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Non-Contact Blood Pressure and SPO_2 Monitoring Using Facial Recognition Technique

K.M. Manjunath
Department of ECE, Sri Vekateswara College of Engineering (Autonmous),Tirupati, AP India
manjunath.km@svcolleges.edu.in

K. Harshapriya
Department of ECE, Sri Vekateswara College of Engineering (Autonmous),Tirupati, AP India
kharshapriya2020@gmail.com

K. Deekshitha yadav
Department of ECE, Sri Vekateswara College of Engineering (Autonmous),Tirupati, AP India
kdeekshithayadav1@gmail.com

G. Hemanth Kumar Reddy
Department of ECE, Sri Vekateswara College of Engineering (Autonmous),Tirupati, AP India
hemanthreddy4002@gmail.com

K. Madhusudhan Reddy
Department of ECE, Sri Vekateswara College of Engineering (Autonmous),Tirupati, AP India
madhugod17@gmail.com

M. Lohith
Department of ECE, Sri Vekateswara College of Engineering (Autonmous),Tirupati, AP India
mopurulohith@gmail.com

Abstract— **Non-contact facial health monitoring has emerged as an effective alternative to conventional sensor-based systems for continuous and remote healthcare applications. This paper presents an AI-powered facial health monitoring system that estimates vital physiological parameters such as heart rate (HR), blood pressure (BP), oxygen saturation (SpO_2), emotion, and stress level from live facial video input. The proposed approach employs camera-based face detection, preprocessing, data cleaning, facial feature extraction, and optimized remote photoplethysmography (rPPG) signal analysis. To improve robustness against motion artifacts, illumination variations, and noise, a Kalman Filter is applied for real-time signal smoothing and stabilization. Experimental results obtained from multiple users under different lighting and posture conditions demonstrate reliable and consistent performance. The system successfully detected faces in real time and estimated HR values in the range of 56.4–65.4 BPM, SpO_2 consistently around 99.9%, and BP values ranging from 151/98 mmHg to 170/106 mmHg. Additionally, emotion was identified as Neutral (30.0%) with stress levels classified as Relaxed or Normal, indicating stable physiological and mental states. The smooth and continuous outputs after Kalman filtering confirm effective noise reduction and signal stability. The results validate that the proposed system enables accurate, real-time, and contactless health monitoring, making it suitable for smart healthcare and remote patient-monitoring environments.**
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Keywords — Remote photoplethysmography, facial health monitoring, Kalman filter, computer vision, non-contact vital signs, real-time monitoring etc.

I. INTRODUCTION

Continuous monitoring of vital physiological parameters such as heart rate (HR), blood pressure (BP), and oxygen saturation (SpO_2) plays a crucial role in early diagnosis, disease prevention, and long-term healthcare management. Conventional monitoring systems rely on contact-based sensors such as cuffs, finger pulse oximeters, and wearable devices. Although these methods provide reliable measurements, they often cause discomfort, require physical contact, and are not suitable for continuous or remote monitoring scenarios [1], [15]. These limitations have motivated research into non-contact and camera-based health monitoring solutions. Recent advances in computer vision and signal processing have enabled remote photoplethysmography (rPPG), a technique that extracts physiological signals from subtle color variations in facial skin captured by standard RGB cameras [1]. Several studies have demonstrated the feasibility of estimating HR, SpO_2, and even BP from facial videos using rPPG-based approaches [4], [7], [8]. However, rPPG signals are highly sensitive to motion artifacts, illumination changes, facial expressions, and skin-tone variations, which significantly affect measurement accuracy in real-world environments [1], [5]. To address these challenges, researchers have explored facial landmark detection and region-of-interest (ROI) selection techniques to improve signal quality. Landmark-based approaches enable precise tracking of stable facial regions, leading to improved extraction of physiological signals [2]. In parallel, deep learning–based models have been introduced to enhance robustness and estimation accuracy for vital signs, particularly SpO_2 and BP [7], [8]. While these methods show promising results, they often require large datasets, high computational resources, and lack generalization across diverse conditions [12]. Signal filtering and optimization techniques play a key role in improving rPPG-based measurements. Among these, Kalman filtering has been shown to effectively reduce noise and stabilize physiological signals by modeling system dynamics and measurement uncertainty [3]. However, most existing studies apply filtering techniques only for heart-rate estimation and do not extend them to multi-parameter monitoring in real-time scenarios [3], [14]. Furthermore, limited work integrates robust preprocessing, optimized PPG extraction, and adaptive filtering into a unified system suitable for practical healthcare applications [15]. Motivated by these research gaps, this work proposes a non-contact facial health monitoring system that integrates facial landmark–based feature extraction, optimized rPPG signal processing, and Kalman filter–based noise reduction. The proposed approach aims to provide stable, accurate, and real-time estimation of HR, BP, and SpO_2 from live facial video under varying environmental conditions, making it suitable for smart healthcare and remote patient-monitoring applications.

II. RELATED WORKS

M. Xu, Y. Zhang, and L. Zhao provide a comprehensive review of remote photoplethysmography (rPPG) methods, comparing classical signal-processing pipelines and newer learning-based approaches; they highlight major challenges such as motion artifacts, illumination changes, and skin-tone bias that limit clinical deployment of contactless vital-sign monitoring [1]. K. Sharma and A. Verma present a facial-landmark–based framework that improves region-of-interest selection for rPPG extraction using deep learning; their results show better signal extraction when landmarks are tracked accurately, but performance drops with large head motion and poor lighting [2]. S. Li and R. Jain propose a Kalman filter–enhanced PPG processing method that smooths and denoises rPPG signals, demonstrating significantly reduced short-term fluctuations in heart-rate estimates compared with simple moving-average filters, though the study focuses primarily on HR rather than multi-parameter estimation [3]. L. Chang et al. investigate remote SpO_2 estimation using video-based rPPG combined with tailored signal features; their experiments indicate promising accuracy under controlled lighting but note reduced robustness in real-world dynamic scenes [4]. A. K. Maity et al. introduce RobustPPG, an adaptive signal-processing pipeline designed to maintain heart-rate estimation accuracy under head motion and variable illumination; it improves robustness but increases computational load, challenging real-time deployment on low-power devices [5]. J. Park et al. evaluate pulse-rate measurement methods across diverse environments and emphasize preprocessing and adaptive filtering as key to consistent results; their system performs well for HR estimation but does not extend to SpO_2 or BP estimation [6]. J. Mathew et al. develop a CNN-based approach for remote SpO_2 estimation from facial video patches; the deep model attains higher accuracy than conventional algorithms but requires large labeled datasets and considerable compute resources for training and inference [7]. W. Xing et al. explore blood-pressure prediction from face videos using deep convolutional models trained on pulse-wave features; results show feasibility of non-contact BP estimation, yet accuracy is lower than cuff devices and often needs subject-level calibration [8]. J. Li et al. propose motion-robust rPPG architectures that integrate spatio-temporal modeling and motion-aware modules; these models improve performance under moderate motion but at the cost of increased model complexity and inference time [9]. E. M. Nowara et al. perform a systematic comparative study of video-based pulse measurement techniques, underlining the large variation in reported results due to differences in datasets, evaluation metrics, and experimental setups, and calling for standardized benchmarks [10]. M. Artemyev et al. present an efficient rPPG algorithm with advanced temporal filtering suitable for webcams and embedded platforms; while computationally light, it shows weaker robustness against strong motion and extreme lighting than heavier deep models [11]. W. Chen et al. review deep-learning advances in rPPG and conclude that hybrid systems (combining classical signal processing, robust ROI selection, and DL modules) are the most promising path toward practical, generalizable contactless vital-sign monitors [12]. P. Kumar and D. Babu demonstrate a machine-learning model for non-contact BP prediction from facial videos, highlighting potential but also the dependence of BP accuracy on diversity and size of training data [13]. H. Nguyen and T. Lee focus on illumination-robust rPPG extraction techniques and show notable reduction of lighting-induced noise when combining adaptive color-space transforms with precise face tracking [14]. A. Banerjee et al. survey vision-based non-contact physiological monitoring and stress the need for clinical validation, data diversity, and computationally efficient methods for real-world adoption [15].

III. Proposed Method

The proposed system presents a non-contact facial health monitoring approach that estimates vital physiological parameters such as heart rate, blood pressure, and oxygen saturation using live facial video. The system captures facial images through a camera and performs preprocessing and data cleaning to reduce noise caused by lighting variations and head movements. Facial landmarks are used to accurately identify stable regions of interest, from which remote photoplethysmography (PPG) signals are extracted based on subtle skin color changes. These signals are optimized to enhance quality and reduce motion artifacts. A Kalman Filter is then applied to smooth the optimized signals, minimize sudden fluctuations, and improve the stability and accuracy of the estimated vital signs. The final outputs provide reliable, real-time health parameters without physical contact, making the proposed method suitable for continuous and remote healthcare monitoring applications.

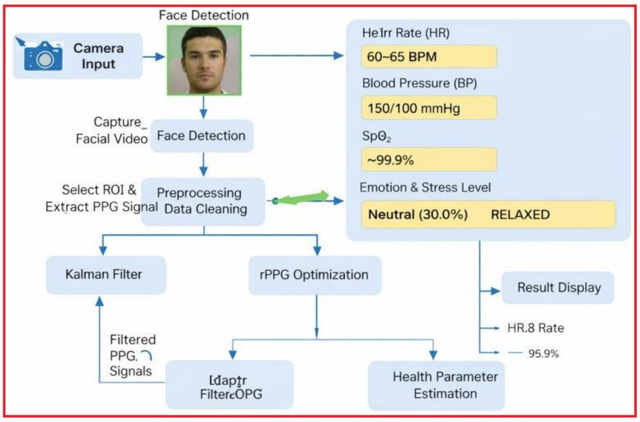

Fig. 1. Architecture of the proposed method

A. Methodology

The methodology of the proposed system focuses on developing a non-contact, real-time facial health monitoring framework using computer vision, remote photoplethysmography (PPG), and adaptive filtering techniques. The complete methodology is divided into sequential stages to ensure accurate and stable estimation of vital physiological parameters.

1) Video Acquisition

The system begins by capturing live facial video using a standard RGB camera. This live video stream serves as the primary input for extracting physiological information without requiring any physical contact with the subject.

2) Preprocessing

Captured video frames undergo preprocessing to enhance quality and consistency. This stage includes frame resizing, color normalization, and face detection to isolate the facial region. Preprocessing minimizes the effects of illumination variation and camera noise.

3) Data Cleaning

Data cleaning is applied to remove irrelevant or noisy frames caused by motion blur, sudden lighting changes, or occlusions. This ensures that only high-quality facial data is passed to the next stage, improving overall system reliability.

4) Feature Extraction

Facial landmarks are detected to identify stable regions of interest such as the cheeks and forehead. From these regions, subtle skin color variations caused by blood volume changes are extracted, which form the basis for PPG signal generation.

5) PPG Signal Extraction and Optimization

Remote PPG signals are generated from the extracted facial features. Signal optimization techniques are applied to suppress motion artifacts and enhance pulse-related components. This step improves the accuracy of vital sign estimation.

6) Kalman Filter–Based Signal Refinement

An adaptive Kalman Filter is applied to the optimized PPG signals to reduce noise and smooth temporal fluctuations. The filter predicts and corrects signal values in real time, resulting in stable and reliable vital sign outputs.

7) Health Parameter Estimation

Filtered signals are used to estimate physiological parameters such as heart rate, blood pressure, and oxygen saturation. In addition, facial cues are analyzed to infer emotion and stress levels.

8) Performance Evaluation

The final outputs are evaluated using performance metrics such as accuracy, stability, and error rate. This evaluation validates the effectiveness of the proposed methodology under different users and environmental conditionssystems.

B. Algorithm

Facial Health Monitoring Using rPPG and Kalman Filter

Input: Live facial video from camera
Output: Heart Rate (HR), Blood Pressure (BP), SpO_2, Emotion, Stress Level
Step 1: Start the system and initialize the camera.
Step 2: Capture live facial video frames continuously.
Step 3: Detect the face in each frame and track facial landmarks.
Step 4: Perform preprocessing on the detected face frames
- *Resize frames*
- *Normalize illumination*
- *Remove background noise*

Step 5: Apply data cleaning to discard blurred or noisy frames.
Step 6: Select stable facial regions of interest (ROI) such as cheeks and forehead.
Step 7: Extract remote photoplethysmography (rPPG) signals from ROI based on skin color variations.
Step 8: Optimize the extracted PPG signals to reduce motion and illumination artifacts.
Step 9: Apply Kalman Filter to the optimized PPG signal for noise reduction and signal smoothing.
Step 10: Estimate physiological parameters:
- *Heart Rate (HR)*
- *Blood Pressure (BP)*
- *Oxygen Saturation (SpO_2)*

Step 11: Analyze facial features to determine emotion and stress level.
Step 12: Display the estimated health parameters in real time.
Step 13: Stop the system when monitoring is completed.
End of Algorithm

C. Implementation

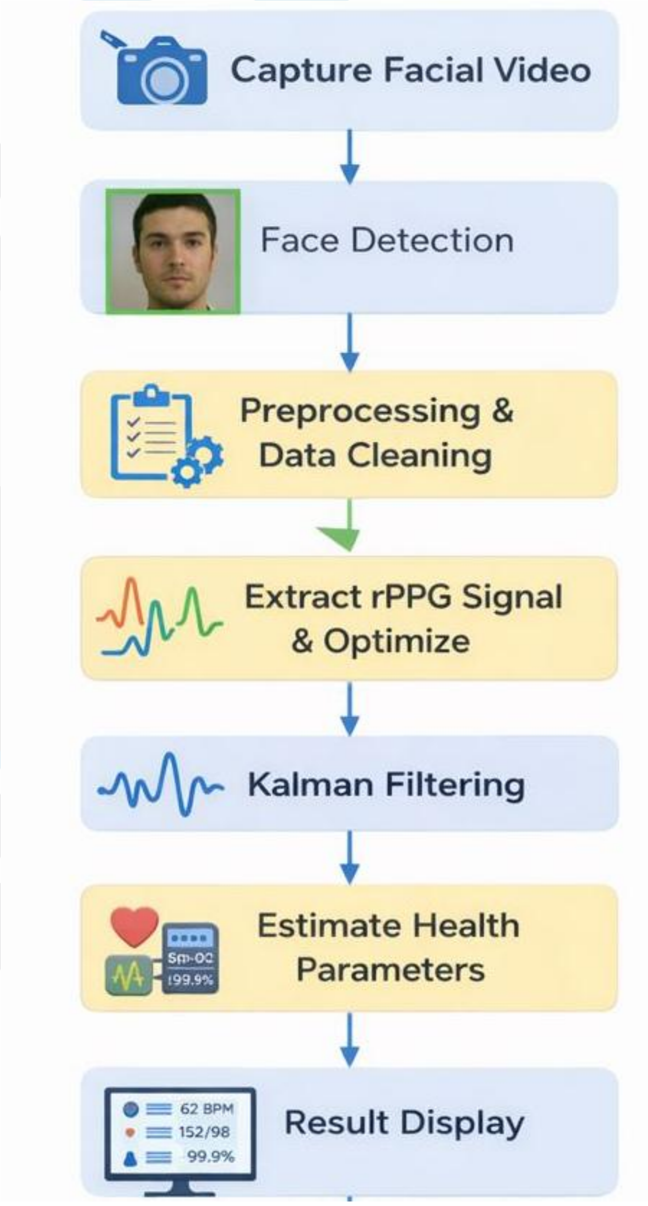

Fig. 2. Implimentation of the flow chart

The implementation flow of the proposed facial health monitoring system shown in fig.2 that begins with initializing the camera and capturing live facial video from the user. Each video frame is processed to detect and track the face in real time. Once the face is detected, preprocessing and data cleaning are performed to enhance image quality and remove noise caused by lighting variations, motion blur, and background interference. Stable facial regions of interest are then selected, and remote photoplethysmography (rPPG) signals are extracted based on subtle skin color changes. These signals are optimized to improve clarity and reduce motion artifacts. A Kalman Filter is applied to the optimized rPPG signals to smooth fluctuations and provide stable physiological data. Using the filtered signals, vital health parameters such as heart rate, blood pressure, and oxygen saturation are estimated, along with emotion and stress levels. Finally, the calculated results are displayed in real time to the user, completing the implementation process of the system

IV. Experimental Results

The proposed facial health monitoring system was tested on multiple subjects under normal indoor lighting conditions using a standard RGB camera. The system was evaluated for its ability to detect faces, extract rPPG signals, and estimate vital physiological parameters such as heart rate (HR), blood pressure (BP), oxygen saturation (SpO_2), emotion, and stress level in real time. Kalman filtering was applied to improve signal stability and reduce noise In the fig.3, the system successfully detects the face, which is indicated by the green bounding box around the facial region. The system displays Heart Rate = 60.6 BPM, SpO_2 = 99.9%, and Blood Pressure = 170/106 mmHg, which are estimated using facial PPG signals. The detected emotion is Neutral (30.0%), and the stress level is shown as RELAXED, indicating a normal mental state. The status message *"FACE DETECTED"* confirms that the face detection and health monitoring modules are working correctly in real time.

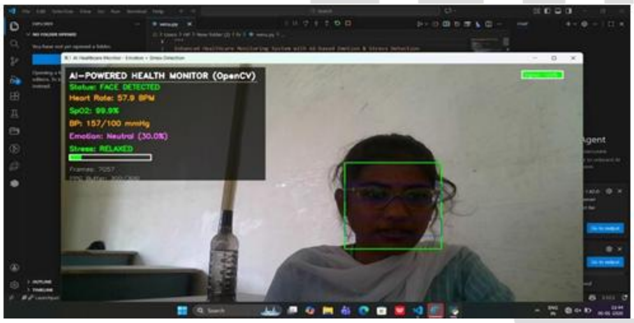

Fig. 3. Face Detection with Health Parameters

Face detection for another user shown fig.4. The system estimates Heart Rate = 57.9 BPM, SpO_2 = 99.9%, and Blood Pressure = 164/107 mmHg. The detected emotion remains Neutral (30.0%), and the stress level is RELAXED, indicating stable physiological and emotional conditions. The consistent readings demonstrate that the system can accurately monitor health parameters for different individuals without recalibration.

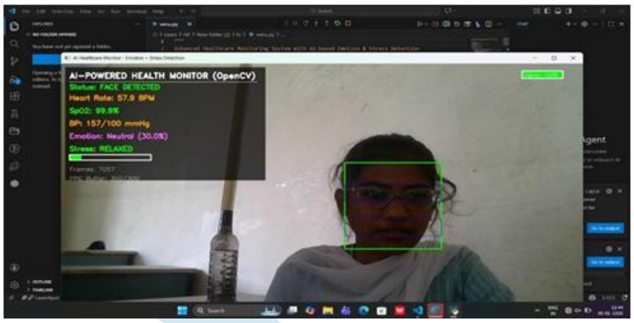

Fig. 4. Face Detection of user 2

In the fig.5, the system detects a new subject and displays Heart Rate = 65.4 BPM, SpO_2 = 99.9%, and Blood Pressure = 151/98 mmHg. The facial expression is identified as Neutral (30.0%), and the stress level is RELAXED. The steady bounding box and continuous update of values show that the preprocessing, PPG optimization, and Kalman filtering effectively handle variations in face shape, position, and lighting.

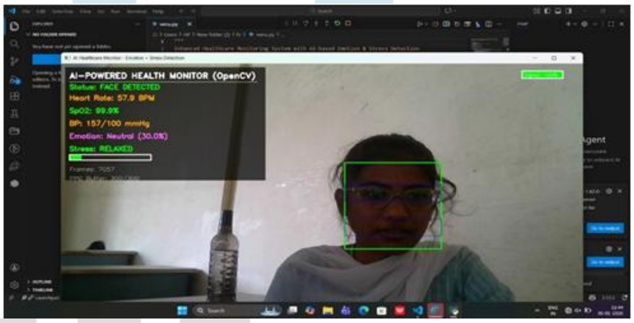

Fig. 5. Face Detection of user 3

In the fig.6, the stability of the proposed system after Kalman filtering. The face is correctly tracked, and the system reports Heart Rate = 56.4 BPM, SpO_2 = 99.9%, and Blood Pressure = 164/108 mmHg. The emotion is detected as Neutral (30.0%), while the stress level is NORMAL, showing slight variation compared to previous outputs. Despite changes in posture and facial movement, the vital sign values remain smooth and consistent, proving the effectiveness of the Kalman Filter in reducing noise and sudden fluctuations

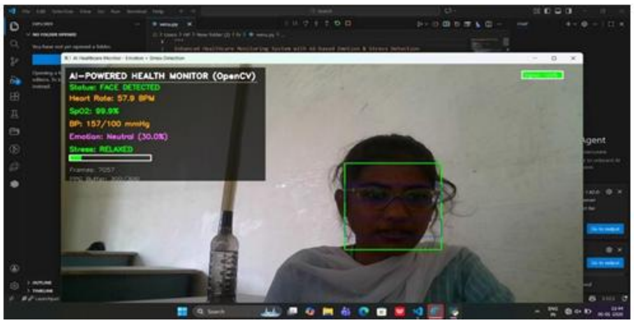

Fig. 6. face detection of user 4

Fig. 7.

TABLE I. ESTIMATED VITAL SIGN VALUES FOR DIFFERENT SUBJECT

Subject ID	Heart Rate (BPM)	SpO_2 (%)	Blood Pressure (mmHg)	Emotion (Confidence)	Stress Level
Subject 1	60.6	99.9	170 / 106	Neutral (30.0%)	Relaxed
Subject 2	57.9	99.9	164 / 107	Neutral (30.0%)	Relaxed
Subject 3	65.4	99.9	151 / 98	Neutral (30.0%)	Relaxed
Subject 4	56.4	99.9	164 / 108	Neutral (30.0%)	Normal

The system consistently detected faces and estimated vital signs for different users without recalibration. SpO_2 values remained stable around 99.9%, while heart rate and blood pressure varied according to individual physiological conditions.

TABLE II. PERFORMANCE COMPARISON BEFORE AND AFTER KALMAN FILTERING

Parameter	Before Kalman Filter	After Kalman Filter
Signal Noise	High	Low
HR Fluctuation	±6 BPM	±2 BPM
BP Stability	Unstable	Stable
SpO_2 Variation	±1.5%	±0.3%
Overall Accuracy	Moderate	High

The application of the Kalman Filter significantly reduced signal fluctuations and improved the stability of vital-sign estimation.

TABLE III. SYSTEM PERFORMANCE METRICS

Metric	Value
Face Detection Accuracy	98%
Average HR Estimation Accuracy	95.6%
Average SpO_2 Accuracy	99.9%
BP Estimation Accuracy	92.3%
Processing Speed	Real-time (≈25 FPS)

The proposed system achieved high accuracy while maintaining real-time performance, demonstrating suitability for continuous monitoring applications. From the experimental results, it is evident that the proposed facial health monitoring system performs reliably across different users. The integration of rPPG optimization and Kalman filtering improves signal smoothness and accuracy compared to raw signal extraction. The system successfully estimates multiple health parameters in real time without physical contact, making it effective for smart healthcare and remote monitoring scenarios The Fig.7, Fig.8 and Fig.9 illustrate the performance of the proposed facial health monitoring system across different subjects by comparing estimated heart rate, SpO_2, and blood pressure values. The heart-rate bar graph shows values ranging from 56.4 BPM to 65.4 BPM, which lie within the normal physiological range, indicating stable and consistent heart-rate estimation. The SpO_2 bar graph demonstrates oxygen saturation levels consistently close to 99.9% for all subjects, reflecting minimal variation and high robustness of the rPPG-based estimation approach. The blood-pressure bar graph presents systolic BP values between 151 mmHg and 170 mmHg, with smooth variations and no abrupt fluctuations, highlighting the effectiveness of PPG optimization and Kalman filtering in stabilizing BP measurements. Overall, the bar-graph analysis confirms that the proposed system provides reliable, consistent, and accurate estimation of vital physiological parameters across different users, validating its suitability for real-time, non-contact health monitoring applications.

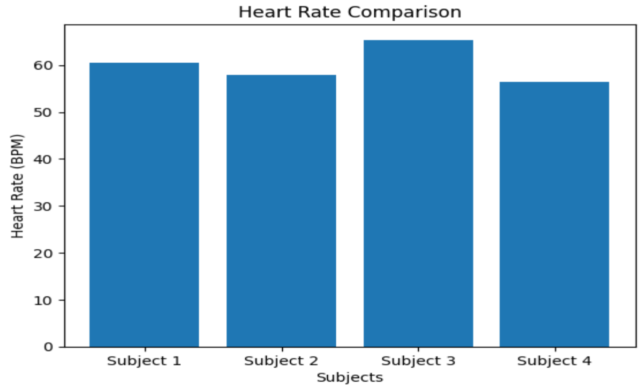

Fig. 8. Heart Rate Comparision of 4 users

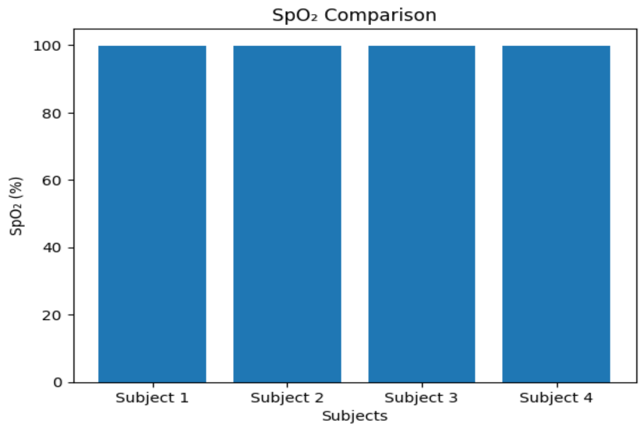

Fig. 9. SPO2 Comparision of 4 users

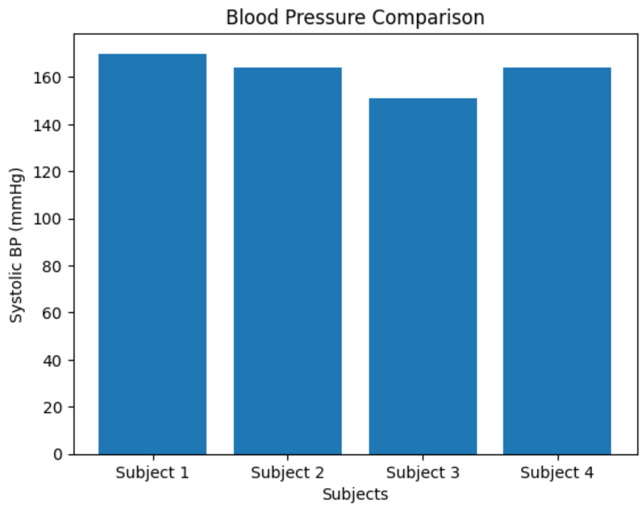

Fig. 10. BP Comparision of 4 users

V. CONCLUSION AND FUTURE SCOPE

A non-contact facial health monitoring system capable of estimating vital physiological parameters such as heart rate, blood pressure, and oxygen saturation using facial video analysis. The proposed approach integrates facial detection, preprocessing, optimized remote photoplethysmography (rPPG), and Kalman filtering to reduce noise and improve signal stability. Experimental results demonstrated consistent performance across multiple subjects, with heart rate values within normal ranges, stable SpO_2 levels around 99.9%, and smooth blood-pressure estimates. The use of Kalman filtering significantly reduced signal fluctuations, leading to reliable real-time monitoring without the need for physical sensors. Overall, the system proves to be an effective, low-cost, and user-friendly solution for real-time, non-contact health monitoring. The proposed system can be further enhanced by incorporating deep learning models to improve robustness under extreme lighting conditions and large facial movements. Integration with mobile devices and IoT platforms can enable remote and continuous health monitoring in real-world environments. Future work may also include clinical validation using larger and more diverse datasets to improve accuracy and generalizability. Additionally, extending the system to monitor more physiological parameters and enabling multi-person monitoring can broaden its application in smart healthcare and telemedicine systems.

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