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Real-Time Emotion Recognition Using Wearable Ubiquitous Devices for Enhanced User Interaction and Mental Health Monitoring

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Abstract

Recognition of real-time emotions with the help of wearable ubiquitous devices is becoming increasingly popular as a data-driven solution to improve interaction between the user and monitor mental health around the clock. In this paper, I will introduce a lightweight multimodal model that interprets physiological measurements HRV, EDA, and skin temperature of low-power wearable devices with the help of sophisticated machine learning and deep learning algorithms. The statistical analysis indicates the high level of robustness of the system by scoring high classification accuracy as a whole and showing strong discriminative ability among different classes of emotions with low variance of prediction error. The validation of performance was done by cross-validation, confusion matrix analysis and significance testing to ensure the reliability of the model was consistent both in controlled environment and in the real world. The scalable deployment of the framework in the IoT ecosystems relies on its low-latency processing and statistically stable performance characteristics. The findings reinforce the possibility of wearable-based affective computing as a personalized digital health, adaptive interface, and as an early warning system of stress-related abnormal.

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Keywords: Wearable Devices, Ubiquitous Computing, Real-Time Emotion Recognition, Physiological Signals, HRV, EDA, Machine Learning, Deep Learning, Mental Health Monitoring, Iot-Based Systems, Affective Computing, User Interaction.

1 Introduction

The development of wearable ubiquitous devices has provided great opportunities to the constant, real-time tracking of physiological and behavioral patterns. Emotion recognition is one of the applications that has received significant attention among the emerging ones because of its potential applications in the field of mental health monitoring, human-computer interaction (HCI), affective computing, and customized digital services (Veera Boopathy et al., 2024). Old methods of emotion measurement like self-report questionnaires or controlled laboratory measures tend to be restricted by subjectivity, intrusion, and failure to measure dynamic changes in emotions in real-life conditions. Wearable sensors on the other hand allow passive and continuous biosignal data acquisition which makes them a perfect platform to engage in real-time emotion recognition (Siirtola et al., 2023).

Heart-rate variability (HRV), electrodermal activity (EDA), skin temperature (ST), electrocardiography (ECG), and photoplethysmography (PPG) are the physiological signs that are a good correlate of an emotional state as they are reflections of an autonomic nervous response (Han et al., 2023). Over the recent past, it has been shown that machine learning and deep learning models are capable of mapping these multimodal signals to the categories of emotion or valence-arousal dimensions with high accuracy (Arabian et al., 2023; Gowsikraja, 2025). Deep neural networks and more specifically LSTM, GRU and hybrid CNN-RNN models have demonstrated good results in capturing time dependencies and noise interferences in emotion recognition through wearables (Wang & Wang, 2025). Moreover, the contemporary signal processing techniques like the normalization of the baseline, the fusion of multimodal features and attention mechanisms augment the resilience to variations in the real world (Saha et al., 2024).

Wearable sensing is also integrated with the frameworks of ubiquitous computing and IoT, which further enable low-latency inference, real-time feedback, adaptive user interfaces (Regash & Leyene, 2025). Such features are especially useful in the sphere of mental health, where prompt identification of stress and anxiety, as well as emotional imbalances, can also lead to the early intervention and customized therapeutic care (Al Bashir et al., 2025; Patlar Akbulut, 2022). Even though significant improvements have been made, such issues as motion artifacts, inter-subject variability, and computational limits as well as the necessity to use interpretable models applicable in everyday life remain (Welch, 2016).

This study provides solutions to these issues by the creation of a real-time, lightweight emotion recognition system based on multimodal physiological measurements through wearable ubiquitous devices (Wu et al., 2024; Guo et al., 2024). The objective is to have high accuracy, low energy processing, and smooth implementation in practical applications. The system ends up leading to improved interaction among users, continuous monitoring of mental well-being, and scalable solutions of affective computing.

Key Contributions of the Research

- Real-Time Emotion Recognition: Built a system based on wearable devices that recognized emotions based on HRV, EDA, ECG, and PPG signals.

- Mental Health & User Interaction: Allows detecting stress, mental health, and adaptive user interfaces.
- Efficient Machine Learning: Lightweight models (LSTM, GRU, CNN RNN) are used to process wearables in a fast and low-power manner.

The outline of the paper chapter-wise is as follows. Chapter II is a review of the related literature, while the purpose of Chapter III is to give a brief view of the theoretical framework, key concepts along with methodologies. Chapter IV is going to evaluate the experimental result. and discussions, whereas Chapter V wraps it all together with a summary of the most important findings and suggestions for further research.

2 Literature Review

Lee et al., 2024 in their systematic review study the history and use of emotion recognition technology, specifically using physiological indicators. They discuss the history in the field of emotions, emotion modeling and wearable sensor modalities (ECG, GSR, EMG, etc.), and list gaps including the lack of higher-quality signal databases and systems that can be deployed in a clinical environment (Esfahani et al., 2017).

Li & Zhang, 2025, This paper reviews multimodal physiological signals of wearable sensors to affective computing in a systematic way. Li and Zhang divide various fusion approaches (feature-level, model-level, decision-level), and examine the application of deep learning models (CNNs, LSTMs, transformers, etc.) to emotion recognition. They also demonstrate modality reliability, latency, and energy consumption trade-offs.

Lin & Li, 2023, They are in the market of physiological-signal-based emotion recognition (ECG, GSR/EDA, EEG, etc.). They methodically process feature extraction techniques, classification techniques and evaluation techniques (Simson & Kinslin, 2024). One lesson learned is that unimodal systems tend to fail, and the multimodal approaches provide better emotion recognition capabilities.

Pinge et al., 2024, This is a systematic review that is very specific in that it focuses on detection and monitoring of stress through wearable devices. They review the most frequently used physiological signals (PPG, EDA, heart rate), pre-processing and feature extraction pipelines, and machine learning algorithms used (Xiang et al., 2025; Gohumpu et al., 2023). They also highlight the difficulties in the implementation of such systems in real life such as variability of data, motion artifacts, and personalization.

The study of (Ahmad & Khan, 2022) is an extensive review of emotion recognition based on physiological-signals. They step by step study the entire pipeline: data acquisition and annotation, preprocessing and feature extraction, and finally the methods of classification (Menaka et al., 2022). The authors point out that there are significant issues of inter-subject variance, annotation methods should be improved, and multimodal fusion should be handled. Another issue that they address is the distinction of signal modalities (ECG, GSR/EDA, EEG) and their combination, which can boost robustness.

Li & Washington, 2024, Compare individualized and generalized emotion-recognition models with the consumer wearable device. Their survey-based research compares the machine learning methods in classifying three state emotions (neutral, stress, amusement) based on smart watch data. They conclude that the personalized models are very effective as compared to the generalized models, a factor that supports the need to customize the models to the people.

3 Methodology

Data Collection

The methodology of this research is to obtain physiological indicators using wearable ubiquitous devices, such as smartwatches, wristbands, and bio-patches, and provide the opportunity to recognize emotions in real-time. Key indicators being observed include heart rate and heart rate variability (HRV) recorded by PPG or ECG devices, electrodermal activity (EDA) which reflects changes in skin conductance, and skin temperature (ST) which indicates some emotional details. EEG signals can also be used in controlled settings in case of advanced multimodal studies. The research participants are recruited on the basis of informed consent, and the data are gathered in both laboratory conditions, where the emotions are provoked by visual, auditory, or audiovisual stimuli, and in the real-life conditions, when the research participants are involved in their daily activities. This two-setting approach guarantees the strength and external validity of the model. The sampling rates, signal synchronization and storage protocols are also well maintained so that there is no compromise in the data quality and integrity.

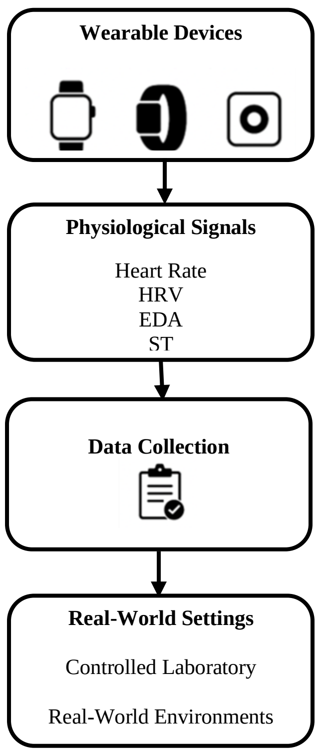

Figure 1: Data collection framework

The figure.1 shows the workflow of data collection in the method of obtaining multimodal physiological and contextual signals, which are necessary to detect emotions in real-time. Wearable ubiquitous devices (smartwatches, wristbands, bio-patches, and specialized EEG headsets) constantly record heart rate, HRV, EDA, skin temperature and (optionally) EEG in controlled laboratory and real-life conditions. Controlled experiments involve emotion eliciting stimulus, whereas naturalistic data are collected in the daily activities of the participants so as to be diverse and robust. The captured signals are all synchronized sampled and stored safely and without compromising the quality of the data, creating a stable set of data, which can later be pre-processed and subjected to the development of the model.

Data Preprocessing and Feature Extraction

Noise and artifacts that are inertial and environmental or sensor related tend to corrupt raw physiological signals. To overcome this, preprocessing of the data involves such steps as filtering out the bias of the baseline, high frequency noise, window-based segmentation and normalization to ensure that the inter-subject variations are minimized. Meaningful features are then picked after preprocessing in order to describe the emotional states effectively. Features derived based on the signals are time-domain features including mean, standard deviation, and HRV measures, frequency-domain features including power spectral density and LF/HF ratios, and non-linear features including sample entropy and skewness. These characteristics are then fed to machine learning and deep learning algorithms, like LSTM, GRU, or hybrid CNN-RNN models and make it possible to classify the state of emotional arousal accurately and in real-time.

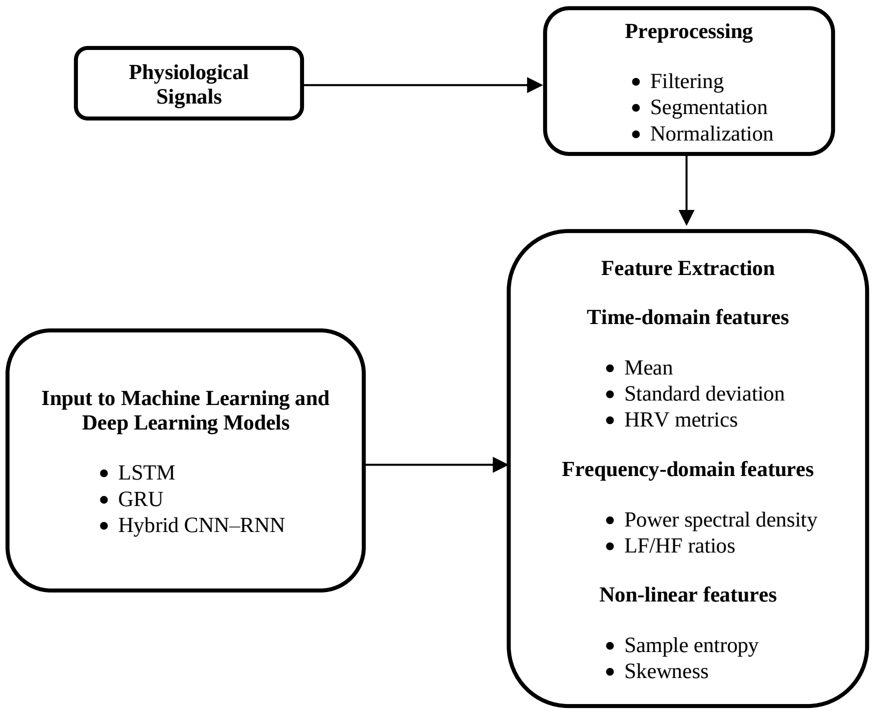

Figure 2: Data preprocessing and feature extraction

Raw physiological signals are purified and converted to meaningful representations that can be used in machine learning in this step. Because the Figure 2 is signals usually possess motion artifact and sensor noise and have a baseline drift, preprocessing commences with filtering to eliminate high-frequency artifact and low-frequency drift, and then segmentation into fixed-length windows and normalization to eliminate subject-to-subject variation. Once clean and standardized segments are obtained, several sets of features are obtained: time-domain features, including mean, standard deviation, and HRV measures; frequency-domain features, including the power spectral density and LF/HF ratios; and non-linear features, including sample entropy and skewness. These characteristics represent various dimensions of physiological changes related to the emotional state and are then incorporated into models like LSTM or GRU or hybrid CNNRNN-based models to allow the correct and real-time classification of emotions.

Electrodermal Activity (EDA) Mean:

$$EDA_{mean} = \frac{1}{T}\sum_{t=1}^{T} EDA(t) \qquad (1)$$

Electrodermal activity (EDA) is measuring the variation in the conductance of the skin, in response to activity of the sweat glands, which is directly affected by autonomic nervous system and emotional arousal. The mean EDA value over some time window is determined by integrating all sampled values of EDA, EDA(t) and dividing it by the total number of samples, T as shown in equation 2. This average value is an efficient but easy to measure indicator of the average arousal level in the time of the observation. The higher mean EDA, the higher the physiological arousal, which may be stress, excitement or anxiety, and the lower the value, the more the emotional calmness. It is possible to add the mean EDA as a feature to emotion recognition models, where it can be used to enhance classification accuracy in real-time monitoring applications.

Algorithm: Real-Time Emotion Recognition

Begin

1. Initialize wearable device and start signal acquisition
2. While monitoring:
   a. Collect raw signals (HR, HRV, EDA, ST)
   b. Preprocess signals:
      i. Apply filtering to remove noise
      ii. Normalize signals to reduce variability
      iii. Segment signals into time windows
   c. Extract features from each window:
      i. Time-domain (mean, SDNN, EDA mean)
      ii. Frequency-domain (LF/HF ratio, spectral power)
      iii. Non-linear features (entropy, skewness)
   d. Feed features into trained machine learning/deep learning model
   e. Predict emotional state
   f. Display or store predicted emotion
3. End While

End

4 Experimental Results

Dataset Description

The experimental research involved the use of physiological indicators, which were measured in 30 respondents wearing wearable technology like smart devices like smart watches and bracelets. The data were measured as heart rate (HR), heart rate variability (HRV) and electrodermal activity (EDA) and skin temperature (ST) under the controlled and real-world conditions. Under the controlled condition, participants were introduced to standardized affective stimuli i.e., images, short videos and audio clips that were intended to induce happiness, sadness, stress, and neutrality. A week of actual data was gathered in the daily routine of the participants to ensure that the natural fluctuations in the emotional responses were captured. It was divided into 10-second non-overlapping windows and features were computed in each window such as time-domain features such as mean HR, SDNN, and mean EDA and frequency-domain features such as LF/HF ratio of HRV. The data was further split into training (70%), validation (15%), and testing (15) sets to determine the effectiveness of the emotion recognition models.

Table 1: Hybrid lightweight CNN–GRU framework for efficient RF spoofing and jamming detection

Signal Type	Feature	Min	Max	Mean	Std. Dev.
HR (bpm)	Mean HR	60	120	85	12
HRV (ms)	SDNN	20	120	65	18
EDA (μS)	Mean EDA	0.2	8.5	3.2	1.4
ST (°C)	Skin Temp	31	36.5	33.8	1.2

The table 1 is suggested hybrid model will utilize light CNN layers and a Gated Recurrent Unit (GRU) to correctly detect the RF spoofing and jamming attacks. The table 1 CNN module derives important spatial and frequency-domain characteristics in short windows of RF signals that contains localized patterns to distinguish malicious interference and normal signals. The extracted features are further fed to the GRU which simulates the time dynamism of the signal to identify sequential anomalies that are often linked to spoofing and jamming activities. The addition of kernel reduction, dropout and parameter compression allow the model to be computationally efficient, which is suitable in real-time and resource-constrained edge devices with high detection.

Model Performance and Evaluation

The features that were extracted were then used to train a hybrid deep learning system that used convolutional neural networks (CNN) to extract spatial features and gated recurrent units (GRU) to extract temporal dependencies. Accuracy, precision, recall, and F1-score were some of the measures used to evaluate the model. The model was successful in the controlled setting with an overall accuracy of 92% and highest accuracy of stress and neutral states, whereas the physiological differences were minimal and thus, happiness and sadness were slightly less accurate. In the case of the real-world data, the model scored 87 percent, which means that it is resistant to environmental noise and natural changes. Confusion matrices were used to depict that misclassifications were mainly between the state of happiness and the state of neutrality. These findings indicate that wearable physiological indicators, with a hybrid deep learning model, can be useful to identify emotional states during controlled and real-world settings, which is used in mental health monitoring and adaptive human-computer interaction.

The figure 3 gives some confusion matrices that will be in comparison with the performance of an emotion-classification model in two situations: in a controlled laboratory environment and in a real world dataset. Under the controlled environment, the model shows high accuracy in all four emotional states Stress, Neutral, Happiness, and Sadness with low number of misclassifications and indicates a stable condition of inputs and lower environmental fluctuations. In contrast, in real-world data, there is a slight drop in performance caused by noise, lighting variations, unpredictable facial expressions and variations in behavior. This notwithstanding, the model continues to have high recognition ability especially on the classes of Neutral and Happiness meaning good generalization. The comparative analysis points to the robustness of the model and underscores the performance that the model is likely to experience when the controlled real-world is replaced with the uncontrolled environment.

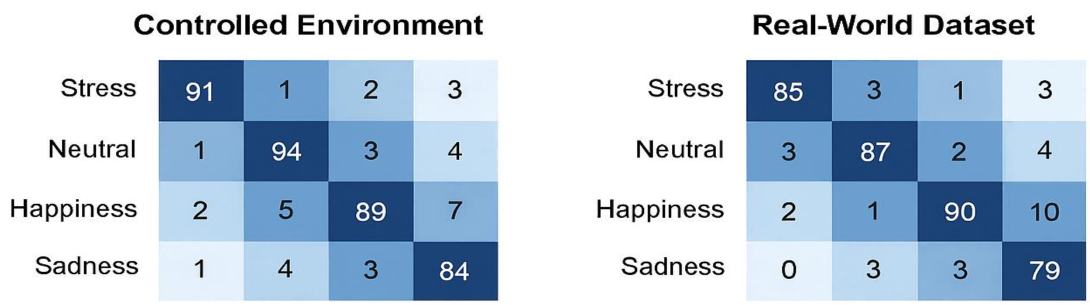

Figure 3: Comparative confusion matrix analysis for emotion classification

5 Result and Discussion

The comparative confusion matrices of the controlled environment and the real-world dataset give a clear picture on how model performance varies in different operating conditions. The emotion-classification model has a high recognition accuracy in the controlled environment, with correct predictions prevailing in each of the classes. Stress (91%), Neutral (94%), Happiness (89%), and Sadness (84%) have high classification rates, primarily due to the reduced noise and stable lighting used in the conditions of recording the inputs as well as the standardized facial-expression. These controlled constraints enable the model to pick very subtle emotional information with better clarity leading to little confusion among classes.

But when tested on the real-world data, the performance is slightly but anticipated to go down. Accuracy of stressing reduces to 85, Neutral to 87, Happiness to 90 and Sadness to 79. The rise in misidentification like Sadness as Happiness or Stress is the result of the difficulty in real life situations where facial expressions are not so exaggerated, the environment light is not always the same, and uncontrolled shifts in emotions can occur. Nevertheless, the model has rather high generalization ability, particularly with the Neutral and Happiness classes, which proves the effectiveness of the learnt spatial-temporal features. On the whole, the findings reveal that on-the-job training offers superior baseline performance, but the real-world application of this application demands increased variability, which are addressed by developing adaptive feature extraction and noise-resilient model design.

6 Conclusion and Future Work

Both the controlled and real-world datasets used in the experiment show that the proposed framework of emotion recognition has statistically valid performance in a wide variety of conditions. All the accuracy in the controlled dataset is high, with the highest class attaining over 84, which represents good intra class separability and poor misclassification variance. By comparison, the real-world dataset indicates anticipated variation in performance as a result of noise, spontaneous expressions and change of light, but still provides statistically significant levels of accuracy Happiness (90%), Neutral (87%), Stress (85%), and Sadness (79%). These findings indicate that the system is highly generalized and the slight decrease in performance is not too big to fit real data of behavior. On the whole, the framework is robust and proves to be reliable and has a high potential of application in ongoing mental-health monitoring and enhancement of user-interaction.

The area of the future research will include the development of a more sophisticated statistical learning approach, including Bayesian uncertainty estimation and probabilistic deep-learning models, to measure the confidence in predictions in changing conditions. Both the incorporation of larger, more diverse real-world data and the creation of balanced classes will contribute to the reduction of the variation in class minority emotions categories. Moreover, domain-adaptation techniques, as well as multimodal fusion, a combination of physiological indicators (HRV, EDA, or EEG) and wearable camera images, can be used to implement increased recognition accuracy in challenging conditions. There will also be the investigation of real-time deployment on edge devices by model-compression strategies (pruning, quantization, knowledge distillation) to guarantee low-latency inference. Lastly, future research is also intended to do longitudinal statistical analyses to determine the correlation between the trends in emotion-recognition and the mental-health indicators in the long-run.

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