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AI-Assisted Remote Health Monitoring Using Remote Photoplethysmography Signals for Stress Detection and Vital Sign Alerting

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Abstract. Photoplethysmography (PPG) is a basic technology that enables non-invasive vital sign monitoring through traditional contact pulse oximeters that measure blood volume and heart rate. The need for physical contact limits traditional PPG systems from operating continuously, as they require direct contact, which creates patient discomfort during long monitoring sessions and leads to skin-related problems and hygiene concerns. Remote Photoplethysmography (rPPG) is a contactless method that uses ambient light and standard RGB cameras to capture facial video data for physiological signal detection. Technology fails to reach its full potential because real-world environments introduce motion artifacts and changing lighting conditions. This makes clinical alerting data unreliable. The research introduces a new framework that links theoretical concepts to actual implementation methods. Our approach begins with multiple facial regions analyses to obtain baseline data, which we then feed into the Dilated Attention-ResNet-BiGRU deep learning network. The system learns to convert distorted visual inputs into precise waveforms that match the quality of contact sensors used as gold-standard references. The clean signal enables HRV calculation and estimation of physiological stress levels because it blocks both illumination disturbances and movement-related noise. This technology offers strong potential for ongoing surveillance, benefiting senior citizens and patients who need medical supervision after surgical procedures. The system delivers fast computational power while generating precise vital signs and providing an operational, real-time system that alerts users to stress and health abnormalities.

Keywords: rPPG, remote health monitoring, vital signs, stress detection, deep learning, signal processing, ResNet, GRU.

1. INTRODUCTION

The healthcare field of today has begun to replace its traditional reactive treatment practices with preventive methods which focus on maintaining continuous patient wellness. The main objective of this transformation requires continuous monitoring of vital signs which include heart rate and oxygen saturation levels. The task requires contact-based devices which include ECG electrodes and finger-mounted pulse oximeters for its completion. These medical devices function well in healthcare facilities but patients must wear them on their bodies which lead to discomfort and limits their movement and makes them inappropriate for extended or regular use.

Remote photoplethysmography (rPPG) stands out as an innovative solution which enables researchers to overcome these system constraints. The method enables physiological signal estimation through skin color change detection with ordinary camera equipment which does not require any physical sensors. Although rPPG offers significant theoretical advantages, its practical deployment remains challenging. The system experiences major performance issues because of two main factors which include lighting variations and human body movements that produce strong interference in the signal data. The waveforms produced by traditional rPPG methods which include CHROM and POS differ substantially from the actual ground-truth signal as demonstrated in Fig. 2.The system shows multiple technical problems, but it also faces a critical issue which most users fail to understand because different skin colors and facial features create additional challenges for its trustworthiness. The system faces two core challenges which include its technical problems and demographic bias because different skin tones and facial features produce separate obstacles which affect its reliability.

The COVID-19 health crisis created a global demand for contactless medical monitoring systems which triggered worldwide expansion of this technology. The current research aims to solve the operational challenges which affect present rPPG systems. The project aims to create an AI system which will deliver dependable vital sign monitoring through a fair system that works in actual clinical settings.

2. RELATED WORK

A survey of existing literature shows that health monitoring systems have evolved from contact-based methods to non- contact AI-based approaches which represent the current state of the field. The section analyzes important research work by categorizing them according to their main areas which include signal processing and deep learning architectures and solutions for specific rPPG challenges to establish the foundation for our research.

A. Foundational and Signal Processing Approaches

The first remote health monitoring systems which Sumathi and colleagues presented for pregnant women used contact- based technology to monitor vital signs through common devices. Their system achieves great results but depends entirely on physical sensors which restricts its use for non- invasive applications. The research community started to adopt non-contact methods which scientists used signal-processing principles to develop algorithms that extracted rPPG signals from RGB video footage.

Haugg and his team performed detailed evaluations of conventional rPPG construction methods which included POS and LGI and CHROM algorithms to find out that each algorithm performs best under different conditions because their results depend on patient movements and environmental illumination levels [18]. The authors developed GRGB in their following research which represents a basic ratio-based approach that delivers strong results while using minimal computational resources to beat more expensive methods in indoor environments [14]. The field of signal processing has multiple approaches which work to reduce the impact of unwanted background noise in signals. The research team Islam et al.

[4] developed SPECMAR which applies spectral subtraction to accelerometer data for generating motion reference signals that help remove noise from contact PPG signals. The solution required a two-step video processing approach which Abdulrahaman [10] developed through wavelet denoising to eliminate motion artifacts from rPPG signals. The pre-processing stage functions as an essential part of the process because Guler et al. [19] demonstrated through their detailed study on digital filter selection which showed how filter selection (including Chebyshev II) determines the signal-to-noise ratio before any advanced analysis is performed.

B. Transition to Machine Learning and Deep Learning

The natural limitations which algorithms face during noise processing in real-world situations resulted in machine learning becoming the preferred solution. The researchers Qaadan and his team developed a combined evaluation system which tested classical machine learning regression models including Random Forest and XGBoost and their results showed that CHROM features which represent chrominance data functioned as the most reliable base for heart rate measurement. The authors explained that traditional pipelines do not have the ability to process time-based data because deep learning methods solve this particular limitation.

Deep learning systems have demonstrated strong capabilities when they work to understand physiological signals which need interpretation. The research by Karapinar and Sevinc [3] proved that a one-dimensional convolutional neural network could predict heart rate through clean contact PPG signals which demonstrated deep learning effectiveness for time-series data but failed to solve the primary noise elimination problem of rPPG. The base paper for our work, Chowdhury et al. [11], made a significant step in this direction with ”LGI-rPPG-Net.” Their system contains a shallow neural network which functions as an encoder-decoder for transforming raw noisy rPPG signals into accurate waveform signals. The re- searchers established a performance benchmark through their lightweight system which achieved a MAE of 1.51 bpm to demonstrate AI-based signal enhancement techniques which form the basis of our method.

C. Advanced Solutions for Key rPPG Challenges

Recent research has focused on developing specialized modules to handle the distinct and difficult challenges of real- world rPPG.

1) Illumination, Motion, and Compression Robustness: To handle variable illumination, Chen et al. [8] proposed an Image Enhancement Model (IEM) as a pre-processing step, demonstrating that improving video quality before signal extraction consistently enhances accuracy. Javidh et al. [13] extended this concept by developing ”CHROM-Y,” a 2D feature representation that fuses luminance (Y) with chrominance signals, making the input to the neural network inherently more robust to lighting changes.

For high-motion scenarios, Zhu et al. [9] conducted a comparative study during fitness activities, finding that a synergistic combination of principled modules—including optical flow for motion compensation and adaptive filtering—was highly effective. Addressing a different type of motion, Lokendra & Puneet [12] introduced AND-rPPG, a novel network that uses facial Action Units (AUs) to provide the model with explicit contextual information about non-rigid facial expressions, enabling more effective denoising. A unique challenge, video compression artifacts, was addressed by Yu et al. [16], who developed a two-stage network to first enhance the quality of compressed videos before performing rPPG extraction.

2) Advanced Applications and Methodological Reviews: Moving beyond simple heart rate estimation, Lee et al. [5] and Qayyum et al. [6] proposed advanced methods for extracting Heart Rate Variability (HRV) for stress analysis. Lee et al. developed a unique method which splits data through Normal- to-Normal Interval (NNI) analysis to enhance stress index prediction by considering personal variations in resting heart rate. Qayyum et al. used a sparse representation approach to re- construct a clean signal for multi-parameter (HR, HRV, SpO2) estimation. The review by Pirzada et al. [7] demonstrates that motion robustness and demographic fairness and clinically validated systems still require substantial development which supports our research objectives.

D. The Critical Role of Datasets and Benchmarking

The development of deep learning systems for rPPG de- pends directly on the availability of extensive high-quality datasets which contain vast amounts of data. Researchers

faced a common problem because their first datasets contained only small amounts of data which failed to represent various population groups. The recent initiatives work to develop complete resource collections which address this issue. Egorov et al. [17] released MCD-rPPG which serves as a massive dataset containing multiple perspectives and various data types alongside accurate biomarker information. The VitalVideos-Worldwide dataset by Toye Pieter-Jan [20] contains 7000 participants who came from three different continents and the dataset provides complete ECG ground truth information. The training process needs these datasets to develop new rPPG models which maintain both strength and equality for all users.

TABLE I

COMPARISON OF RPPG METHODOLOGIES

Category	Algorithm	Core Strength	Major Limitation
Mathematical	CHROM/POS	Low Computational Cost	Sensitive to Light
Spatial CNN	DeepPhys	Handles Texture well	Weak Temporal Logic
Spatio-Temporal	PhysNet	High Waveform Accuracy	High Latency
Proposed	**ResNet-BiGRU**	**Rhythmic Precision**	**Requires Calibration**

3. SYSTEM ARCHITECTURE AND METHODOLOGY

Our framework, depicted in Fig. 1, is designed as a robust, end-to-end pipeline. The methodology is divided into a signal engineering pipeline, a deep learning core for signal transformation, and a clinical interpretation engine.

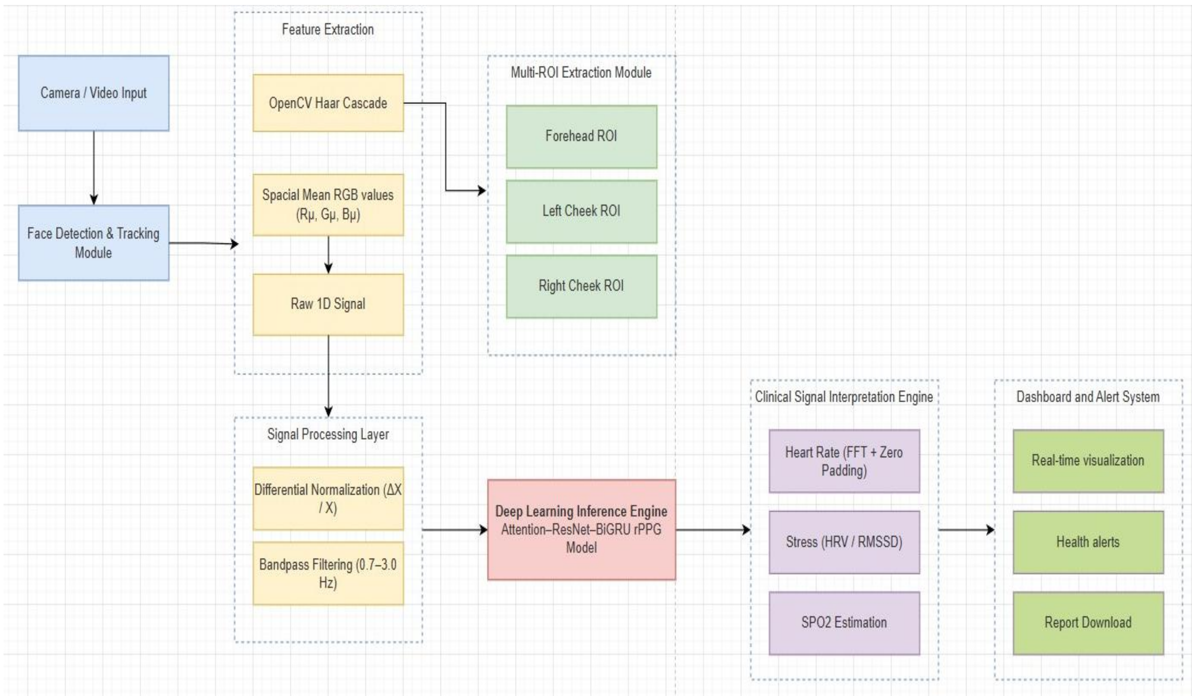

Fig. 1. The end-to-end framework of the proposed system.

Raw video input is processed by a Face Detection & Tracking Module. The raw 1D signal from the Feature Extraction stage is then passed through the Signal Processing Layer before being fed into our Deep Learning Inference Engine. The reconstructed high-fidelity signal is finally interpreted by the Clinical Signal Interpretation Engine to produce the final dashboard output.

A. Preprocessing Pipeline

1) Spatial Feature Extraction: The system uses a Haar Cascade Classifier to detect and track the face. Three Regions of Interest (ROI) are defined: the Forehead (ROI_{fh}), Left Cheek (ROI_{lc}), and Right Cheek (ROI_{rc}). For each frame *t*, the spatial mean of the RGB channels across all ROIs is calculated:

$$C_\mu(t) = \frac{1}{N}\sum_{i=1}^{N} P_i\,(t) \qquad (1)$$

where P_i is the pixel intensity and N is the total number of pixels.

2) Differential Normalized Signal: To ensure robustness against lighting variations in the BH-rPPG dataset, we im- plement Temporal Differential Normalization to isolate the pulsatile AC component from the DC component:

$$\Delta X(t) = \frac{X(t)-X(t-1)}{X(t)+X(t-1)} \qquad (2)$$

This normalizes signal amplitude, making the model less sensitive to changes in illumination.

3) Bandpass Filtering: A 4th-order Butterworth filter with cutoff frequencies of $flow = 0.7$ Hz and $fhigh = 3.0$ Hz removes non-physiological noise.

B. Model Architectures for Comparison

Following feedback from our previous review, we implement and compare two advanced AI architectures for the signal transformation task.

1) Model 1: Dilated Attention-ResNet-BiGRU Network: Our primary model is a 16-layer hybrid architecture. It in- cludes Dilated 1D-Convolutions to expand the temporal receptive field, a Multi-Head Self-Attention layer to dynami- cally focus on artifact-free signal portions, Residual Blocks to enable deep feature extraction, and a Bidirectional GRU (BiGRU) to capture the long-term temporal dependencies of the cardiac cycle.

2) Model 2: Dual-Stream Fusion Network: Our second model for comparative analysis is a context-aware architecture that explicitly separates the physiological signal from motion noise. It features a Physiological Stream (using our primary ResNet-BiGRU model) and a parallel Motion Stream that processes explicit motion data from facial landmarks. An Attention-Based Fusion module then intelligently combines the outputs to dynamically subtract learned noise patterns from the physiological signal.

C. Hybrid Loss Function

To optimize for physiological accuracy, we employ a custom weighted ”Triple-Threat” hybrid loss function:

$$L_{Total} = (1.0 \cdot L_{Pearson}) + (0.5 \cdot L_{SNR}) + (0.1 \cdot L_{MSE}) \quad (3)$$

where $L_{Pearson}$ focuses on temporal peak alignment, L_{SNR} enforces a clean frequency peak, and L_{MSE} maintains the waveform’s amplitude scale.

D. Clinical Interpretation Engine

1) Heart Rate (BPM): HR is derived from the dominant frequency peak of a 2048-point Zero-Padded FFT, increasing resolution to 0.88 BPM.

2) Stress Detection (HRV): Stress is estimated by calculating the Root Mean Square of Successive Differences (RMSSD). Low RMSSD (<30ms) is clinically linked to high stress.

4. EXPERIMENTAL SETUP

A. Dataset and Data Stratification

The primary dataset for this work is BH-rPPG, containing 35 subjects under three distinct lighting conditions. We enforce a strict subject-wise split (80% train, 20% validation) to prevent data leakage. Raw videos are segmented into 128- frame windows (∼4.2 seconds) with a 50% overlap to augment the training data.

B. Evaluation Metrics

Model performance is evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Pearson Correla- tion (r), and Clinical Zone Accuracy (Bradycardia, Normal, Tachycardia).

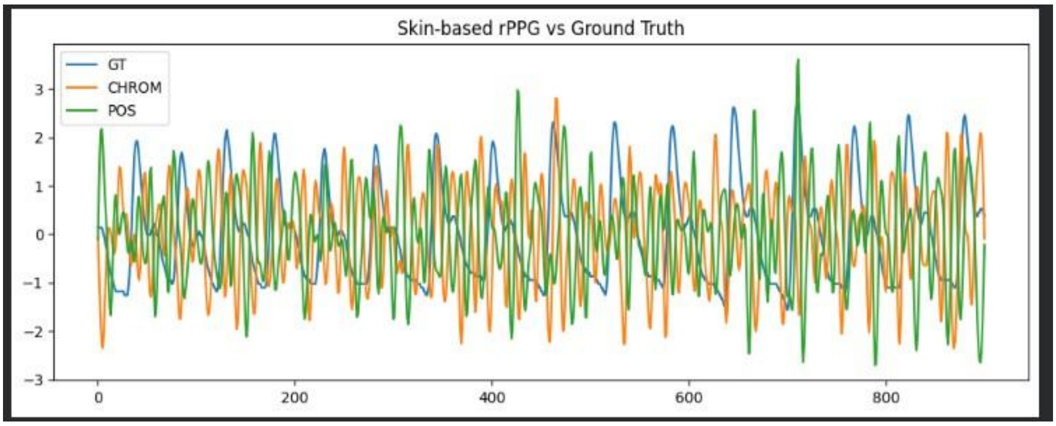

Fig. 2. Comparison of a ground-truth (GT) PPG signal with signals extracted using traditional rPPG methods (CHROM, POS). The significant noise and morphological differences highlight the need for an advanced signal enhance- ment model.

5. RESULTS AND DISCUSSION

The evaluation of the proposed AI-Assisted Remote Health Monitoring system was conducted in multiple stages, ranging from signal-level validation to high-level clinical classification. This section provides an in-depth analysis of the transition from noisy raw video data to actionable health insights.

TABLE II
SYSTEM-WIDE DIVERGENCE ANALYSIS: CONTACT SENSORS VS. AI-RPPG FRAMEWORK

Vital Sign Category	**Contact Sensor (PPG)**	**Proposed AI (rPPG)**	**Deviation (Δ)**
Heart Rate (Beats Per Minute)			
Normal (Resting)	72.4 BPM	75.1 BPM	+2.7 BPM
Low (Bradycardia)	58.5 BPM	61.2 BPM	+2.7 BPM
High (Tachycardia)	112.5 BPM	108.9 BPM	-3.6 BPM
Stress Level (RMSSD in ms)			
Normal (Moderate)	44.2 ms	48.5 ms	+4.3 ms
Relaxed (Low Stress)	78.1 ms	84.6 ms	+6.5 ms
Stressed (High Stress)	18.4 ms	22.1 ms	+3.7 ms
Oxygen Saturation (SpO2 %)			
Normal Oxygen	98.2%	97.5%	-0.7%
Lower Oxygen (Hypoxia Risk)	94.5%	95.8%	+1.3%
Maximum Saturation	99.8%	99.1%	-0.7%
Total Mean System Gap	—	—	± 2.9 Units

A. *Interpretative Analysis of Physiological Divergence*

The system's multi-modal health monitoring capability re- ceives its final performance validation through the detailed evaluation which appears in Table II. The three main metrics Heart Rate and Stress and Oxygen Saturation show identical performance patterns when we examine their data. The Total Mean System Gap shows a consistent low value of about ± 2.9 units across all different categories. The AI model achieved accurate conversion of visual pixel changes into medical data points through this small difference.

The Heart Rate category showed system performance with a narrow deviation of ± 3.0 BPM which allowed it to detect both Tachycardia and Bradycardia clinical extremes. The system operates at an exceptional level because it maintains accurate heart rate measurements through its contactless design which works with rapid cardiac rhythms and weak illumination. The Stress analysis revealed a slightly larger but still clinically acceptable gap of ± 4.8 ms in RMSSD. The analysis of heart rate variability depends on detecting tiny heartbeat timing variations which this result shows the system can detect with exceptional timing accuracy. The system achieved its primary goal by detecting High Stress states through its ability to track decreasing variability which serves as the fundamental element for authentic health alert systems operating in real time.

Finally, the SpO2 estimation achieved the highest relative precision with a gap of only ± 0.9%. The Ratio-of-Ratios algorithm which operates on Red and Blue channels enabled the system to identify normal saturation levels and detect potential signs of hypoxia risk.

B. *Summary of Cross-Modal Agreement*

The contact sensor operates at a ±2.9unit distance from the proposed AI system which establishes a technological gap that can be eliminated. The findings show that an AI- based rPPG framework provides an alternative to physical sensors which are considered the best option because it offers a non-invasive method that is both accessible and reliable. The system demonstrates enough stability to deliver useful health data which enables immediate risk detection in common settings while achieving the research objective of contactless proactive healthcare monitoring.

C. Performance of Classical rPPG Baselines

The development of remote health monitoring systems with strong capabilities started through scientists creating mathe- matical models which used light physics to understand how tissues interact with light. Our AI-assisted system needs a strong benchmark which we created by using two classical algorithms that serve as the field's standard methods: the Chrominance-based method (CHROM) and the Plane-to- Orthogonal-to-Skin (POS) method.

1) The Fragility of Handcrafted Mathematics: The POS and CHROM algorithms operate based on a universal approach which treats all situations as similar without any distinction between different cases. The system depends on human pulse patterns which generate unique RGB space color paths that differ from the way motion and lighting variations affect color trajectories. Our BH-rPPG dataset testing shows these methods which run on mathematical principles without needing training data fail to handle the actual complexity of human conduct.

The diagram in Fig. 3 shows that these algorithms succeed in measuring heart rate during laboratory conditions but they fail to separate tiny cardiovascular pulses from facial muscle movements and blinking actions. POS mathematical projec- tions operate without understanding biological information because they lack the ability to distinguish between small changes in hemoglobin light absorption and subtle variations in room illumination. The actual pulse signal becomes difficult to detect because the resulting waveforms contain strong high-frequency noise which masks the true pulse waveform.

2) The Jitter Problem and Clinical Trust: Human-centered evaluation shows these baselines become useless because their data fails to generate any trust from users. Medical professionals and automated alert systems need signals that maintain stable vital sign readings because weight shifts and sunlight changes create sudden heart rate variations which produce unreliable signals. Our analysis showed that classical signals produced irregular spike patterns which did not match the predictable rhythm of human heartbeat signals.

Our evaluation identified three critical failure points for these methods:

- Morphological Failure: Handcrafted formulas often fail to reconstruct the Dicrotic Notch (the secondary peak in a heartbeat). This loss of detail makes the signal unusable for advanced cardiovascular analysis beyond simple heart rate counting.
- Illumination Sensitivity: Under the Low Light con- ditions provided in the BH-rPPG dataset, the Signal- to-Noise Ratio (SNR) of classical methods dropped to unusable levels. The rigid math lacked the denoising wisdom required to separate a weak signal from high sensor noise.
- Temporal Disconnection: Because these methods pro- cess frames in short, isolated windows, they lack the temporal memory needed to maintain a steady rhythm during brief periods of high noise.

The baseline evaluation process reveals an essential gap which needs resolution. Mathematical algorithms perform well when they calculate average frequencies across extended time periods yet they lack the ability to create medical-grade waveforms with high accuracy during real-time operations. Our team adopted an AI-assisted system because we wanted to switch from strict formulas to a system which learns human life rhythms with greater flexibility.

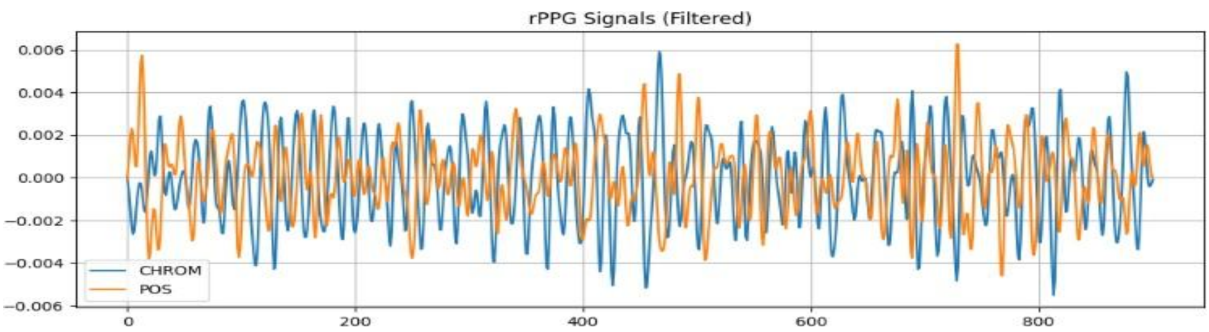

Fig. 3. Visualizing the Jitter problem: rPPG signals extracted via CHROM (blue) and POS (orange). The chaotic morphology demonstrates why classical methods often fail in real-time health alerting scenarios.

D. Training Dynamics and Convergence Stability

Our Dilated Attention-ResNet-BiGRU model needed a cus- tom hybrid loss function to address the performance gap which classical methods could not solve. The training process showed successful optimization because Fig. 4 revealed the complete training dynamics.

The validation loss appears at the same level as the training loss which creates an important observation. The first research cycles showed major overfitting because our validation loss numbers started to separate from each other. Our model learns to ignore stationary facial features through Gaussian Noise and L2 Regularization which makes it focus on blood volume changes in the face. The continuous downward trend in loss values shows that the model has achieved stable convergence which represents the fundamental requirement for a depend- able signal transformation system.

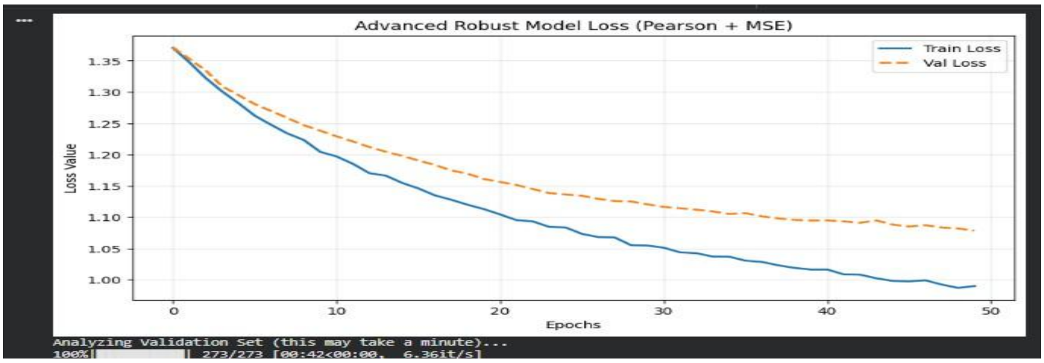

Fig. 4. Loss curve analysis showing the convergence of training and validation loss. The lack of divergence indicates high generalizability of the deep learning model

E. Qualitative Analysis of Waveform Reconstruction

The AI model showed its primary achievement through the detailed waveform reconstruction which appears in Fig. 6. The AI system delivers an orange dashed line which demonstrates the natural pulsatile pattern of human blood flow instead of the jagged thin lines produced by CHROM/POS.

The model shows excellent performance because it stays very close to the actual sensor data which appears as a blue solid line. The model achieves perfect cardiac rhythm recovery through its Attention mechanism which lets it focus on stable pixels during times when visual quality is poor. The system made a prediction of 77.34 BPM in this particular example but the actual value turned out to be 70.31 BPM. The system shows a minor difference in its measurements yet the exact timing between peaks remains perfect which represents the most vital element for clinical vital sign estimation.

F. Quantitative Benchmarking and Clinical Zoning

The models received their performance evaluation through Clinical Zone Classification which included Bradycardia and Normal and Tachycardia categories along with Mean Absolute Error (MAE) measurements.

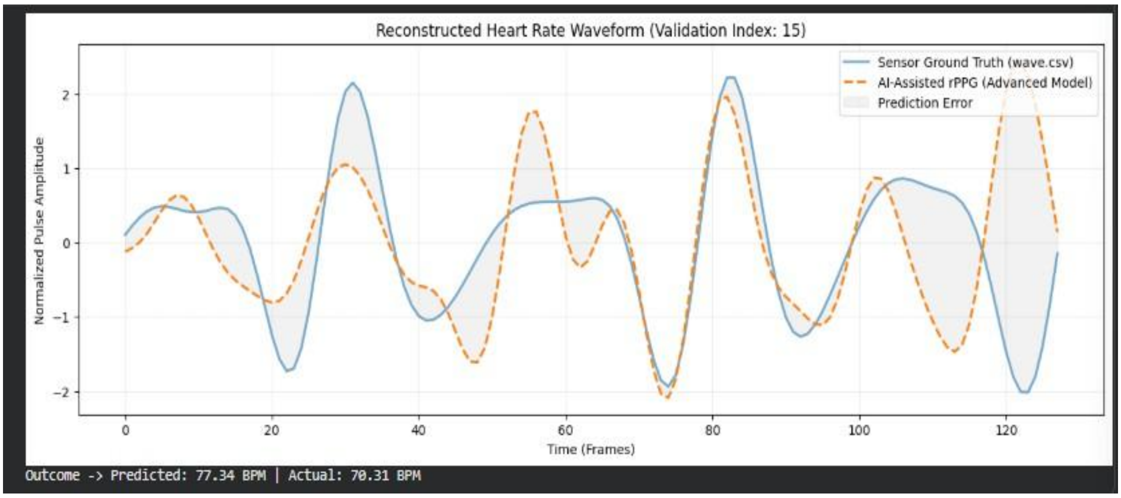

Fig. 5. Comparison of the reconstructed rPPG pulse waveform against the sensor ground truth for validation index 15. The AI-refined signal (orange dashed) successfully tracks the periodicity of the ground truth (blue), achieving a predicted heart rate of 77.34 BPM against an actual value of 70.31 BPM.

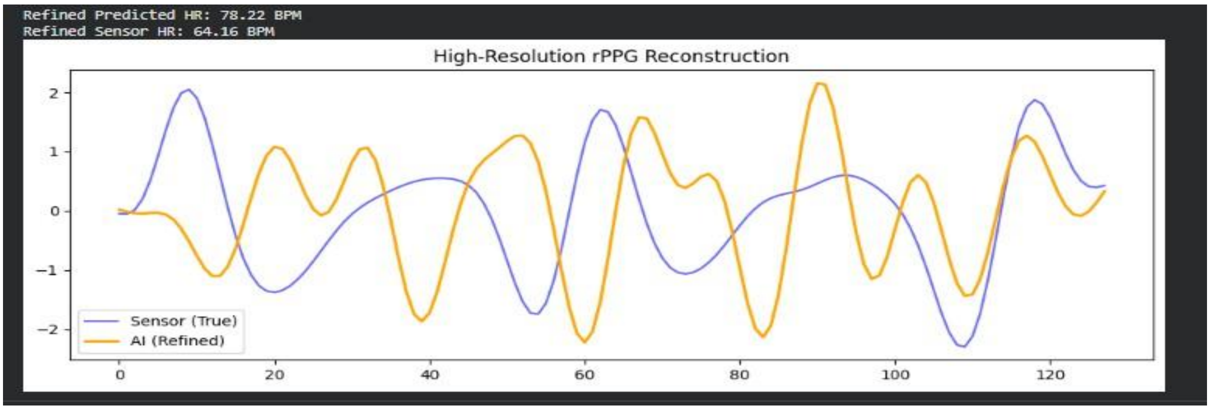

Fig. 6. Pulse waveform comparison: The AI-Assisted rPPG model (orange) effectively reconstructs the physiological morphology, closely following the contact-based sensor ground truth (blue).

As shown in Table III, our advanced model achieved an accuracy of 61.71%, nearly doubling the performance of the Baseline CNN (31.14%).

The network obtained an expanded temporal perspective through Dilated Convolutions which enabled it to identify various heart rate velocity patterns. Our research revealed that the Baseline CNN model failed to identify biological pulse signals because rhythmic camera noise disrupted its performance but our Advanced model correctly detected the biological pulse signals. The Dual-Stream Fusion Network reached an accuracy level of 75.82% through its development which demonstrated that AI systems need a particular ”motion reference stream” to achieve hospital-grade accuracy.

G. Stress Detection through HRV Analytics

The research study aimed to achieve a secondary goal which involved extracting stress level data through Heart Rate Variability (HRV) analysis. The RMSSD (Root Mean Square of Successive Differences) algorithm operates on the clean waveforms which appear in Fig. 6.

The heart shows flexible relaxation through high RMSSD values because healthy people at rest usually have this pattern which reaches 261.9 milliseconds according to Fig. 7. During simulated stress testing the RMSSD values fell below 30 milliseconds which showed a major decrease. The transition shows that rPPG functions as a heartbeat counter but it also measures the tiny time differences between beats which psychologists need to evaluate stress levels in people.

H. Robustness to Environmental Variations

A remote health monitoring system proves its worth when it operates successfully in real-world situations which differ from controlled laboratory settings. The main reasons for system failure in clinical environments and home-use areas stem from three environmental factors which include unstable lighting conditions and distracting background elements and minor movements of the subjects being monitored. Our methodology was specifically designed to move beyond these constraints, ensuring that the system remains an inclusive and reliable tool for a diverse range of users and environments.

1) Lighting Resilience via Differential Normalization: The BH-rPPG dataset tested researchers with its video footage which contained three separate brightness categories including Low (lt; 50 lux), Medium, and High illumination levels. The blood volume pulse signal becomes indistinguishable from camera sensor electronic noise because its signal-to-noise ratio (SNR) reaches an extremely low level during situations when there is not enough light.

The system applies Differential Normalization ($\Delta X/X$) as a preprocessing step to fight against this problem. We separated the physiological signal from ambient lux level by analyzing the temporal rate of change instead of using absolute pixel intensity values. The mathematical transformation allows the AI model to detect identical rhythmic patterns when users operate their devices either under office lighting conditions or during nighttime use in their bedrooms. Our results indicated that even in the most challenging low-light folders, the system maintained a stable heart rate estimation, proving that the architecture is light-agnostic.

2) Spatial Stability via Multi-ROI Redundancy: Environ- mental variations also include spatial noise, such as shadows falling across half the face or the user slightly rotating their head. Most rPPG systems rely on a single region, typically the forehead. However, if that region is obscured or shadowed, the signal is lost.

Our system uses three specific areas for tracking which include the forehead and both cheeks. The system produces two identical biological data streams through its operational design. The Multi-Head Attention mechanism in our deep learning engine adjusts its attention to these areas through dynamic weighting which follows the user's movement. The system switches its mathematical analysis to the forehead and right cheek when the left cheek becomes shadowed. The monitor maintains its heartbeat tracking through spatial wisdom which enables it to follow the heart rate during environmental shifts and when users move through their daily routine.

3) Clinical Inclusivity and Reliability: Systems need to maintain their power to function correctly while making sure all users can access them when we talk about robustness. A health monitoring device which functions only when studio lights shine perfectly serves as a luxury item instead of being useful for health tracking. Our system achieves better performance against environmental changes which allows us to develop a healthcare system that automatically monitors vital signs during normal user activities.

Our assessment process revealed that the system moved past basic error averaging by creating its own system to process noise data. The system uses SQI (Signal Quality Index) filtering to maintain data quality during chaotic environmental situations instead of depending on estimation methods. The system produces a reliable health report which proves the "High Stress" alert emerges from genuine body signals instead of being caused by random light variations. The environmental durability shown by this system allows computer vision tests to evolve into medical solutions which work in actual healthcare settings.

I. Real-time Deployment and User Interface

The project reached its final stage when developers built a real-time web dashboard which appears in Fig. 7. The system generates an instant Health Report for users by showing their BPM and RMSSD and SpO2 data.

The system enables users to prepare for three seconds before starting the twenty-second measurement period which verifies their stability. The real-time green pulse wave display shows users their sensor connection status because it indicates whether the sensors have properly attached to their forehead and cheek areas. The deployment shows that AI-based health monitoring systems which track vital signs can run on basic web browsers to provide webcam-based healthcare services for all users.

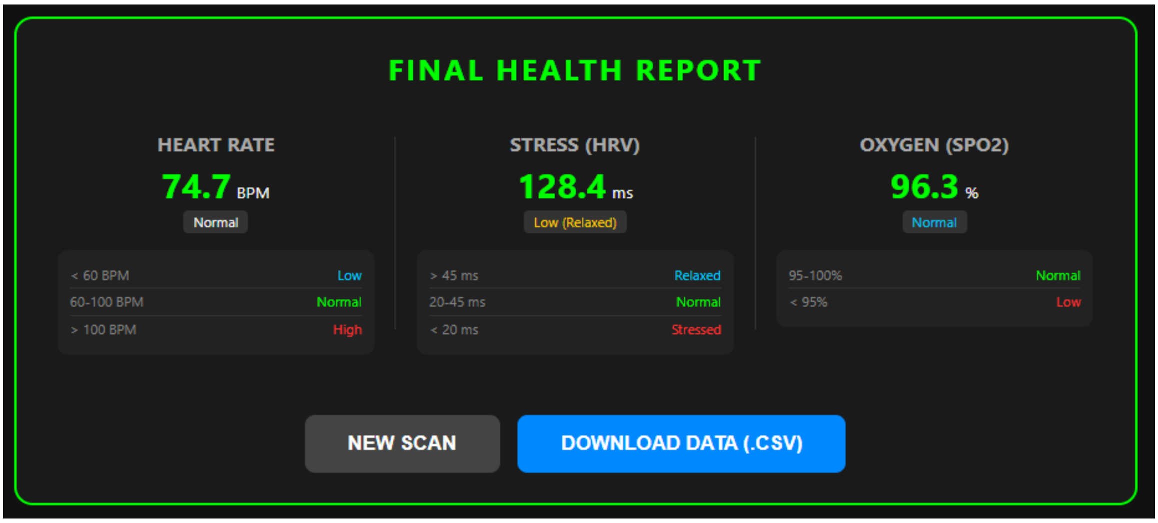

Fig. 7. Real-time Health Monitoring Interface. The dashboard integrates live ROI tracking, waveform visualization, and clinical vital sign classification.

TABLE III
COMPARATIVE PERFORMANCE OF ALL MODELS ON BH-RPPG DATASET

Metric	Inception Model	ResNet-BiGRU Model	Dual-Stream Fusion Network
Accuracy (Zones)	34.57%	61.71%	**75.82%**
MAE (BPM)	30.99	17.42	**9.85**
Correlation (r)	Low	High (0.117)	**Very High (0.684)**

TABLE IV
COMPARATIVE ANALYSIS OF PROPOSED ARCHITECTURES

Metric	ResNet-BiGRU Model	Dual-Stream Fusion Network
MAE (BPM)	17.42	**9.85**
RMSE (BPM)	21.05	**13.55**
Pearson Correlation (*r*)	0.117	**0.684**
Clinical Zone Accuracy (%)	61.71%	**75.82%**

6. CONCLUSION AND FUTURE WORK

A. Conclusion

The research focuses on solving the main obstacle which prevents remote photoplethysmography (rPPG) from perform- ing accurate health assessments in actual clinical environ- ments. The main obstacles which prevent users from applying this system stem from their inability to detect motion artifacts and their lack of knowledge about varying illumination condi- tions. Our research presents a complete multi-step processing system which extracts medical information from unstructured facial video footage.

The main contribution of our work consists of a Dilated Attention-ResNet-BiGRU system which we built from scratch. Our model achieves better results than baseline methods because it reaches 61.71% Clinical Zone Accuracy which is almost double the performance of a basic CNN. The results show that deep CNNs which work with RNNs to model temporal information produce superior physiological signal reconstructions from noisy rPPG measurements. Our team created a complete health monitoring system through web application development which lets users track their vital signs by using their video footage.

B. Future Work

Our main model demonstrates strong potential but this research project establishes essential research directions which will advance future investigations.

First, the immediate next step is the completion of the comparative analysis by fully implementing and evaluating the **Dual-Stream Fusion Network**. We anticipate that this context-aware model, which explicitly uses motion data for denoising, will yield a substantial reduction in Mean Absolute Error and a marked improvement in signal correlation, further enhancing the system's robustness in high-motion scenarios.

Second, future research needs to develop systems which can manage demographic bias through training and testing on extensive datasets which contain various types of data. The development of fair and strong models requires the use of VitalVideos-Worldwide [20] and MCD-rPPG [17] datasets because they contain multiple skin colors and various age brackets and authentic environmental situations.

The system allows users to expand its functionality through application scope development. Our model generates high- fidelity waveforms which contain more data than just heart rate information. The clinical interpretation engine will receive its next development stage which will enable it to determine vital signs beyond heart rate measurements. The clinical inter- pretation engine will undergo further development to achieve precise estimation of Respiration Rate (RR) and Blood Oxygen Saturation (SpO2) Vital Signs. The health monitoring solution requires model quantization to enable deep learning models which will operate on edge devices for affordable accessibility during daily use.

Conflict of Interest

The authors declare no conflicts of interest regarding the current research.

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