International Research Journal on Advanced Engineering Hub (IRJAEH)
e ISSN: 2584-2137
Vol. 02 Issue: 11 November 2025
Page No: 4143-4147
https://irjaeh.com
https://doi.org/10.47392/IRJAEH.2024.0607

A Flexible Random Forest Regressor-Based Algorithm for Predicting Heart Rate Through Facial Video

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Abstract

A continuous, non-invasive monitoring of vital signs like heart rate is crucial in modern healthcare for early detection of cardiovascular abnormalities and supporting telemedicine growth. Traditional methods, such as ECG and PPG, rely on contact-based sensors that are often uncomfortable, costly, and unsuitable for long-term or remote monitoring. This project introduces a fully software-based, contactless heart rate estimation system utilizing a standard webcam. The system applies computer vision techniques to detect facial regions of interest (forehead and cheeks) and machine learning models to interpret subtle blood-flow-induced color variations from facial video. The proposed pipeline includes face detection, region tracking, signal extraction, preprocessing, feature computation, and machine learning prediction using Random Forest Regressor Model. The developed system performs reliably across different lighting conditions, skin tones, and facial movements, achieving near real-time operation. This work highlights the potential of using accessible consumer hardware for accurate, contactless physiological monitoring, paving the way for integration in telemedicine, remote patient monitoring, and personal fitness applications.

Keywords: *Machine Learning, Heart Rate Estimation, Facial Video, Computer Vision, Remote Photoplethysmography (rPPG), Artificial Intelligence, Contactless Monitoring, Telemedicine.*

1. Introduction

1.1. Overview

In recent years, remote health monitoring has become a key area of research in biomedical engineering and artificial intelligence. Traditional heart rate measurement methods such as Electrocardiography (ECG) and Photoplethysmography (PPG) require wearable sensors that make continuous use inconvenient and uncomfortable. With the advancement of computer vision and machine learning, researchers are now able to analyze facial video signals to estimate vital signs without physical contact. The core principle of this work relies on Remote Photoplethysmography (rPPG) — the measurement of pulse signals from facial color changes caused by the periodic flow of blood beneath the skin. These color variations, although invisible to the human eye, can be captured by a webcam and processed to predict the user's heart rate. The proposed system implements this principle by combining computer vision, signal processing, and machine learning to develop a reliable and affordable solution for continuous health monitoring [1-3].

1.2. Motivation

Current heart rate monitoring devices are either contact-based or costly, and they require user compliance for consistent results. Prolonged use of wearables may cause discomfort and skin irritation, especially during exercise or sleep. Moreover, in the era of telemedicine and home-based healthcare, there is an increasing demand for non-invasive and real-time monitoring systems that can operate using commonly available hardware such as webcams. Artificial intelligence (AI) and computer vision offer a promising direction for this purpose, enabling accurate physiological measurements without physical contact. This project aims to provide a low-cost, contactless, and intelligent system that can track heart rate continuously and efficiently using facial video.

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1.3. Problem Statement
To develop a smart, contactless heart rate monitoring system that leverages facial video analysis and the Random Forest Regressor model to accurately predict heart rate in real time, providing a non-invasive, low-cost, and user-friendly solution for remote and continuous health monitoring.

1.4. Objectives
- To monitor heart rate using a standard webcam without any physical contact.
- To detect the face and identify stable regions such as the forehead and cheeks for analysis.
- To track subtle color changes in these regions caused by blood flow and convert them into usable signals.
- To apply machine learning algorithms, particularly Random Forest, to estimate heart rate in BPM.
- To ensure real-time accuracy under varied lighting and facial motion.
- To deliver a user-friendly, low-cost, and portable system suitable for telehealth applications [4-7].

2. Literature Review
Researchers have explored various contactless methods for heart rate estimation, focusing on optical signal processing and machine learning models. Duan et al. (2025) proposed an improved Singular Spectrum Analysis (SSA)-based algorithm for video heart rate detection, optimizing noise reduction. Nam et al. (2025) presented a remote photoplethysmography approach using unsupervised learning to improve accuracy acrossusers. Acharya et al. (2025) developed machine learning-based systems to generalize heart rate estimation across different datasets. Bondarenko (2025) highlighted that selecting appropriate facial regions of interest (ROI) greatly influences estimationaccuracy. Li et al. (2024) utilized feature-based machine learning approaches, improving real-time performance and model adaptability. From these studies, it is evident that while existing approaches achieve good accuracy, most struggle with variations in lighting, movement, and camera quality. This research bridges these gaps by integrating Random Forest regression with efficient ROI selection to provide stability and precision in practical settings.

3. Methodology
3.1. System Overview
The proposed system is designed as a sequential pipeline that transforms raw video frames from a webcam into a real-time heart rate (BPM) estimate. The core principle is Remote Photoplethysmography (rPPG), enhanced with machine learning for improved robustness. The system operates by capturing facial video, locating regions with strong blood perfusion, extracting color signals, processing them to isolate the cardiac component, and feeding the resulting features into a trained ML model for final prediction [8-10].

3.2. System Architecture
The high-level architecture of the system is modular, consisting of six core stages that ensure a clean separation of concerns and facilitate development and testing. The data flow through the system is illustrated below:

Figure 1 Flowchart

3.3. Detailed Workflow
3.3.1. Video Acquisition Module
This is the entry point of the system. • Input: Live feed from a standard USB webcam. • Specifications: The system is configured to capture video at 30 frames per second (fps) with a resolution of 640x480 pixels. This resolution provides a good balance between computational load and sufficient spatial detail for face detection, Shown in Figure 1.
- **Process:** The OpenCV library is used to interface with the webcam. Each captured frame is converted from the default BGR color space to RGB for consistent processing.

3.3.2. Face Detection and ROI Selection Module
This module identifies the user's face and pinpoints

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the areas for signal analysis.

- **Face Detection:** We employ Haar Cascade classifiers and MediaPipe Face Detection for their speed and accuracy. The face is detected in the first frame and tracked in subsequent frames to reduce computational cost and jitter.
- **Landmark Detection & ROI Selection:** Upon face detection, facial landmarks (e.g., using MediaPipe) are located. Based on these landmarks, rectangular regions are defined for the forehead and both cheeks. These ROIs are selected for their relatively stable skin exposure and rich subsurface blood perfusion.
- **ROI Tracking & Validation:** The ROIs are tracked across frames. A skin-segmentation check can be applied to exclude non-skin pixels, and the system can revert to face detection if tracking is lost.

3.3.3. Signal Extraction and Preprocessing Module

This module is responsible for isolating the weak physiological signal from the raw video data.

- **Signal Extraction:** For each frame and for each selected ROI, the average pixel intensity for the Red, Green, and Blue (RGB) channels is computed. This results in three raw temporal signals: R(t), G(t), and B(t), where t is the frame index. The green channel typically carries the strongest PPG signal due to hemoglobin's absorption characteristics.
- **Preprocessing Pipeline:** The raw signals are noisy and contain artifacts. A multi-stage preprocessing pipeline is applied:
- **Detrending:** A smoothing filter (e.g., Savitzky-Golay) is used to remove slow, non physiological trends caused by ambient light changes or major movements.
- **Bandpass Filtering:** A zero-phase Butterworth bandpass filter (0.7 Hz - 4.0 Hz) is applied. This corresponds to a heart rate range of 42 to 240 BPM, effectively filtering out noise outside the physiological range (e.g., high-frequency camera noise and very low-frequency drift).
- **Signal Quality Assessment**: The Signal-to-Noise Ratio (SNR) is estimated for the filtered signal within the cardiac band. This can be used to weight or select the most reliable ROI signal for further analysis.

3.3.4. Feature Extraction Module

To enable machine learning, the preprocessed signal is transformed into a set of descriptive features.

- Time-Domain Features:
- Mean, Standard Deviation, Skewness, Kurtosis of the signal.
- Peak count and inter-peak intervals.
- Frequency-Domain Features:
- Dominant Frequency: The frequency with the highest power in the bandpass range, found using a Fast Fourier Transform (FFT). This is directly converted to a nominal BPM.
- Spectral Power: The total power and the ratio of power inside the cardiac band to the power outside it.
- Cross-Channel/ROI Features:
- Correlation coefficients between signals from different ROIs and color channels.

3.3.5. Machine Learning Model

This is the core intelligence of the system, where the extracted features are mapped to a heart rate value.

- Model Selection: We evaluate and compare several regression models:
- Random Forest Regressor: Chosen for its robustness to non-linear data and feature scaling, and its inherent resistance to overfitting.
- Support Vector Regressor (SVR): Effective in high-dimensional spaces, especially with non-linear kernels like the Radial Basis Function (RBF).
- XGBoost Regressor: A high-performance gradient-boosting algorithm known for its predictive accuracy.
- 1D-CNN/LSTM (Deep Learning): These models are explored to learn features directly from the preprocessed signal sequences, potentially capturing more complex temporal patterns.
- Training Strategy:
- Data Segmentation: The continuous signal is divided into overlapping windows (e.g., 30

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second windows with a 15-second stride).

- Ground Truth: Each window is labeled with the average heart rate from a synchronized reference PPG sensor.
- Validation: Subject-Independent (Leave-One-Subject-Out) cross-validation is used to rigorously test the model's ability to generalize to new, unseen individuals.

3.3.6 Output and Visualization Module

This module presents the sresults to the user in an intuitive manner.

- **Real-Time Display:** The estimated BPM is displayed numerically on the live video feed.
- **Graphical Feedback:** A real-time plot of the filtered PPG-like signal is shown, providing visual confirmation of the signal quality.
- Confidence Indicator: A simple indicator can inform the user about the reliability of the current reading based on the estimated SNR.

3.4. Hardware and Software Specifications

A clear specification ensures reproducibility and defines the system's requirements, shown in Table 1.

Table 1 Hardware and Software Specifications

Hardware

Category	Specification
Computer	Standard Desktop/Laptop
Processor (CPU)	Intel i5 or equivalent
RAM	8 GB
Webcam	Standard USB Webcam

Software

Category	Specification
Operating System	Windows 10/11, Linux
Programming Language	Python 3.8+
Key Libraries	OpenCV, Scikit-learn, NumPy, SciPy, Matplotlib, MediaPipe, TensorFlow/PyTorch

4. Implementation

The proposed system for heart rate prediction is implemented in multiple stages — from data acquisition to prediction and evaluation. Each stage performs a crucial role in ensuring accurate and stable real-time heart rate monitoring.

4.1. Tools and Technologies Used

The system is developed using Python programming language for its flexibility and wide library support in data processing, computer vision, and machine learning.

Tool / Library	Purpose / Functionality
Python 3.10	Core development language
OpenCV	Video capture, face detection, image preprocessing
MediaPipe / Haar Cascade	Facial landmark and ROI (Region of Interest) detection
NumPy & SciPy	Mathematical operations, signal filtering, normalization
Matplotlib	Visualization of extracted signals and model performance
Scikit-learn	Machine learning (Random Forest Regressor model)
VS Code / Anaconda	Development environment and runtime management
Hardware	Standard laptop webcam (720p), Intel i5 processor, 8 GB RAM

Figure 2 Image

4.2. Data Collection

Facial videos were recorded from 30 individuals under controlled, low-light, and motion conditions. Ground truth heart rate values were obtained using a pulse oximeter for model training and evaluation, Shown in Figure 2.

4.3. Preprocessing

The input video is divided into frames, and the face is detected using Haar Cascade or MediaPipe. Regions like the forehead and cheeks are extracted as ROIs. The average RGB values from each frame form a time-series signal, which is then filtered using a Butterworth Bandpass Filter (0.7–4 Hz) to remove noise and illumination drift.

4.4. Feature Extraction

From the filtered signal, both time-domain (mean, variance) and frequency-domain (dominant frequency, spectral power) features are extracted for model input.

4.5. Machine Learning Model

A Random Forest Regressor is trained on labeled feature data to learn the relationship between extracted features and heart rate. The trained model predicts BPM in real time, updating every few seconds.

4.6. Performance

Testing under different conditions yielded high accuracy with an average MAE of 3.1 BPM and correlation coefficient of 0.93. The system works efficiently on standard hardware and produces consistent results across varying lighting and motion scenarios.

5. Results and Discussions

The proposed system was tested using facial videos from multiple users under different lighting and motion conditions. The Random Forest Regressor

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model accurately predicted heart rate by analyzing color variations from facial regions. The system achieved an average accuracy of 95%, with a Mean Absolute Error (MAE) of 3.1 BPM. Results show that the predicted heart rate values closely matched the ground truth data obtained from a pulse oximeter. The model performed well in controlled and natural lighting, with minimal deviation during slight head movements. Thus, the proposed method proved to be reliable, efficient, and suitable for real-time, contactless heart rate monitoring applications.

Conclusion

The proposed system provides an effective contactless heart rate estimation method using facial video analysis and machine learning techniques. By employing the Random Forest Regressor, the system successfully predicts heart rate with high accuracy in real time. It eliminates the need for physical sensors and ensures comfort and convenience for continuous monitoring. The model performs efficiently under different lighting and motion conditions, making it suitable for applications in telemedicine, fitness tracking, and remote health monitoring. Overall, the system is low-cost, non-invasive, and user-friendly, demonstrating that camera-based heart rate prediction can serve as a promising alternative to traditional contact-based devices.

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