Health Vitals Monitoring Using PPG With Smartphone Camera

Presented by:

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Introduction

"Health Monitoring Using PPG With Smartphone Camera" explores a novel method for estimating Heart rate (HR), Blood oxygen saturation (SpO2),Pulse rate, Respiratory rate (RR), Blood pressure (to some extent), through the use of smartphone cameras, leveraging the photoplethysmography (PPG) technique.

Applications:

- Sleep Analysis: Monitoring sleep patterns and disturbances.
- Stress Level Assessment: Evaluating physiological responses to stress.
- Health Monitoring in Wearables: Integrating into smartwatches and fitness trackers.

Vitals Monitoring

Objective: To develop a method for estimating health vitals using smartphone cameras without relying on traditional sensor devices. The method utilizes photoplethysmography (PPG) principles applied to fingertip videos captured by a smartphone camera.

- Core Concepts:
  Technique: PPG detects cardiovascular activity by tracking subtle color changes in the skin, which are imperceptible to the human eye but detectable by cameras. These changes reflect variations in blood volume due to the heartbeat.

Literature Survey

<table>
<tr><th>S.No</th><th>Title</th><th>Methodology</th><th>Performance Metrics</th><th>Research Gaps</th></tr>
<tr>
<td>1</td>
<td>Heart Rate Monitoring Using PPG with Smartphone Camera [1]

2021</td>
<td>

Used videos of the fingertip captured with a smartphone camera to estimate heart rate (HR) using the photoplethysmography (PPG) technique.
Used videos of the fingertip captured with a smartphone camera to estimate heart rate (HR) using the photoplethysmography (PPG) technique.
Extracted the Blood Volume Pulse (BVP) signal.

</td>
<td>
<table>
<tr><th>Metrics</th><th>Value</th></tr>
<tr><td>Mean Absolute Error (MAE)</td><td>7.01 bpm</td></tr>
<tr><td>Error Percentage</td><td>8.3%</td></tr>
</table>
</td>
<td>

Lack of a public dataset containing fingertip video recordings with ground truth HR readings.
Limited testing with subjects engaged in various physical activities.
Need for testing with different smartphone cameras and various skin colors.

</td>
</tr>
<tr>
<td>2</td>
<td>Smartphone Apps Using Photoplethysmography for Heart Rate Monitoring: Meta-Analysis [2]

2018</td>
<td>

the use of smartphone apps to measure heart rate using photoplethysmography (PPG) compared to validated methods.
fixed effects and random effects models to pool outcomes.
Compared heart rate measurements using smartphones with a validated method, such as ECG or pulse oximeter.

</td>
<td>
<table>
<tr><th>Metrics</th><th>Adults</th><th>Children</th></tr>
<tr><td>Mean Difference</td><td>0.32 bpm (99</td><td>Varied by study</td></tr>
<tr><td>Correlation Coefficient</td><td>.90 (adults)%</td><td>Varied (lower during tachycardia)%</td></tr>
<tr><td>Average</td><td>97.16%</td><td>97.25%</td></tr>
</table>
</td>
<td>

smartphone apps are not validated for use in pediatric populations, especially during periods of tachycardia.
Limited data on the influence of motion, skin color, and varying heart rates on PPG measurement accuracy.

</td>
</tr>
<tr>
<td>3</td>
<td>Respiration Rate Estimation from Remote PPG via Camera in Presence of Non-Voluntary Artifacts [3]</td>
<td>

A smartphone camera to extract remote PPG (rPPG) signals from the face, with focus on removing artifacts caused by non-voluntary motion and light variations. Techniques include SNR-based artifact removal, deep learning for facial recognition, and RGB channel analysis for signal extraction

</td>
<td>
<table>
<tr><th>Methodology</th><th>MAE (bpm)</th><th>90th Percentile MAE (bpm)</th></tr>
<tr><td>Baseline</td><td>6.68</td><td>5.60</td></tr>
<tr><td>SNR-Based Peak Selection</td><td>5.43%</td><td>4.73%</td></tr>
</table>
</td>
<td>

Further improvement needed in reducing error for low respiratory rates (e.g., 5 bpm)
Explore dynamic filtering for artifact removal

</td>
</tr>
</table>

Literature Survey

<table>
<tr><th>S.No</th><th>Title</th><th>Methodology</th><th>Performance Metrics</th><th>Research Gaps</th></tr>
<tr>
<td>4</td>
<td>Non-Invasive Methodology for Detection of Vital Signs by PPG Signals Collected from the Finger via Smartphone Camera for Individuals Aged 18 to 70: Randomized Controlled Trial [4]

2024</td>
<td>The study used the CarePlix Vitals app to collect PPG signals from the finger using a smartphone camera.
Participants' vital signs (pulse, respiration rate, oxygen saturation, heart rate variability, and blood pressure) were measured using PPG signals.
The study compared the app's readings with those obtained from traditional medical devices (e.g., Polar H9, Omron HEM 7120 BP monitor).
The accuracy of the CarePlix Vitals app was validated through statistical analyses, with a 95</td>
<td><table><tr><th>Metrics</th><th>Accuracy</th></tr><tr><td>Heart Rate (HR)</td><td>98.56%</td></tr><tr><td>Respiratory Rate (RR)</td><td>98.18%</td></tr><tr><td>Oxygen Saturation (SpO2)</td><td>98.14%</td></tr><tr><td>Systolic BP</td><td>91.20%</td></tr></table></td>
<td>Need for robust algorithms to differentiate clean PPG signals from noise and motion artifacts in real-world conditions.
Lack of understanding regarding how age affects PPG signal characteristics and vital sign accuracy.</td>
</tr>
<tr>
<td>5</td>
<td>Pulse Rate Estimation Using PPG and Smartphone Camera [5]

2016</td>
<td>Smartphone camera records fingertip video with flash.
Red channel PPG signal is extracted for pulse rate.
Simple calculations used to estimate pulse rate, reducing processor load and energy consumption.</td>
<td><table><tr><th>Metrics</th><th>value</th></tr><tr><td>Max Error</td><td>3 beats/min%</td></tr><tr><td>Accuracy</td><td>98.02%</td></tr><tr><td>Standard Deviation (Error)</td><td>0.68%</td></tr></table></td>
<td>algorithm to estimate blood pressure.
Improve energy efficiency for mobile use.</td>
</tr>
<tr>
<td>6</td>
<td>Review on Remote Heart Rate Measurements Using Photoplethysmography [6]

2024</td>
<td>Use of deep learning and computer vision techniques for heart rate estimation.
Implementation of motion artifact and illumination variation reduction techniques.
Review of hybrid methods combining deep learning and conventional approaches.</td>
<td>Heart rate estimation accuracy
Motion artifact robustness
llumination variation tolerance</td>
<td>Public datasets lack diversity in motion artifacts and illumination variations. focus on areas other than the face for remote heart rate estimation.</td>
</tr>
</table>

Literature Survey

<table>
<tr><th>S.No</th><th>Title</th><th>Methodology</th><th>Performance Metrics</th><th>Research Gaps</th></tr>
<tr>
<td>7</td>
<td>A pulse rate estimation algorithm using PPG and smartphone camera. [7]

2016</td>
<td>Use of smartphone cameras and PPG signals for heart rate estimation.
Motion detection algorithm to reduce input data corruption.
Comparison of performance across different color channels (Red, Green, Blue) to determine the most effective for heart rate estimation.</td>
<td><table>
<tr><th>Performance Metric</th><th>Algorithm</th><th>Value</th></tr>
<tr><td>Accuracy</td><td>CHROM, Siddiqui Algorithm%</td><td>60, 98.02 (Siddiqui)%</td></tr>
<tr><td>Motion Artifact Robustness</td><td>2SR Algorithm%</td><td>SNR: 6.55 dB%</td></tr>
<tr><td>Illumination Variation Tolerance</td><td>2SR Algorithm%</td><td>SNR 5 dB (dark skin tones)%</td></tr>
</table></td>
<td>Public datasets lack diversity
Limited focus on non-facial areas for pulse estimation.
Lack of comprehensive studies on hardware and software configurations to optimize performance.</td>
</tr>
<tr>
<td>8</td>
<td>Smartphone as a Pulse-Oximeter and Single-lead ECG Tool [8]

2024</td>
<td>Video recording of fingertip using smartphone camera.
Preprocessing with wavelet transform for noise/artifact removal.
Custom-built CNNs and deep learning models (ViT, CLIP) for estimating vitals (PR, SpO2, RR) and generating single-lead ECG.</td>
<td><table>
<tr><th>Performance Metric</th><th>Algorithm</th><th>Value</th></tr>
<tr><td>Heart Rate Accuracy</td><td>MT-Net</td><td>1.74 bpm</td></tr>
<tr><td>SpO2 Estimation Accuracy</td><td>CNN-Net</td><td>1.66</td></tr>
<tr><td>Respiratory Rate Accuracy</td><td>ViT-Net</td><td>0.89 breaths per minute</td></tr>
</table></td>
<td>Lack of large public datasets for video-PPG.
Few studies on generalization capability and robustness of DL models in diverse conditions.
Limited stand-alone smartphone-based solutions without external hardware for ECG and vitals estimation.</td>
</tr>
</table>

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<tr><th>S.No</th><th>Title</th><th>Methodology</th><th>Performance Metrics</th><th>Research Gaps</th></tr>
<tr>
<td>9</td>
<td>Real-time Heart Rate Measurement based on Photoplethys-mography using Android Smartphone Camera [9]

2017</td>
<td>Real-time Heart Rate Measurement based on Photoplethysmography using Android Smartphone Camera1
Signal Processing: MATLAB for algorithm development and Android for real-time application.
Algorithm: Moving Average Filter (MAF) and peak detection for heart rate calculation.</td>
<td><table><tr><th>Smartphone Model</th><th>Standard Error of Estimate (SEE)</th></tr><tr><td>S3</td><td>2.4268%</td></tr><tr><td>S4</td><td>1.8071%</td></tr><tr><td>Note3</td><td>1.6666%</td></tr><tr><td>Mega</td><td>1.6567%</td></tr></table></td>
<td>Motion Artifacts: Need for better handling of motion artifacts.
Device Compatibility: Limited testing on Samsung devices; broader testing needed.
Real-time Performance: Further optimization for real-time processing on various devices.</td>
</tr>
<tr>
<td>10</td>
<td>Monitoring of Heart Rate, Blood Oxygen Saturation, and Blood Pressure Using a Smartphone [10]

2017</td>
<td>The study employs a smartphone's rear camera and microphone to estimate vital signs using photoplethysmography (PPG) for heart rate (HR) and blood oxygen saturation (SpO2).
Blood pressure (BP) is calculated via pulse transit time (PTT) using PPG and phonocardiogram (PCG) signals.
An Android application was developed for data collection, providing real-time feedback on signal quality.</td>
<td><table><tr><th>Vital Sign</th><th>MAE</th></tr><tr><td>Heart Rate (bpm)</td><td>Testing: 1.4 bpm</td></tr><tr><td>Blood Oxygen Saturation (SpO2)</td><td>1.11%</td></tr><tr><td>Blood Pressure (BP)</td><td>Blood Pressure (BP)</td></tr></table></td>
<td>Synchronization Issues: Inaccurate synchronization between PPG and PCG signals, requiring manual adjustment for better accuracy.
Device Limitations: Discomfort during longer measurements due to heat from the LED light on the camera.
Dual Camera Challenges etc.</td>
</tr>
</table>

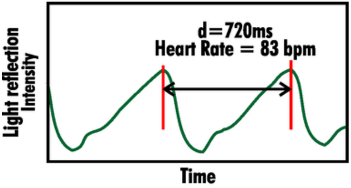
Research Gaps

1. **Accuracy in challenging conditions:** PPG is prone to noise from motion artifacts, ambient light, and skin tone variations, affecting accuracy in real-world scenarios.
2. **Blood pressure estimation:** Estimating blood pressure from PPG signals is still unreliable and needs improvement in accuracy and consistency.
3. **Limited multi-vital monitoring:** Comprehensive multi-vital monitoring (e.g., HR, SpO2, blood pressure) from a single PPG signal remains underdeveloped.
4. **Real-time processing and integration:** Achieving efficient real-time signal processing in mobile and wearable devices without compromising performance is a challenge.
5. **Detection of complex health conditions:** PPG-based systems are still not fully capable of detecting more complex health issues like arrhythmias or heart failure.

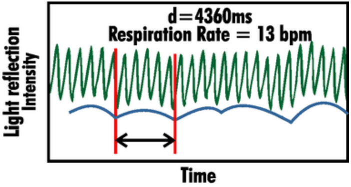
Problem Statement

Develop a non-invasive, cost-effective method for estimating health vitals (HV) using a smartphone camera by leveraging the photoplethysmography (PPG) technique, eliminating the need for wearable sensor devices.

The method aims to extract HV from fingertip videos captured by a smartphone and reduce noise using signal processing techniques, with the HV estimation performed via CNN, LSTM.



(a)



(b)

Objectives

Objective 1: Non-voluntary motion artifacts and inconsistent respiration rate estimation under varying conditions.

Objective 2: Difficulty in estimating blood pressure accurately with PPG alone. Accurate blood pressure estimation from PPG signals is still a challenge due to signal complexity and noise.

Objective 3: Inconsistent heart rate estimation under different lighting and environmental conditions, as well as real-time performance limitations.

Overview of Methodology

Methodology for Estimating Vital Signs from PPG Signals

Objective: To estimate multiple vital signs including Heart Rate (HR), Blood Pressure (BP), SpO2, Respiration Rate (RR), and Pulse Rate (PR) using PPG signals extracted from videos.

Input: Videos containing PPG signals (extracted via smartphone camera).

Steps:

- **1. PPG Signal Extraction:** Use OpenCV to capture frame intensities from video, preprocessing the raw signal.
- **2. Signal Normalization:** Normalize the signal using MinMaxScaler to prepare it for feature extraction.
- **3. Model Training:** Use a CNN-LSTM hybrid model to process the extracted features and predict vital signs.

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Data Preprocessing and Feature Extraction

- **Data Collection:** Videos are extracted from a predefined dataset with associated heart rate values. PPG signals are obtained by calculating the average pixel intensities of the video frames.
- **Preprocessing Steps:**
  - **Normalization:** Signal values are normalized for consistency using MinMaxScaler.
  - **Truncation/Padding:** PPG signal is adjusted to a fixed length of 600 frames to maintain uniformity across inputs.
- **Feature Extraction:**
  - **Multichannel PPG Signal:** Signals from the RGB channels of the video are combined to form a multi-dimensional signal.
  - **Sliding Window:** Time-series data is organized using a sliding window approach to capture temporal dependencies.

Architecture

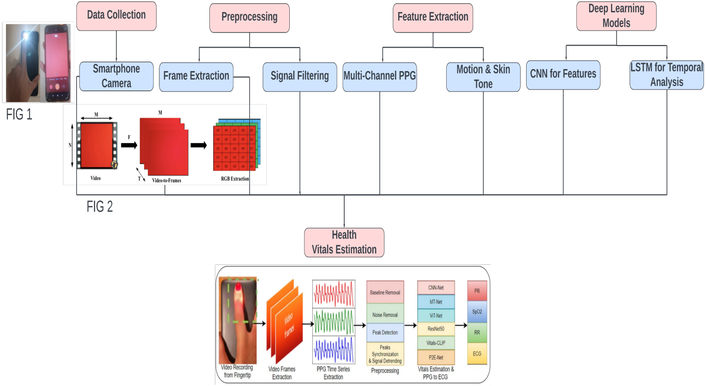

FIG 3
ProposedModelArchitecture

Model Architecture and Vital Sign Estimation

Model Architecture:

- **CNN Layers:** Convolutional layers (Conv1D) to extract spatial features from the multichannel PPG signal.
- **LSTM Layers:** Long Short-Term Memory layers capture temporal dependencies across frames.
- **Dense Output Layer:** A final dense layer predicts the desired vital sign (HR, BP, SpO2, RR, PR).

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- **Vital Sign Estimation:**
- **Heart Rate (HR):** Estimated directly from the PPG signal.
  Blood Pressure (BP): Estimated indirectly using PPG signal characteristics related to pulse wave dynamics.
  Other Vitals: SpO2, PR, and RR are estimated using additional signal features and auxiliary models.
- **Model Evaluation:**
  Metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2) for model performance.
  Validation: Cross-validation is employed to ensure robustness of the model.

Dataset

PPG Signals Dataset Overview

- **Data Set:** Fingertip video recordings for HR measurement, Videos recorded using Redmi Note 8 smartphone, 24 participants (ages 5 to 77, both male and female)
- **Recording Details:** 20 seconds per video. 30 frames per second (fps).Ground truth HR recorded with Andesfit Health pulse oximeter. HR Range: 59 to 119 bpm. Total Samples: 51 videos.

  The following methods are applied to modify the dataset:
  - **Data Preprocessing:** Clean and normalize PPG signals using adaptive filters to remove noise and segment data into smaller windows for better temporal analysis.
  - **CNN-LSTM Hybrid Modeling:** CNN-LSTM Hybrid Modeling: Use CNNs for feature extraction from PPG signals and LSTMs for temporal analysis to improve heart rate and respiration rate predictions.

Fig. Samples of the Dataset.

Experimentations and Results

Table: **Performance Metrics**

Metric	Value
Training	61.81 bpm
Validation	46.53 bpm
Validation Main Absolute Error	4.76 bpm
Mean Absolute Error (MAE) - Test	4.07 bpm
Root Mean Squared Error (RMSE)	5.75 bpm
R-squared (R^2)	0.88

Experimentations and Results

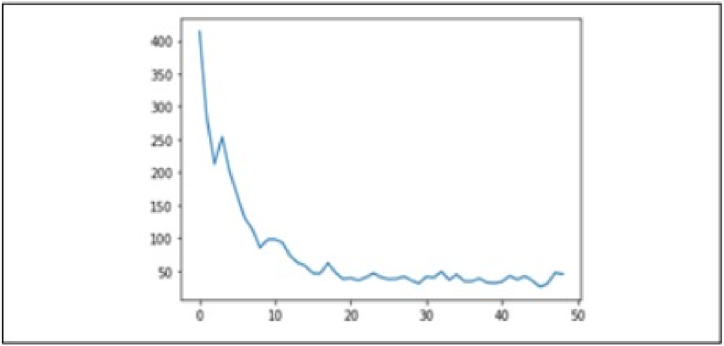

Fig. Base Paper Results

Experimentations and Results

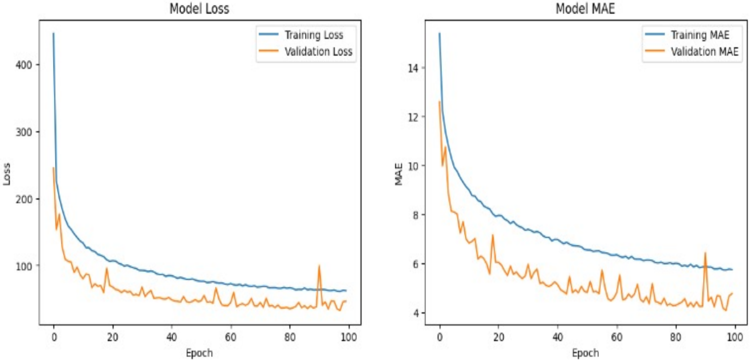

Fig. Our Methodology Results

Experimentations and Results

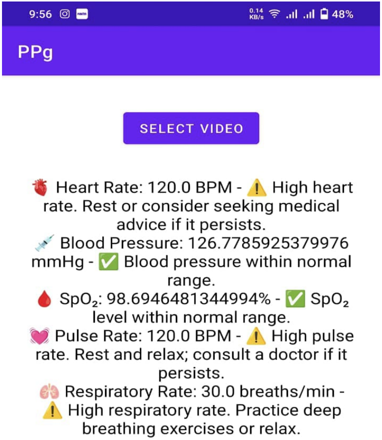

Fig. Our Methodology Results

Conclusion

Accurate Heart Rate Estimation: The model achieved strong performance with an MAE of 4.07, RMSE of 5.75, and R-squared of 0.88, demonstrating effective heart rate estimation from PPG signals extracted from video data.

Accurate Heart Rate Estimation: The model achieved strong performance with an MAE of 4.07, RMSE of 5.75, and R-squared of 0.88, demonstrating effective heart rate estimation from PPG signals extracted from video data.

Real-Time Application: The model, integrated into a mobile app, proved capable of providing real-time heart rate monitoring via smartphone cameras, offering a promising solution for non-invasive health tracking.

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[2]]De Ridder, B., Van Rompaey, B., Kampen, J. K., Haine, S., 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

[3]]Vatanparvar, K., Gwak, M., Zhu, L., Kuang, J., Gao, A. (2022). Respiration Rate Estimation from Remote PPG via Camera in Presence of Non-Voluntary Artifacts. 2022 IEEE-EMBS International Conference on Wearable and Implantable Body Sensor Networks (BSN), 1-6. https://doi.org/10.1109/BSN56160.2022.9928485

[4] Paul, S., Banik, B., Basak, B., Moin, I. (2024). Non-Invasive Methodology for Detection of Vital Signs by PPG Signals Collected from the Finger via Smartphone Camera for Individuals Aged 18 to 70: Randomized Controlled Trial. JMIR Preprints. https://doi.org/10.2196/preprints.57055

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References II

[9] N. V. Hoan, J.-H. Park, S.-H. Lee, and K.-R. Kwon, "Real-time Heart Rate Measurement based on Photoplethysmography using Android Smartphone Camera," Journal of Korea Multimedia Society, vol. 20, no. 2. Korea Multimedia Society, pp. 234–243, 28-Feb-2017. https://doi.org/10.9717/kmms.2017.20.2.234

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Expressing Gratitude

Thank You