

*Design and Development of IoT based Wearable Device
& Algorithm for Emotion Detection*

EXECUTIVE SUMMARY OF THESIS

For

**DOCTOR OF PHILOSOPHY
in
COMPUTER SCIENCE & ENGINEERING**

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MARCH 2026**

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ABSTRACT

Reliable emotion recognition is a cornerstone of next-generation Human-Computer Interaction (HCI) and personalized healthcare, yet current systems are often hindered by the high cost of medical-grade hardware, the "black-box" nature of proprietary algorithms, and a lack of subject-independent generalizability. This research addresses these gaps through a multi-layered approach encompassing custom hardware engineering, bio-adaptive signal acquisition, and psychometric-enhanced machine learning.

The technical foundation of this work is a custom-developed **IoT-based multi-sensor wearable platform** built around the ESP32-S3R8 microcontroller. To ensure research-grade data fidelity at a low cost, the device integrates an **18-bit Analog-to-Digital Converter (ADC)** for the high-resolution acquisition of Photoplethysmography (PPG), Galvanic Skin Response (GSR), and Skin Temperature (ST) signals. Empirical validation against the Apple Watch Series 7 demonstrated high reliability, with a Pearson correlation coefficient of $r > 0.95$ for heart rate measurements.

A major methodological contribution of this research is the implementation of a **Bio-Adaptive Dynamic Sampling Strategy**. Unlike traditional static sampling, this firmware-level algorithm modulates the sampling frequency (ranging from 50Hz to 3200Hz) in real-time based on the user's instantaneous heart rate. This approach ensures high-fidelity capture of physiological transients during peak emotional arousal while significantly optimizing power and memory during neutral states.

To validate the system, the **PhysioEmotion Dataset** was curated, featuring multimodal signals from **60 participants** across nine elicitation sessions using unconstrained YouTube video stimuli. This dataset uniquely integrates the **"Big Five" personality traits**, enabling the development of personalized emotional profiles that account for individual differences in physiological reactivity.

The computational pipeline utilizes tree-based ensemble classifiers, specifically **Extra Trees and XGBoost**, achieving a benchmark accuracy of **66% for 7-class discrete emotion recognition** on unbalanced dataset. To ensure robust real-world performance, models were validated using **Leave-One-Subject-Out (LOSO)** cross-validation. The results yielded a **mean**

accuracy of 0.77 ± 0.13 and a mean macro F1-score of 0.76 ± 0.14 , demonstrating effective subject-independent generalizability. Finally, this work establishes the **Cognitive-Computational Synthesis Framework (CCSF)**, providing a theoretical foundation for **Explainable AI (XAI)** by mapping physiological markers to underlying cognitive processes such as attentional allocation and arousal regulation.

Ultimately, this research provides a complete vertical stack—from high-resolution hardware to theoretically grounded AI—moving affective computing out of the laboratory and into practical applications for safe driving, mental health monitoring, and assistive technologies for neurodiverse populations.

1. INTRODUCTION

Human interaction has conventionally been observed through the perspectives of language and gestures. Yet, in situations where spoken communication is lacking or deliberately concealed, emotion act as a key and potent means of conveying messages. Emotion refers to a multifaceted psychological condition that encompasses behavioral reactions, personal feelings, and physiological changes, commonly classified by degrees of pleasure and intensity. Emotions are closely connected to mood, temperament, and character. The influence of emotions on human existence is significant; whereas positive emotion promote health and cognitive performance, while long-term negative emotional conditions often lead to serious health issues like depression, heart disease, and asthma[1]. Regardless, worldwide mental health continues to be a challenge owing to insufficient timely diagnoses and restricted resources. This has resulted in an increase in cross-disciplinary studies centered on automated emotion recognition.

1.1 THE PROBLEM STATEMENT & RESEARCH GAPS

Detecting emotions in time using physiological signals is difficult due to the complexity of the signals and the differences between people. Existing devices often have to choose between battery life and signal quality and algorithms do not take into account personality differences.

There is a need for a system that combines high-quality sensing, adaptive data acquisition and personalized machine learning to provide emotion recognition.

RESEARCH GAP

This analysis draws attention to the shortcomings in algorithmic validation, hardware accessibility, and dataset composition in the field of affective computing.

1. Dataset and Elicitation Gaps

The following gaps exist in the current datasets:

- **Static sampling inefficiency** refers to fixed sample rates that waste electricity during neutral states or fail to collect high-fidelity signals at peak arousal.
- **Lack of Psychometric Integration:** Few datasets systematically combine personality traits that can influence physiological signals, despite the fact that emotional experience is highly individualised.
- **Ecological Validity and Stimuli Weaknesses:** The dynamic context of real-world emotional experiences is absent from traditional elicitation techniques, which frequently use static visuals or music. This may result in genuine but feeble or erratic emotional responses that are difficult to apply in practical situations.

2. Hardware and Technological Gaps

Additionally, there are gaps in technology and hardware, such as:

- **Proprietary "Black-Box" Restrictions:** Top commercial research equipment use closed-source firmware and proprietary algorithms that limit customisation and research-focused uses.
- **Cost-Deployment Trade-offs:** Large-scale field research and extensive deployment in IoT-based telehealth and mental health monitoring infrastructures are restricted by the high cost of medical-grade wearable sensors.

3 Algorithmic and Validation Gaps

Lastly, there are validation gaps, such as:

- The necessity for more rigorous **subject-independent validation** procedures like Leave-One-Subject-Out (LOSO) is highlighted by the fact that many models attain great accuracy on certain subjects but fail to retain performance when applied to new, unfamiliar users.
- **Adversarial and Robustness Concerns:** The field lacks comprehensive analysis regarding the adversarial robustness of emotion recognition systems, particularly as they move into mission-critical applications like safe driving or clinical diagnostics.

1.2 THE OBJECTIVES

To solve these problems this research has the following objectives:

1. To Develop a wearable device that can detect physiological signals like heart rate, skin conductance and skin temperature.
2. To create a sampling strategy that adjusts the frequency of data collection based on the users heart rate.
3. To collect a dataset of physiological signals and personality traits from 60 participants.
4. To develop a machine learning pipeline that can recognize emotions using the collected data.
5. To create a framework that explains how emotions are recognized using signals.

1.3 THE RESEARCH CONTRIBUTIONS

This work makes the following major and minor contributions to the field:

Major Contributions:

- **High-Resolution IoT Platform:** Development of custom wearable with optimized **Peripheral Beat Amplitude (PBA)** algorithm, providing research-grade data at low cost.

- **Adaptive Sampling Methodology:** Introduced a first-of-its-kind firmware-level strategy that adjusts sampling frequency (50Hz–3200Hz) dynamically with respect to heart rate of person.
- **The PhysioEmotion Dataset:** Creation of novel datasets featuring 60 subjects that systematically integrates psychometric "Big Five personality" profiles to enable personalized emotion modeling.
- **Generalizable ML Pipeline:** A machine learning pipeline with subject-independent classification using **LOSO validation**, proving the system's effectiveness for new, unseen users.
- **Cognitive-Computational Synthesis Framework (CCSF):** Proposed a theoretical framework that bridges the gap between raw physiological signals and cognitive science.

Minor Contributions:

- **Validated Stimuli Resource:** Validated a library of 9-session video stimuli through a self assessment reports.
- **Empirical Validation:** Statistically proved the device's reliability through benchmarking against the **Apple Watch Series 7 ($r>0.95$)**.

2. RESEARCH METHODOLOGY FOR WORK DONE

In order to achieve our goal, we divided our work into five phases, named, Design and development of Wearable Device, Emotion Elicitation, Dataset's creation, Machine learning pipeline and Cognitive-Computing Synthesis Framework. Following Figure 1 & 2 shows respectively the system architecture and system deployment flow: from sensing to emotion detection of our work.

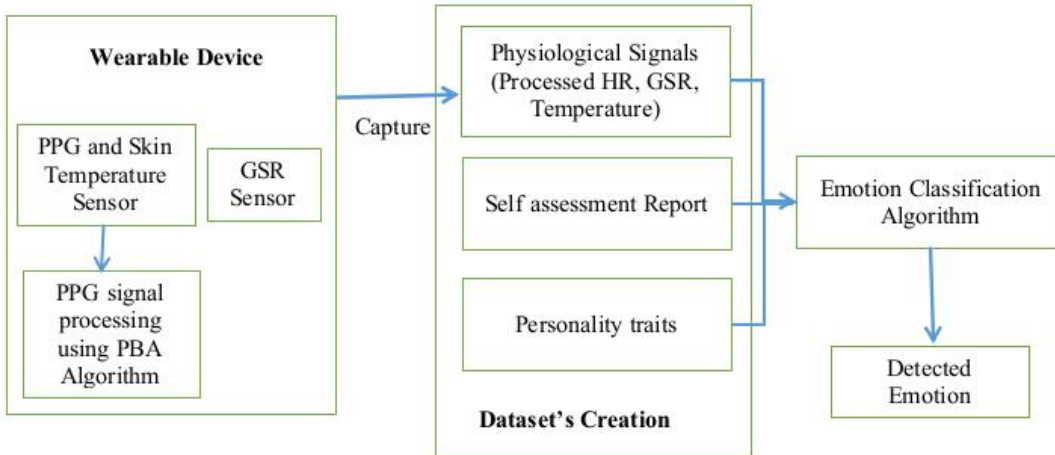


Figure 1: Block diagram of the wearable emotion detection system architecture.

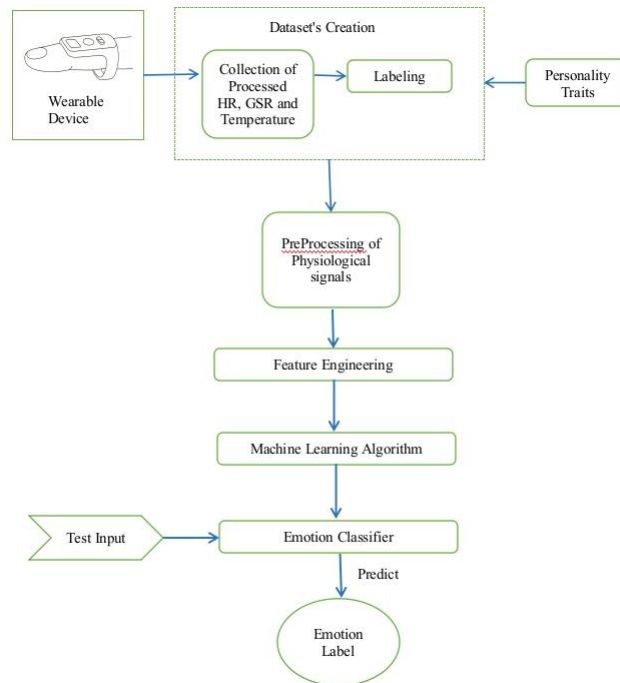


Figure 2: System deployment flow: from sensing to emotion prediction.

3. PERFORMANCE SUMMARY

In order to maintain the initial class distribution in each subset, we used stratified sampling to divide our dataset into 70% training (1,357 trials), 15% validation (292 trials), and 15% testing (292 trials). Then on 70% training set we have apply SMOTE. In other approach, we have used

soft voting ensemble combining Extra Trees and XGBoost. This setup achieved an overall accuracy of 0.66. While the model excelled at identifying Neutral and Happy states, the macro F1 score of 0.53 reflects the persistent challenge of distinguishing minority emotions such as Fear or Disgust (Table 1).

Table 1 Comparative performance of baseline classifiers on the 15% test set

Model	Accuracy	Macro F1	Weighted F1	Notes
Extra Trees + PCA + SMOTE	0.61	0.45	0.60	SMOTE on train only, PCA=2
XGBoost + PCA + SMOTE	0.60	0.46	0.59	SMOTE on train only, PCA=4
Soft voting (ET + XGB) + SMOTE	0.59	0.45	0.59	SMOTE on train only, PCA=30
Ensemble (ET + XGB), class weighted, no SMOTE	0.66	0.53	0.65	Final cost-sensitive baseline

Subject Independent LOSO Evaluation (3 Class)

To assess cross subject generalization under a coarser affect representation, we conducted a leave-one-subject-out (LOSO) evaluation using a 3-class mapping of the original labels: Negative (Angry, Disgust, Fear, Sad), Positive (Happy, Surprise), and Neutral. For each fold, trials from one participant were held out for testing, while all remaining participants formed the training set; all preprocessing steps (imputation, one-hot encoding, scaling, and class-weight estimation) were fitted exclusively on the training subjects and applied to the held-out subject.

Across 60 LOSO folds, the cost-sensitive Extra Trees classifier achieved a mean accuracy of 0.77 ± 0.13 and a mean macro F1-score of 0.76 ± 0.14 . The aggregated normalized confusion matrix (Figure 1) shows high recalls for Negative (~ 0.88) and Neutral (~ 0.81), while Positive (~ 0.74) is primarily confused with Neutral, reflecting partial physiological overlap in medium-arousal states. Negative emotions like fear and anger trigger more pronounced sympathetic "fight-or-flight" responses, making them easier for sensors to detect across different people compared to subtle positive states.

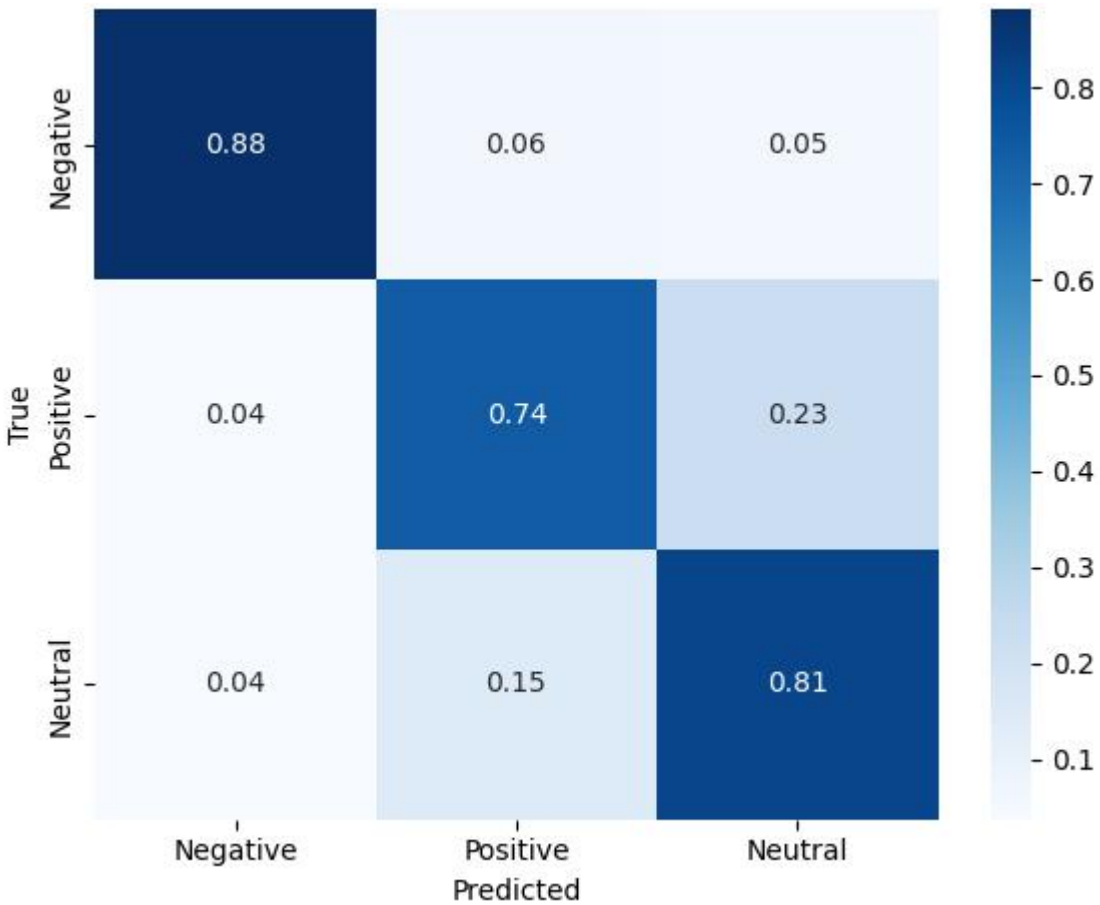


Figure 1. Aggregated LOSO confusion matrix for the 3- class mapping (Negative, Positive, Neutral). Values are per-class recalls normalized over the true labels.

Cross-subject discriminability is further characterised by per-class LOSO F1-scores in addition to aggregate metrics. Negative trials had the highest mean F1 (0.89 ± 0.10), followed by Positive (0.73 ± 0.16) and Neutral (0.71 ± 0.24). This suggests that while Positive and Neutral states show more variability among participants, strongly negative experiences with prominent sympathetic activation are most reliably recognised.

4. APPLICATIONS

The developed system and framework have diverse real-world applications, including:

1. **Safe Driving Systems[16]**: That can detect driver emotions and prevent accidents
2. **Personalized Healthcare[17]**: Real-time stress and anxiety monitoring via IoT-based telehealth platforms.
3. **Mental Health Research[18]**: Providing a low-cost, high-fidelity tool for researchers to conduct longitudinal affective studies in naturalistic environments.
4. **Assistive Technology**: Supporting individuals with **Autism Spectrum Disorder (ASD)** in recognizing and communicating their emotional states to caregivers [19].
5. **Adaptive HCI**: Creating "emotion-aware" software and games that adjust difficulty or content based on the user's current valence and arousal.

5. CONCLUSIONS & FUTURE WORK

This research provide a end-to-end system for emotion detection using multimodal physiological signals, bridging the critical gap between low-cost IoT hardware devices and advanced cognitive-computational theory. It does this by building a custom device and a framework called the **Cognitive-Computational Synthesis Framework (CCSF)**. This work provides a solution for objective mental health monitoring and affective computing.

The custom wearable device, which is based on the ESP32-S3R8 was tested against the Apple Watch Series 7. Its achieved a **Pearson correlation coefficient of $r > 0.95$** and a **mean bias of only -0.90 BPM**. It was also tested to see how well it responded to changes in the body and the

results showed that independent samples t-tests was $p < 0.001$ for GSR and $p < 0.0001$ for skin temperature. This means that the device can collect high-quality data at a lower cost than other devices on the market.

The study collected a multimodal data from **60 participants**, including information about their personality and physiological responses. When this data was analyzed it showed that certain personality traits, such as **Extraversion and Openness** were very important in predicting emotions.

Utilizing a cost-sensitive **Soft-Voting Ensemble (Extra Trees + XGBoost)**, the system achieved a peak accuracy of **0.66** under unbalanced conditions. More significantly, the model maintained a mean accuracy of **0.77 ± 0.13** and a high recall for negative emotional states (**~ 0.88**) under strict **Leave-One-Subject-Out (LOSO)** cross-validation, which represents real-world, subject-independent scenarios, demonstrating the framework's robustness across diverse individuals.

The "Black Box" of AI was successfully unlocked by the suggested **CCSF**. The model prioritized **Valence, Arousal, and Dominance**, which is exactly in line with the Russell Circumplex Model and established **Appraisal Theory**, according to empirical mapping of the feature priority hierarchy.

By integrating the **Bio-Adaptive Dynamic Sampling Strategy**, the power-resolution trade-off is essentially resolved, increasing wearable battery life without sacrificing the 18-bit signal resolution necessary for emotional peak identification.

ROADMAP: FUTURE DIRECTIONS

Phase 1: Hardware Miniaturization

The ESP32-S3R8 is used in the current device. It can be made more compact and effective in the future.

- **Hardware Miniaturization:** To create compact devices like smart rings or thin wristbands, we can employ multi-layer PCBs (Printed Circuit Boards) in place of development boards.
- **Power Optimization:** We can extend battery life by incorporating "Deep Sleep" modes utilizing the Bio-Adaptive Sampling technique.

Stage 2: Advanced Deep Learning and Multimodal Integration

The study uses a basic method for classification of data but in future more advance methods can be used.

- **Transformer Architecture Approaches:** Utilizing Vision Transformers (ViT) or Temporal Convolutional Networks (TCN) to grasp long-range dependencies in PPG and GSR data.
- **Cross-Dataset Validation:** Evaluating the models trained on the PhysioEmotion dataset using public datasets such as WESAD or DEAP to guarantee total subject-independence.
- **Self-Supervised Learning (SSL):** Leveraging the extensive amount of unlabeled physiological data obtained during "neutral" states to pre-train models, which are subsequently refined for particular emotional categories.

Step 3: Digital Twins and Customized Emotional Profiles

The combination of the "Big Five" personality traits creates a distinctive opportunity for hyper-personalization.

- **Emotional Digital Twins:** Developing virtual emotion profiles for individuals that forecast their responses to particular stimuli according to their Conscientiousness or Neuroticism ratings.
- **Expansion of Explainable AI (XAI):** Employing the CCSF Framework to create a dashboard that informs a clinician on the reasons behind the AI identifying "High Stress" (e.g., "Identified a 15% rise in SCR peaks coinciding with reduced HRV, characteristic of attentional overload in high-neuroticism individuals").

Phase 4: Clinical and Ecological Implementation in Real-World Settings

The goal is to see if the system works in real-life situation.

- **Long-term Mental Health Research:** Using the device to study people with anxiety or PTSD for 30 days to see what triggers their emotions.
- **Therapeutic VR/AR Integration:** Using the device to adjust the level of exposure in virtual reality therapy based on the persons physical responses.
- **Emotional Safety in Industrial IoT:** Using system to track worker fatigue and emotional exhaustion in jobs such as air traffic control or surgery.

6. PUBLICATIONS

The research work that has been carried out has become a tree which has given some fruits in the form of publications. Following is the list of these publications.

- 1) Vilas S. Machhi and Apurva M. Shah, "A Review of Wearable Devices for Affective Computing," 2024 International Conference on Advancements in Smart, Secure and Intelligent Computing (ASSIC), Bhubaneswar, India, 2024, pp. 1-6, doi: 10.1109/ASSIC60049.2024.10508031. (**Scopus Indexed**)
- 2) Vilas S. Machhi and Apurva M. Shah, "An empirical study of emotion recognition using physiological signals," Parul University International Conference on Engineering and Technology 2025 (PiCET 2025), Hybrid Conference, Vadodara, India, 2025, pp. 137-144, doi: 10.1049/icp.2025.1287. (**Scopus Indexed**)
- 3) Vilas S. Machhi and Apurva M. Shah, "Emotion Detection Unveiled: A Cognitive-Computational Synthesis of Physiological Models, Machine Learning, and Datasets", Cognitive, Affective, and Behavioral Neuroscience. (**Accepted, SCIE, Scopus Indexed, IF=2.7**)
- 4) Vilas S. Machhi and Apurva M. Shah, "Validation of Video Stimuli for Basic Emotion Elicitation: A Multimodal Approach using Self-Reports and Physiological Signals", Journal of Information and Optimization Sciences (**Accepted, ESCI, Scopus Indexed, IF=0.7**)

- 5) Vilas S. Machhi and Apurva M. Shah, “Design and Development of a Multi-Sensor Wearable platform for Physiological Monitoring with potential for emotion-recognition research” (Under Review)
- 6) Vilas S. Machhi and Apurva M. Shah, “PhysioEmotion: A Multimodal Physiological Signals Dataset for Emotion Recognition with Variable Sampling and Personalized Traits” (Under Review)
- 7) Vilas S. Machhi and Apurva M. Shah, “Benchmarking Electrodermal Activity Decomposition Methods for Real-Time Emotional Arousal Monitoring in HCI” (Under Review)

PATENT & COPYRIGHT

Multimodal fingertip-sensor framework with adaptive sampling and self-reported personality for emotion classification (Application No: 202521084403)

PhysioEmotion: A Physiological Signals Dataset for Emotion Recognition (Diary No: SW-43904/2025-CO)

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