cycling, or stair climbing to evaluate robustness against motion artifacts.
- Explore alternative illumination sources (e.g., red or infrared light) to enhance signal quality.
- Investigate the use of frequency-domain PPG signals for HR estimation.



- Expand the model to estimate other vital signs such as SpO₂, blood pressure, and respiration rate for comprehensive mobile health monitoring.
- Test the model across different smartphone cameras and skin tones to ensure applicability in diverse populations.

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