

Original Article

Predicting Stress Level in Young Minds Using HRV and EDA Signals

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Abstract

Adolescent stress has emerged as an important concern due to its impact on mental well-being, academic performance, and long-term health issue. Wearable sensing devices and machine learning pattern provide opportunities for objective and continuous stress monitoring techniques. This study aims to develop a machine learning-based framework for detecting stress levels in adolescents using wearable devices. We utilized the Fitbit Sense 2 smartwatch to record several physiological metrics from adolescents aged 12 to 16, specifically targeting their heart rate, electrodermal activity (EDA), heart rate variability (HRV), and physical movement levels. After preprocessing, feature engineering and z-score-based composite stress scores were used to generate low, moderate, and high stress labels. Experimental results showed that RF and Gradient Boosting achieved the highest average accuracy of 94.78%, with a peak accuracy of 97.61%. Electrodermal activity and heart rate-based features emerged as significant predictors of stress. The study confirms that wearable-derived biological signals are highly effective for stress identification, indicating a significant opportunity to use artificial intelligence for teenage mental health surveillance. Future work may extend this framework through multimodal integration of psychological measures and physiological wearable data for more comprehensive stress assessment.

Keywords: Adolescent Stress Detection, Machine Learning, Wearable Sensors, Physiological Signals, Multimodal Analysis

Introduction

Stress has taken an important role in among adolescents and young adults due to increasing academic demands, Parents expectation, social pressures, emotional transitions, and changing lifestyles. These stress-related factors can impact adolescents' cognitive functioning, emotional regulation, and physical health[1]. If stress not handle for long period, it leads multiple phases like anxiety, depression, or other persistent mental health problems. Hence, early understanding and prediction of stress have become important in daily life[2].

Early prediction of stress phases is important because timely identification allows preventive intervention before stress becomes critical levels. Because the rely on personal perception, self-reported questionnaires frequently fail to capture the fluid, real-time fluctuations of an individual's stress levels.[2]. Due to these shortcomings, there is a growing demand for objective and continuous stress monitoring approaches, especially wearable device-based methods that utilize physiological indicators such as EDA and HRV[3].

To address this challenge, wearable sensing technologies seen considerable attention for physiological monitoring data. Wearable devices can continuously capture biosignals related to autonomic nervous system (ANS) activity, they used for stress detection. Among various physiological signals, HRV, EDA, ECG, GSR, blood oxygen saturation (SpO₂), and body temperature have emerged as reliable biomarkers for stress assessment[4, 5]. HRV represents changes in heart rhythm, whereas EDA captures variations in skin conductance associated with emotional arousal and stress reactions[6]. The complementary nature of these two signals provides a strong foundation for multimodal stress analysis.

Physiological signals are complex, nonlinear, and dynamic, making manual interpretation difficult to analysis and prediction.

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The utilization of machine learning techniques is driven by their capacity for automated discovery of underlying patterns in heterogeneous physiological streams, yielding superior stress-state classification compared to traditional methodologies[7]. By correlating extracted HRV and EDA features with specific stress states, machine learning algorithms provide a powerful framework for predictive stress analytics[8]. Many research study focus only on binary stress versus non-stress classification rather than predicting multiple stress phases. Some studies rely on a single modality, such as HRV or EDA alone, which may reduce prediction robustness. In addition, relatively fewer studies specifically address adolescents and young populations, where stress patterns may differ significantly. These gaps highlight the need for an integrated machine learning framework capable of predicting stress of young minds using multimodal physiological signals[9].

Based on this motivation, the proposed study aims to develop a stress phase prediction framework using HRV and EDA signals collected through wearable devices[10]. The study focuses on extracting significant physiological features, applying machine learning for stress level classification, and analyzing model performance for accurate prediction. By connecting the problem of adolescent stress with physiological sensing and machine learning-based prediction, this study develops a coherent framework to support wearable-based stress monitoring and early intervention systems.

Related Work of Physiological Signals

Automated stress identification systems powered by machine learning and physiological signals are currently being explored to address the modern epidemic of stress-induced illnesses. A wide array of biological signals has been investigated in current literature to track human stress levels, providing the foundation for the present work[11]. Early research in stress detection study primarily focused on physiological signals because stress produces measurable changes in autonomic nervous system activity[12]. Thermal data, respiratory rates, skin conductance, and cardiac activity have historically served as the primary physiological indicators for mapping human stress reactions. Multimodal physiological monitoring has shown greater effectiveness compared to single-signal approaches, as combining signals often captures complementary stress-related information[13, 14].

Existing literature highlights several studies significant contributions in the use of physiological signals for stress detection.

De Santos Sierra et al. introduced a stress detection framework using galvanic skin response and heart rate signals, applying fuzzy logic for both manual and automatic classification. Despite these strengths of paper, the study was limited by its exclusive focus on female participants[15]. In a study by Delmastro et al., the viability of identifying stress in cognitively impaired and frail older populations was assessed by tracking skin conductance changes during mild exertion and cognitive activities. The work faced limitations, including a very small sample size and the absence of predefined validation of stress responses, which restricts the strength of its conclusions[16]. Zontone et al. presented a driver stress detection system based on Skin Potential Response (SPR) and Electrocardiogram (ECG) signals, employing supervised machine-learning techniques for classification. Their framework introduces a novel motion-artifact removal algorithm that combines SPR signals from both hands to obtain a cleaner physiological signal during steering. Stress-related features extracted from SPR and ECG were classified in short overlapping time windows during simulated driving with induced stress events. The system achieved balanced accuracies of about 77–80%, demonstrating reliable stress recognition. This study was conducted in a driving simulator with a limited number of participants, which may constrain the direct applicability of the results to real-world driving scenarios[17].

Boffet et al. investigated cognitive load modulation using EDA and HRV. Their study showed that specific EDA (EDATVSYMP) and HRV (HF-HRVVFCDM) markers reliably differentiated cognitive load from emotional states during a 2-back task and image viewing. The authors also identified distinct individual autonomic profiles, emphasizing the benefit of combining EDA and HRV rather than relying on a single biosignal[3]. Chen et al. examined the usefulness of short-term heart rate variability (HRV) for the momentary assessment of acute mental stress in young adults using a controlled low–high stress block design. Their systematic evaluation of 42 HRV metrics showed that about one third reliably tracked minute-scale stress variations, while fewer metrics demonstrated both absolute and relative reliability. The study highlights that stress sensitivity strongly depends on careful HRV metric selection, rather than using HRV as a single global indicator. However, the findings are limited to laboratory-induced mental arithmetic stress, which may reduce generalizability to real-world, complex stressors[18]. Morales et al. introduced a novel multimodal dataset designed to study the relationship between electrodermal activity (EDA), heart rate variability (HRV), and stress in software developers, a population particularly exposed to occupational stress. Data collected during relaxation and stress-inducing tasks showed consistent patterns, including increased EDA and HR with reduced HRV metrics under stress. The dataset is intended to support machine-learning-based stress detection, especially personalized models such as ANNs. Its main strength lies in providing well-annotated physiological and subjective stress data (PSS-14) tailored to a real occupational context. However, the relatively small sample size and controlled experimental setting may limit immediate generalization to real-world workplace environments[19]. As per the study of previous study EDA and HRV are important sensor in stress detect study.

EDA and HRV sensors

EDA: An EDA sensor also known as an a GSR sensor measures changes in the electrical conductivity of the skin[20]. These changes occur due to sweat gland activity which is controlled by sympathetic nervous system. The sympathetic nervous system activates due to stress, anxiety, fear, excitement. This causes Sweat secretion even if is not visible. The sensor detect change in conductance. EDA output is in the form of tonic component and phasic component[21].

HRV: Heart rate variability is the measures of the naturally occurring tiny fluctuations in the timing between each consecutive heartbeat. Unlike HR, which counts beats per minutes, HRV measures the specific difference in milliseconds between individual beats[22].

HRV is in the form of time domain metrics and frequency domain metrics. In time domain metrics use RMSSD method is common in stress detection study. It is directly reflect parasympathetic rest and digest activity and SDNN method calculate the standard deviation of all beats interval over a period[23].

Methodology

As illustrated in Figure 1, this research evaluates teenage stress levels by combining physical experimentation with artificial intelligence algorithms applied to wearable biometric data. The proposed methodology consists of data acquisition, preprocessing, feature engineering, stress labelling, feature selection, model training, and performance evaluation.

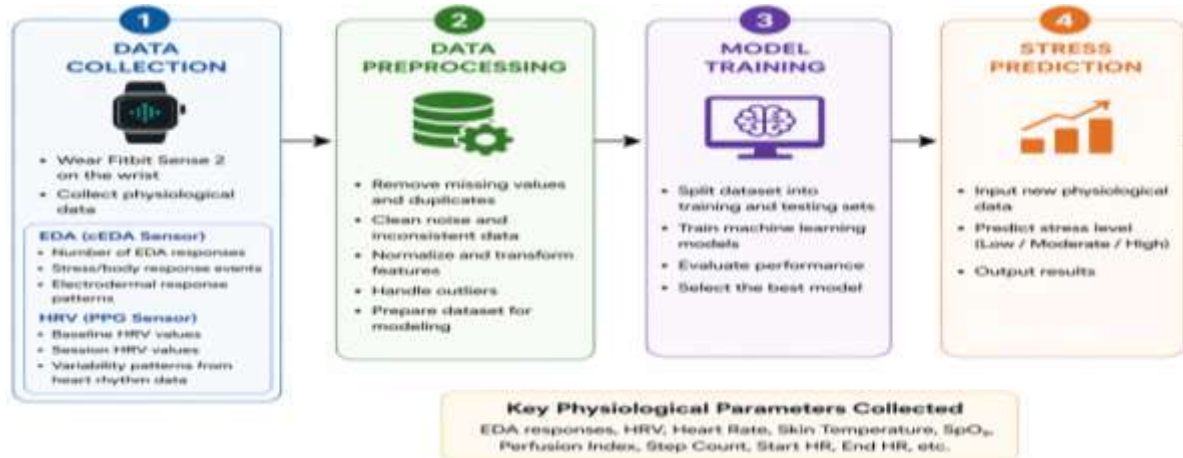


Fig: Stress detection Workflow diagram

Data Collection- During a data collection experiment tailored to trigger stress reactions, we gathered 231 physiological data records from teenagers between 12 and 16 years of age. The Infrared thermometer gun, pulse oximeter and Fitbit Sense 2 smartwatch was used to monitor stress-related signals such as heart rate, electrodermal activity (EDA), heart rate variability, and activity-related measures. This protocol enabled observation of physiological changes associated with stress responses.

Data Preprocessing

After data collection, the physiological data were used to enhance quality of data and ensure reliability for further analysis. The preprocessing stage involved identifying and removing records with missing values in key physiological variables, filtering invalid or physiologically implausible readings, and minimizing sensor noise. Duplicate and inconsistent observations were also examined and handled to improve dataset integrity.

The refined data were compiled into a standardized matrix encompassing vital metrics like heart rate (HR), heart rate variability (HRV), electrodermal activity (EDA), thermal readings, and associated biological metrics. To maintain consistency across features, continuous variables were normalized where required. In addition, derived measures such as heart rate changes and HRV variations were computed to better capture stress-related physiological responses. Outliers were detected and treated using threshold-based and statistical approaches to reduce the influence of noise and abnormal values. By executing these data cleaning and modification procedures, we generated a high-quality, dependable dataset ready for the extraction of features and automated stress classification.

Feature Engineering

To better characterize stress-related physiological responses, additional features were derived from the raw sensor signals. Heart rate change (Delta_HR) was calculated as the difference between end heart rate and start heart rate to capture immediate cardiovascular response during the session. Heart rate deviation from baseline (HR_Dev) was computed to measure how much an individual's heart rate differed from their normal resting state. Electrodermal activity response rate (EDA_Rate) was also derived by relating EDA responses to session duration, providing an indicator of sympathetic nervous system activation associated with stress. In addition, step count was retained as a contextual feature to help distinguish physiological changes caused by stress from those influenced by physical movement. These derived features enriched the dataset by capturing meaningful patterns related to stress reactivity and improving its suitability for machine learning analysis.

Stress Label Generation- As direct ground-truth stress labels were not available; stress categories were generated using a composite stress scoring approach based on physiological indicators. To ensure comparability among features, selected stress-related variables were first normalized using z-score normalization. A weighted stress score was then computed by combining electrodermal activity (EDA), heart rate change, and deviation from baseline heart rate, reflecting multiple dimensions of physiological stress response. Based on the distribution of these stress scores, participants were classified into three levels—low stress, moderate stress, and high stress—using a quantile-based labeling approach. This process enabled the creation of a multiclass labeled dataset suitable for supervised machine learning.

Feature Selection

To identify the most informative variables for stress classification, feature selection was performed using both statistical and machine learning-based methods. Analysis of Variance (ANOVA) was applied to assess the significance of individual features, while Random Forest feature importance and permutation importance were used to evaluate the contribution of each variable to model prediction. Features demonstrating stronger discriminatory capability and higher predictive relevance were selected for model development, helping improve classification performance while reducing redundancy. To address class imbalance, Synthetic Minority Oversampling Technique (SMOTE) was applied to generate balanced training samples and improve model generalization.

Model Development

To evaluate the stability and reliability of the framework, we partitioned the tagged dataset into separate training and evaluation blocks under multiple distribution ratios (specifically 80:20, 70:30, and 60:40 ratio). Multiple machine learning algorithms were trained and compared to identify the most effective approach for stress classification. Model performance was evaluated using standard metrics selected for stress prediction [7, 24].

Result and Discussion

After data preprocessing task and model development, experimental results were analyzed to measure the practical impact of the proposed methodology on stress detection. This paper discusses the obtained results in terms of feature significance, model performance, and overall classification outcomes.

To evaluate the effectiveness of the proposed stress detection framework, multiple machine learning classifiers were tested using three train–test split ratios (60:40, 70:30, and 80:20). The performance of each model was assessed based on classification accuracy, and the comparative results are presented in Table 1.

Among the evaluated models, Gradient Boosting and Random Forest achieved the highest average classification accuracy of 94.78%, showing consistently strong performance across all split ratios. Both models reached their best accuracy of 97.61% under the 80:20 split, indicating excellent predictive capability for multiclass stress classification.

Model	60:40	70:30	80:20	Average
Gradient Boosting	91.57	95.16	97.61	94.78
Random Forest	91.57	95.16	97.61	94.78
Logistic Regression	91.57	95.16	92.86	93.19
SVM	92.77	93.55	90.48	92.27
KNN	89.16	91.94	90.48	90.52
Decision Tree	83.13	80.65	85.71	83.16
Naïve Bayes	77.11	83.87	85.71	82.23

Table 1- Comparative analysis proposed system

Overall, the results indicate that ensemble learning methods provide superior performance for multiclass stress classification and are well suited for developing complex physiological stress patterns.

Conclusion

In conclusion, the comparative results show that ensemble-based classifiers, particularly Random Forest and Gradient Boosting, achieved the highest accuracy and proved most effective for multiclass adolescent stress classification using physiological signals. The findings also confirm that physiological parameters derived from wearable devices are valuable indicators for stress detection and can support reliable predictive modelling [5, 7]. In the future, this work can be extended by developing a multimodal stress detection framework that integrates psychological measures with physiological wearable data using task-based study to provide a more comprehensive and robust assessment of student stress.

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Conflicts of interest

The authors declare that there are no conflicts of interest regarding the publication of this paper

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