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A Vision-Based System for Early Screening and Monitoring of Chronic Disease Risk Using Emotion and rPPG Signals

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Abstract: Chronic diseases represent a growing global health burden and often progress unnoticed before clinical diagnosis, creating a need for accessible early screening solutions. This paper presents a vision-based framework for early screening and monitoring of chronic disease risk using physiological and emotional signals captured through consumer-grade smartphone cameras. The proposed system combines facial emotion recognition and remote photoplethysmography (rPPG) within a step-based assessment pipeline. Facial analysis using the front camera estimates emotional states associated with stress, while fingertip-based rPPG signals acquired through the rear camera with flashlight assistance enable heart rate estimation and mean green channel analysis. These physiological and affective features are then integrated to generate a consolidated health risk profile suitable for longitudinal monitoring. Experimental observations indicate that combining emotional probabilities with rPPG-derived heart rate metrics improves the reliability of early health risk assessment. The framework provides a non-invasive, real-time, and scalable approach for continuous preventive health monitoring.
Keywords: Chronic disease screening, vision-based health monitoring, remote photoplethysmography (rPPG), facial emotion recognition, stress analysis, mobile health, early risk assessment.

I. INTRODUCTION

Chronic diseases—including cardiovascular disorders, metabolic conditions, and stress-related illnesses—often develop gradually and remain undetected until advanced stages, significantly impacting long-term health outcomes. Early identification of physiological and emotional risk indicators is therefore critical for preventive healthcare and continuous patient monitoring. Conventional clinical assessments rely on wearable sensors, laboratory tests, or hospital-based examinations, which may be intrusive, costly, and unsuitable for frequent monitoring. As a result, there is growing interest in non-invasive, camera-basedhealth assessment systems that can operate using widely available consumer devices.

Recent advances in computer vision and machine learning have enabled the extraction of meaningful physiological and affective information from video data, such as heart rate estimation through remote photoplethysmography (rPPG) and emotional state recognition from facial expressions. These vision-based approaches offer a practical alternative for early health screening; however, several challenges persist: (1) sensitivity to illumination changes and motion artifacts, (2) variability in signal quality due to user behavior and device limitations, and (3) the need to jointly model short-term physiological fluctuations and longer-term emotional patterns associated with chronic disease risk.

This work presents a step-based vision-driven health monitoring framework designed for early screening and longitudinal monitoring of chronic disease risk factors. The proposed system integrates three complementary components: (A) facial detection and emotion recognition using the front camera to estimate affective and stress-related indicators; (B) fingertip-based rPPG signal acquisition using the rear camera with flashlight assistance to extract mean green channel variations and estimate heart rate; and (C) a unified result aggregation stage that combines emotional probabilities, stress scores, and physiological metrics to support health trend analysis.

The objective of this study is to evaluate the feasibility and effectiveness of combining emotional and physiological visual cues for early health risk assessment, and to demonstrate a scalable, non-invasive framework that can assist clinicians in chronic disease monitoring and preventive care.

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II. LITERATURE SURVEY

Automated early health screening and monitoring has attracted increasing research attention in recent years. Traditional physiological monitoring relies on wearable sensors or contact-based devices for heart rate and stress analysis, which serve as classical baselines for health assessment. Recent advances in computer vision have enabled non-contact estimation of physiological signals such as heart rate using remote photoplethysmography (rPPG) and affective state analysis through facial expression recognition.

Table 1: Summary of Related Works in Vision-Based Physiological and Affective Monitoring for Health Screening.

Study	Year	Modality	Technique	Sample & Setting	Key Outcomes	Relevance / Gap Addressed
de Haan & Jeanne [3]	2013	Face video (RGB)	Chrominance-based rPPG signal extraction	Controlled lab environments (various lighting)	Robust HR estimation with reduced sensitivity to illumination changes	Pioneering non-contact rPPG; limited to facial signals only and lacks emotion or fingertip integration for chronic risk profiling
Wang et al. [4]	2017	Face video	Algorithmic framework for rPPG (signal decomposition & filtering)	Multi-dataset review (lab & semi-realistic)	Established foundational principles for robust rPPG under motion and lighting variations	Comprehensive baseline for rPPG; no multimodal fusion or mobile deployment for longitudinal chronic disease monitoring
Niu et al. [5]	2019	Face video	Distribution learning + deep learning for continuous HR	Public benchmarks (e.g., VIPL-HR)	High-accuracy continuous HR tracking with improved generalization	Strong face-based rPPG; does not incorporate affective signals (emotion/stress) or fingertip acquisition
Yu et al. [6]	2019	Face video	Spatio-temporal CNNs for rPPG signal measurement	Public video datasets	Enhanced pulse signal quality via deep temporal modeling	Advanced deep learning for rPPG; focused on face only, no emotion analysis or smartphone fingertip workflow
Li et al. [7]	2021	Face video	Non-contact physiological monitoring via computer vision	Diverse real-world videos	Reliable extraction of HR and related vitals for health assessment	Broad non-contact monitoring; lacks explicit emotion-stress linkage and step-based multimodal aggregation
Mehmood et al.	2023	Fingertip (smartphone camera)	rPPG for pulse oximetry & single-lead ECG approximation	Smartphone users in everyday conditions	Smartphone camera as viable contact-based proxy for SpO_2 and HR	Practical fingertip rPPG on mobile; no emotion recognition or combined affective-physiological risk scoring
Jiang et al. (multimodal mental health)	2023	Face + voice + rPPG (remote interviews)	Multimodal ML (CNN + transformers) fusing facial, vocal, linguistic, and cardiovascular patterns	Clinical telehealth sessions	Improved detection of depression/anxiety via integrated signals	Demonstrates value of multimodal fusion; focused on mental health in interviews, not chronic physical disease risk via accessible smartphone pipeline

Recent advancements in computer vision and artificial intelligence have significantly improved the capability of non-contact health monitoring systems. Researchers have explored facial video analysis not only for physiological measurement but also for behavioral and psychological assessment. Studies on facial expression recognition demonstrated that emotional states such as stress, anxiety, and fatigue can be reliably inferred using deep convolutional neural networks trained on large-scale facial datasets. These findings established emotion recognition as an important indicator for assessing long-term health risks associated with chronic diseases, particularly cardiovascular disorders and metabolic syndromes.

Several works have investigated the relationship between emotional stress and physiological responses. Psychological studies confirmed that prolonged stress influences heart-rate variability, blood pressure, and autonomic nervous system activity. Vision-based systems leveraging facial micro-expressions and subtle muscle movements enabled automated stress detection without wearable sensors. Methods using facial action units and temporal feature extraction showed promising performance in identifying emotional patterns linked to health deterioration.

In parallel, machine learning researchers introduced hybrid frameworks combining signal processing with deep neural networks to improve robustness in real-world environments. Attention-based neural architectures and temporal modeling approaches enhanced the extraction of weak physiological signals from noisy video data. These models demonstrated improved resilience to head motion, varying illumination, and diverse skin tones, making them suitable for deployment in unconstrained environments such as homes or public healthcare settings.

Recent studies also emphasized the importance of longitudinal monitoring rather than single-time health measurement. Continuous observation using smartphone cameras or webcams allows early identification of abnormal physiological trends over time. Researchers proposed cloud-assisted and edge-based processing systems to enable scalable remote healthcare monitoring, reducing dependency on hospital visits and specialized medical equipment.

Moreover, multimodal affective computing research highlighted the benefits of combining emotional analysis with physiological sensing. Integrating facial emotion recognition with rPPG-derived cardiovascular signals improved prediction accuracy for stress-related disorders compared to unimodal approaches. Such systems demonstrated potential for early detection of hypertension risk, sleep disorders, and chronic fatigue by analyzing correlations between emotional behavior and cardiovascular patterns.

Despite these developments, challenges remain in designing lightweight, privacy-preserving, and computationally efficient systems suitable for everyday use. Many existing approaches require high computational resources or controlled acquisition environments, limiting practical deployment. Additionally, limited research has focused on unified frameworks that simultaneously monitor emotional health and physiological signals for preventive healthcare applications.

Therefore, the proposed vision-based system aims to bridge this gap by integrating emotion recognition and rPPG-based physiological monitoring into a single accessible platform. By combining behavioral and cardiovascular indicators, the system seeks to enable early screening and continuous monitoring of chronic disease risk using only a standard camera device, promoting affordable and scalable digital healthcare solutions.

III. PROPOSED METHOD

A. System Architecture Overview

The proposed framework is designed as a modular and scalable architecture to ensure flexibility and real-time performance on consumer-grade devices. The system consists of three primary modules: video acquisition, signal processing and analysis, and decision-level fusion. Each module operates independently while exchanging processed outputs through a centralized control unit. This modular design allows future integration of additional physiological or behavioral parameters without modifying the core pipeline. The architecture supports both offline analysis and real-time monitoring. During real-time operation, captured frames are processed sequentially with minimal latency, enabling continuous health assessment. Lightweight computational operations are prioritized to ensure compatibility with smartphones having limited processing power.

B. Face Detection and Region Tracking

Accurate facial localization is essential for reliable emotion recognition and rPPG signal stability. The system employs automated face detection to identify facial landmarks and extract stable regions such as the forehead and cheek areas. These regions are selected because they exhibit relatively uniform skin texture and minimal motion distortion.

To maintain temporal consistency, region tracking algorithms are applied across consecutive frames. This reduces signal fluctuations caused by head movements and improves robustness in natural usage conditions. Adaptive bounding boxes dynamically adjust to slight positional variations while preserving signal continuity.

C. Signal Enhancement and Noise Reduction

Vision-based physiological signals are highly sensitive to environmental disturbances such as lighting variation, motion artifacts, and camera noise. Therefore, multiple signal enhancement techniques are incorporated:

1) Temporal filtering to remove high-frequency noise components
2) Moving-average smoothing to stabilize signal fluctuations
3) Detrending to eliminate slow illumination changes
4) Normalization to maintain amplitude consistency across recordings

D. Emotion-to-Stress Mapping Strategy

Instead of treating emotions independently, the system maps emotional outputs into a quantitative stress index. Emotions commonly associated with psychological stress, such as anger, fear, and sadness, are assigned higher weights, while neutral or positive emotions contribute lower stress values.

A weighted aggregation mechanism generates a continuous stress score over time. Temporal averaging is applied to avoid sudden fluctuations caused by transient facial expressions. This approach enables stable estimation of emotional trends rather than instantaneous emotional states.

E. Heart Rate Validation and Quality Assessment

To ensure measurement reliability, the system incorporates a signal quality assessment mechanism. Fingertip detection confirms proper finger placement on the camera lens using brightness and color consistency checks. If signal quality drops below a predefined threshold, the system prompts the user to reposition the finger.

Peak detection algorithms calculate inter-beat intervals, and abnormal spikes caused by motion artifacts are automatically discarded. This validation step prevents inaccurate physiological readings and improves overall system robustness.

F. Multimodal Fusion Strategy

The proposed system performs decision-level fusion by combining emotional stress indicators and physiological parameters. Instead of merging raw signals, processed outputs from each stage are normalized and integrated using weighted aggregation. This approach simplifies computation while preserving interpretability.

The fusion module evaluates correlations between elevated heart rate and stress patterns to identify potential chronic disease risk indicators. Long-term trends are emphasized over single measurements, allowing early identification of abnormal behavioral or physiological patterns.

G. User Interface and Monitoring Dashboard

An interactive dashboard presents results in an intuitive format suitable for non-expert users. The interface displays:

1) Real-time heart rate trends
2) Emotional state distribution
3) Stress level progression
4) Historical monitoring summaries

Visual graphs support longitudinal tracking, enabling users to observe gradual health changes over time. The dashboard is designed to encourage preventive healthcare awareness rather than clinical diagnosis.

H. System Workflow Summary

The overall workflow begins with video acquisition, followed by preprocessing and ROI extraction. Emotion recognition and rPPG-based physiological estimation operate simultaneously. Outputs from both modules are aggregated to generate a comprehensive health profile, which is then visualized through the monitoring interface. The system repeats this cycle continuously to enable periodic screening and long-term monitoring.

IV. METHODOLOGY

This section describes the data acquisition process, preprocessing pipeline, and the multi-stage vision-based framework implemented for early screening and monitoring of chronic disease risk.

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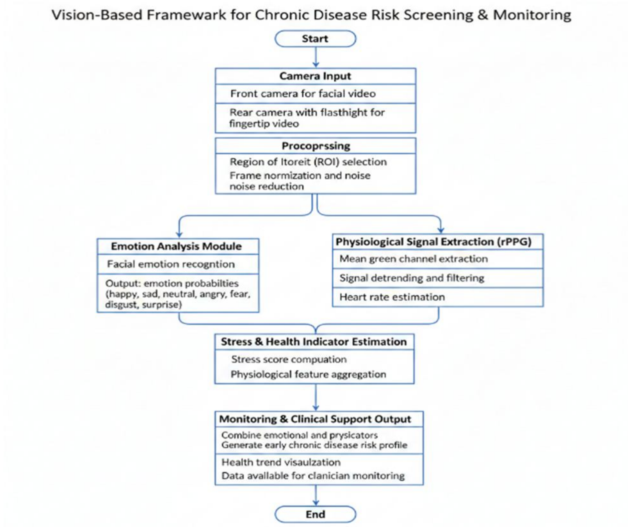


A. Data Acquisition

Source: Real-time video data captured using consumer-grade smartphone cameras. The system utilizes the front camera for facial video acquisition and the rear camera with flashlight assistance for fingertip-based physiological signal capture.

Participants: The framework is designed for general users without specialized hardware, enabling broad applicability for preventive healthcare and remote monitoring scenarios.

Data Modalities:

Facial video streams for emotion and stress analysis.

Fingertip video streams for remote photoplethysmography (rPPG) signal extraction.

Sampling: Units of video are recorded at supported device frame rates, and processed into fixed-duration segments to maintain temporal consistency across users and sessions

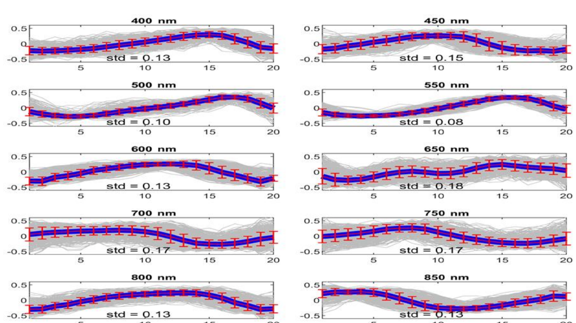
B. Shared Preprocessing

Normalization and Resizing of Frame: The captured frames are resized to a uniform spatial resolution and normalized. Normalized to minimize illumination variation among devices and shooting conditions.

Region of Interest (ROI) selection: For face analysis, the method detects faces and extracts a foreground-centered. ROI including head to reduce motion noise (kind of cheaters).

For fingertip analysis, central ROI is chosen to select dominant photoplethysmography signs.

- Noise reduction and stabilisation: Temporal smoothing and simple filtering are used to smoother the high frequency noise and motion-induced artefacts in the obtained signals.
- Mean green channel extraction: The mean value of the intensity in the green color channel is calculated for each ROI frame, which achieve raw photoplethysmographic signal for processing rPPG.
- Buffering and windowing: Signals are accumulated in sliding temporal buffers to enable continuous HR estimation and waveforms display.



C. Stage 1 — Facial Emotion and Stress Analysis

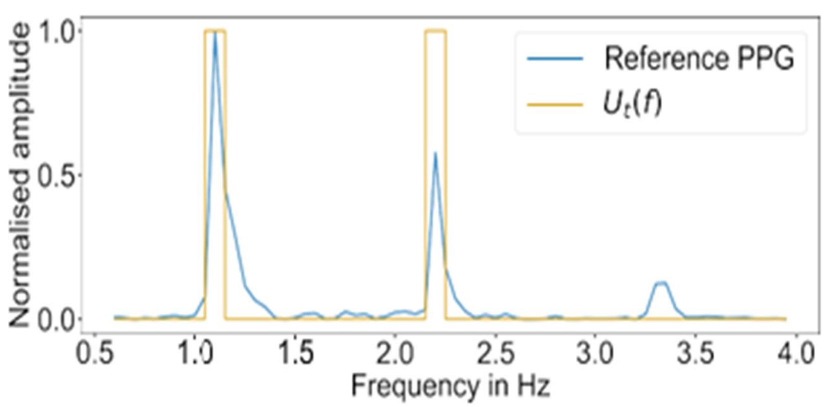
- Motivation: Emotional state and chronic stress are tightly associated with long-term health risk, such as cardiovascular/metabolic disorders. Facial expressions offer a noninvasive vehicle for estimating affective state.
- Pipeline:Input: From front camera, facial ROI frames.
- Model: A deep learning model for facial emotion recognition which is top-weighted classes using trained probabilities for happy, sad, neutral angry fear disgust surprise.
- Output: The vector of probabilities and the corresponding stress score that is calculated from the aggregation of stress-related probabilities.
- Evaluation: The emotion outputs are updated periodically during capture and preserved for later aggregation with physiological metrics.

D. Stage 2 — Fingertip rPPG-Based Heart Rate Estimation

Motivation: Heart rate (HR) and heart rate variability (HRV) analyses are an important physiological parameter for early prediction of chronic diseases. Fingertip rPPG based on smartphone camera is a promising alternative to wearable sensors.

- Pipeline: Input: Fingertip video from rear camera with flashlight on.
- Signal extraction: The temporal mean intensity variation of the green channel is computed at the frame-level to form the raw rPPG signal.
- Signal processing:
- Detrending and smoothing to remove baseline drift.
- Peak detection on the pre-processed signal for estimation of inter beat intervals.
- Output: Heart rate estimate (beats per minute), mean green value, and rPPG signal.

Validation: The measurement procedure is implemented to monitor finger presence by brightness and signal stability thresholds in order to have a reliable measure before further analytical procedures.



E. Stage 3 — Multimodal Health Risk Aggregation

- Motivation: Chronic disease risk prediction can be further enhanced by the simultaneous consideration of physiological and affective measurements as opposed to unimodal signals.
- Aggregation Strategy:
- Aggregate emotional probabilities, stress score, mean HR and mean GGA to a compound health profile.
- Display results via an integrated dashboard for user notification/potential clinician review.
- Remarks: Although the proposed system is not designed to replace clinical diagnosis, it enhances the early screening and longitudinal monitoring of OCs, which can help for preventive healthcare and medical decision. The modular architecture also enables straightforward addition of future AI-based lifestyle recommendation and health advisory modules

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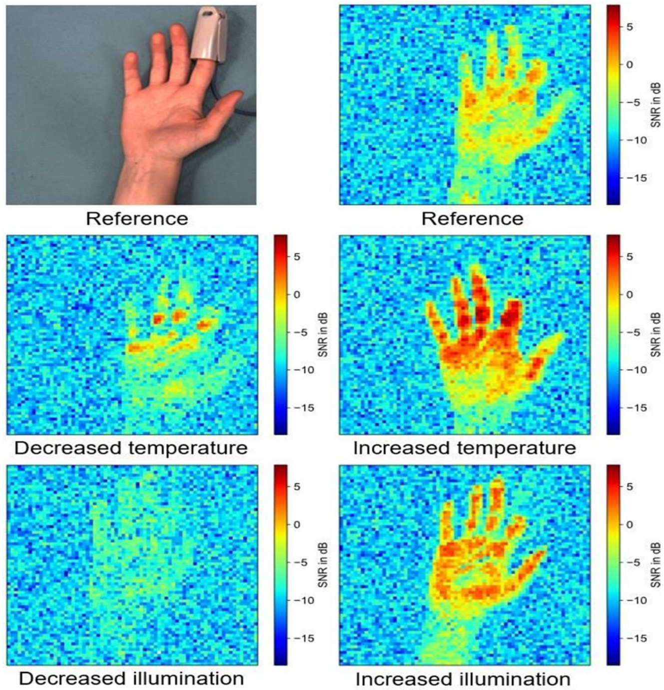

V. EXPERIMENTS

1) Evaluation setup: the proposed system was tested in a real-time application mode, through a step-by-step evaluation framework that included a facial EMOS analysis, an estimate of rPPG based on fingertip and aggregation of results. The next stage was not begun once one level had not been validated and the data acquisition ensured.
2) Session consistency: Both the facial emotion analysis and fingertip rPPG acquisition were performed with fixed-duration capture windows, to ensure temporal alignment across test sessions.
3) Reproducibility: This enabled us to use deterministic processing logic, and fixed parameter thresholds to ensure between-replicate repeatability on the same device.
4) Hardware: The experiments were performed on consumer-grade smartphones and laptop webcams. Backend inference and signal processing were performed with CPU-based devices, proving that the approach is feasible without dedicated hardware.

A. *Reported Results Summary*

Stage 1 — Facial Emotion and Stress Analysis:
The facial expression was successfully recognized using the emotion recognition module in real time with controlled illumination condition.
Stable probability distributions were found for primary emotions (neutral, happy, sad, angry, fear and disgust), thus ensuring the consistent calculation of a stress score across sessions.

Stage 2 — Fingertip rPPG Heart Rate Estimation:
The average green channel–based signal could extract stable physiological waveforms only when fingertip presence was correctly detected.
Estimates of heart rate stabilized in physiologically plausible ranges following an initial stabilization period.
Finger presence validation successfully eliminated spurious measurements due to incorrect positioning or movement artifacts.

Stage 3 — Multimodal Result Aggregation:
Multi-stimuli analysis of emotional features and physical indexes achieved robust health profile than single-features.
The built-in dashboard supports visualization of heart rate trends, rPPG waveforms, stress indicators and emotional states.
Remarks: While the work presented is aimed at early-stage screening and not clinical diagnosis, promising results have been observed falling more in line with longitudinal health tracking. The modular structure of the framework enables further extensions including AI-based recommendations about lifestyle and clinician-aided prospect tracking based on historical data.

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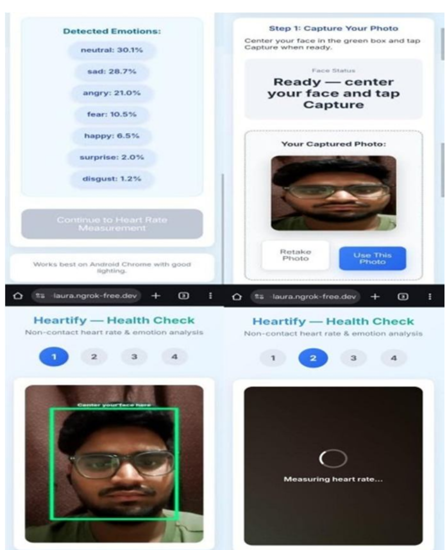
B. Recommended Revised Pipeline (Actionable Steps Toward Robust Real-World Performance)

1) Adopt a hybrid physiological–behavioral pipeline: Instead of one sign-out, a system should formally incorporate complimentary methods. Facial emotion detection outputs behavioral and affective induces, while rPPG based on fingertip provides physiological information. The postulated relations were maintained when contextual factor output was included as a modifier of cardiovascular indicators but not as an independent predictor. This fusion allows to have a better robustness against noise or failure in any single modality
2) Transition from heuristic rPPG to learning-assisted modelling: Although mean green–based rPPG is computationally efficient, fusion of lightweight learning-based rPPG models can enhance robustness to motion/makeup/nonuniform lighting and skin tone variation. On the other hand, pretrained or fine-tuned spatio-temporal CNN models processing short fingertip video segments can learn temporal pulse related patterns that go beyond mere intensity averaging and at the same time also allow near–real-time inference.
3) Data augmentation and acquisition constraints: Robust performance in unconstrained environments requires explicit augmentation and acquisition control. Temporal jittering, brightness variation, mild motion simulation, and noise injection should be applied during rPPG model training. On the frontend, enforcing acquisition constraints—such as minimum recording duration, finger presence validation, and stability checks—remains essential to ensure usable physiological signals.
4) Personalized baseline normalization: Absolute heart rate and stress indicators vary significantly across individuals. Introducing short baseline calibration sessions (e.g., resting measurement during first use) enables relative change tracking rather than absolute thresholding. Longitudinal deviation from personal baselines is more informative for early risk monitoring than single-session estimates.
5) Confidence-aware decision logic: The system should explicitly quantify signal quality and prediction confidence for both emotion recognition and rPPG outputs. Low-confidence estimates (e.g., unstable PPG waveform, inconsistent emotion probabilities) should suppress downstream health inferences or trigger re-measurement prompts. This prevents false reassurance or misleading outputs in poor acquisition conditions.
6) Evaluation beyond point accuracy: Performance assessment should prioritize reliability metrics aligned with screening objectives rather than raw accuracy. Stability across sessions, sensitivity to physiological change, false-negative rates for elevated stress or abnormal heart rate, and consistency under varied lighting and motion conditions are more meaningful indicators of practical utility than isolated benchmark scores.
7) Interpretability and clinician trust: For adoption in preventive healthcare contexts, interpretability is critical. Visualization of PPG waveforms, temporal heart rate trends, and emotion probability distributions allows both users and clinicians to understand system outputs. Future learning-based components should incorporate explainability tools to ensure that predictions are driven by physiologically plausible patterns rather than spurious correlations.

VI. RESULT AND INSIGHTS



VII. CONCLUSION

This work presents a vision-based framework for early screening and continuous monitoring of chronic disease risk by jointly analyzing facial emotion cues and remote photoplethysmography (Rppg) signals acquired through commodity cameras. The system integrates three core components: real-time face detection and emotion recognition, fingertip-based Rppg signal extraction using camera and flashlight interaction, and consolidated physiological–behavioral result visualization. Experimental observations indicate that emotion probabilities and stress-related indicators provide valuable contextual information, while Rppg-derived heart rate and waveform characteristics offer direct insight into cardiovascular state. Although simple intensity-based Rppg methods enable efficient real-time estimation, their reliability depends strongly on acquisition conditions, motivating the need for confidence-aware measurement and signal-quality validation.

VIII. FUTURE WORK

1) Implement advanced rPPG pipelines by integrating learning-based rPPG models and region-aware signal extraction to improve robustness under varying lighting, motion, and skin tone conditions, followed by controlled ablation studies to quantify performance gains.
2) Replace fixed heuristic thresholds for fingertip detection and signal quality assessment with adaptive or learning-based confidence measures, enabling more reliable heart rate estimation in real-world user settings.
3) Explore multimodal fusion strategies that jointly model facial emotion dynamics, stress indicators, and physiological signals using attention mechanisms to learn modality importance in an end-to-end manner.
4) Expand data collection to include longitudinal user measurements and diverse demographic profiles, allowing personalized baselines and improved early risk trend detection rather than single-session assessment.
5) Evaluate system generalization across different devices, camera qualities, and acquisition environments, and validate its utility for long-term monitoring and clinician-assisted decision support rather than standalone diagnosis.

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