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A systematic review of ECG and physiological parameter analysis for stress detection via machine learning

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Abstract

Stress is a major factor for human health in todays fast paced world. It occurs due to work burden, life problems, responsibilities. It is a human response to ventures. This can result in various reactions in the life. The detection of stress at an early stage can be beneficial for prevention of various body problems like nervousness, unhappiness, cardiovascular diseases, and other stress related complications. By analyzing physiological signals which are an indication of response of stress in the body, we can save a human being. By observing heart rate variability, heart activity and various signals like Electrocardiogram (ECG) and other conventional methods detect stress by the electrical activity of the heart. This review describes the favorable and unfavorable methods of Machine Learning (ML) based models. These models provide precise and immediate evaluations of stress levels by using physiological data. These studies report the stress levels from low to high levels, which show the present growth and advancement of these models.

Subject Classification: *62M10, 97K40.*

Keywords: *Stress, ECG, Machine learning (ML), Physiological signals.*

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1. Introduction

Stress, anxiety and depression are physiological parameters which are negatively related to humans' mental stability. Many stressors can affect a person's mental health [1]. Medical Imaging play a vital role for doctors to find the disease[2]. A physiological imbalance can occur stress. Long term stress can lead to mental health issues or illness [3] . Workers also observe mental problems[4]. Due to the mental problem, people commit suicide[5]. According to the World Health Organization (WHO) 970 million people were affected by mental health problems in 2019. A 25% raise was seen in anxiety and depression after the COVID-19 pandemic in 2020 [6]. Comorbid diseases was also a part of COVID pandemic[7]. Heart diseases are a part of mental problem [8]. Stress can be positive (eustress) or negative (distress). The positive stress can allow the person to stay attentive, while negative stress can lead to physiological disorders. Two major properties of negative stress are demarcated as objective or subjective stress. The objective stress id mirrored depending on the various physiological measures like blood pressure, Galvanic Skin Response (GSR), ECG (Electrocardiogram) and EEG (Electroencephalogram). The subjective stress is an individual's observation [9] . Various bio-signals like ECG (Electrocardiogram), GSR (Galvanic Skin Response), Respiration signals, MRI, CT and EEG (Electroencephalogram) are used for stress detection [10] from which ECG is very commonly used [11] [12].

This review examines the various methods developed for stress detection using ECG via Machine Learning algorithms. It also analyzes different data sets related to ECG.

2. Literature Survey

The review surveys the current literature to recognize the success of stress detection models, with the analysis which is presented over various sub categories. The use of physiological signals for accessing human stress levels is described in Section 2.1, and the comparative analysis of ML models for stress detection is depicted in section 2.2.

2.1. *Utilization of physiological signals in assessing human stress levels*

By utilizing a variety of physiological parameters like HRV, GSR, skin temperature, respiration rate, blood pressure, and facial expressions, assessing the stress levels of humans can be significantly enhanced [13]. These physiological parameters are collected by ECG, EEG, EDA, EMG, Photoplethysmography (PPG), and body movement analysis sensors [14]. Utilizing the multimodal approach, where multiple physiological signals are integrated, could offer a more comprehensive and accurate assessment of stress levels [15]. This approach considers the complex interconnection between different physiological parameters and improves the robustness and reliability of stress detection models [16].

Anusha *et al.* [17] examined a wrist wearable sensor device to analyze the pre-surgery stress based on ECG and EDA. For differentiating the wearable sensor data, Linear Discriminant Analysis, KNN, Naïve Bayes, SVM, and Quadratic Discriminant Analysis were deployed. As per the evaluation results, this model robustly detected the pre-surgery stress levels as low, moderate, and high. However, the model's efficiency was minimized by the inter-individual variability like the sweat gland density together with skin thickness. In Table 1, the different physiological signals utilized for stress detection are indicated.

Table 1

Analyzing the physiological signals utilized for stress detection

Author name	**Objective**	**Physiological parameters / signals**	**Findings**	**Disadvantages**
Nazeer *et al.* [18]	Stress detection deploying bio-sensor technology	ECG, BVP, and body movement analysis	Accuracy – 96.12%	This model was susceptible to environmental influences
Affanni [19]	Wireless Sensors System for Stress Detection	ECG, EDA	Accuracy – 80%	However, the signal-to-noise ratio of this model was low
Saeed and Trajanovski [20]	Personalized Driver Stress Detection with Multi-task Neural Networks	Heart rate, skin conductance	F-score – 96.5% Kappa score – 87.9	Had scalability issue
Kyriakou *et al.* [21]	Detecting Moments of Stress	ECG, GSR, skin temperature	Accuracy – 84%	Less significant experimental protocols were employed in this model.

Kuttala, Subramanian, and Oruganti [22]	Multimodal Hierarchical CNN Feature Fusion for Stress Detection	EDA, ECG	Accuracy – 97.61% F1-score – 97%	It required a large amount of data, thus increasing the implementation overhead.
Arsalan and Majid [23]	Human stress classification during public speaking	ECG, EEG, GSR, PPG	Accuracy – 96.25%	A self-report was collected in this stress detection model, and it resulted in biased results.
Minguillon *et al.* [24]	Portable System for Real-Time Detection of Stress Level	ECG, EEG, EMG, GSR	Accuracy – 86%	Yet, the stress levels were not identified, which degrades the efficiency of this model weighed against other state-of-the-art models.
Campanella *et al.* [25]	Stress Detection using Empatica E4 Bracelet based on Random Forest, SVM, and Logistic Regression	Heart rate, HRV, EDA	Accuracy – 76.5% Precision – 71% Recall – 60% F1-measure – 65%	Obtained poor performances in real-world scenarios.
Kuttala, Subramanian, and Oruganti	Hierarchical Auto encoder Frequency Features for Stress Detection	ECG, EDA	Accuracy – 96.5% F1-score – 95%	However, the abnormal signals were not removed, which increased the computational overheads of the system.

Roy *et al.* [27] presented a hybrid deep-learning approach to detect stress using ECG as well as EEG signals. Here, for the physiological signals' feature extraction and stress level classification, the discrete wavelet transform (DWT)-centric CNN, BiLSTM, as well as 2 layers of the GRU network were employed. When analogized to other models, this hybrid approach achieved better classification accuracy. But, while running on edge devices, the model's efficiency was minimized as a large number of parameters were utilized.

2.2 *Various data sets used in stress detection*

By exploring diverse data sets from various sources, the stress classification models accuracy was evaluated. Different data sets were utilized to recognize the variations in stress detection techniques. SWELL dataset, 2D stress image dataset, Wearable Stress and Affect Detection (WESAD), Stress Recognition in Automobile Drivers (SRAD) dataset, were some datasets for evaluating the stress detection model's reliability. [1]

Table 2

Various Data set utilized for stress detection

Author name	**Methods**	**Dataset**	**Number of participants**	**Challenges**
Campanella *et al.* [25]	Random Forest, SVM, and Logistic Regression)	Empatica E4 bracelet	28	Binary classification. Less number of samples
Muhammadamin *et al.* [28]	CNN	Stress Recognition in Automobile Drivers	9	Needs to add more other signals from the same data set
Cho *et al.* [29]	Neural Netwrok	Mental arithmetic and driving data set	16	Data quality no proper.
Rabbani and Khan [30]	Supervised learning	RML and WESAD	12 and 17	Some results were false negative
Zhang *et al.* [31]	SVM	Recording during the exam	16	Limited to the exam stress classification
Chumachenko *et al.*[32]	KNN, radial basis function, decision tree, and random forest	PTBXL	15,014	Focused on binary classification

Table 2 show some public and some private available data sets of ECG recording. These data sets can be utilized to implement the models.

2.3. *Comparative analysis of machine learning models for stress detection*

To estimate the robust stress detection system, the overall comparative analysis of the conventional ML-based stress detection model is carried out. In Table 3, the existing ML-based stress detection models' performance is analyzed and tabulated.

Table 3

Performance evaluation of existing works

Author name	Paper Title	Algorithm used	Accuracy	Conclusion
Amin *et al.* [28]	Driver's stress detection employing deep transfer learning	CNN	98.11%	Only driver's ECG was used in the experiment. Rest the information was not utilized.
Zhang *et al.* [33]	Real-time psychological stress detection by using ECG signals	CNN and BiLSTM	86.5%	Personality differences of the subject were not considered
Han *et al.* [34]	Quadratic Discriminant Analysis (QDA) and SVM	RF and SVM	94%	Only binary stress was classified.
Dahal, Bogue-Jimenez, and Doblas [35]	Global Stress Detection Framework Combining a Reduced Set of HRV Features and Random Forest Model	RF	99%	Possibility of over fitting due to high accuracy.
Zubair and Yoon [36]	Multilevel mental stress detection using ultra-short pulse rate variability series	SVM and QDA	94.33%	Ultra short term recordings were used to record PPG and detect five levels of stress

In Table 4, the comparative analysis of the existing works for detecting stress using physiological parameters is depicted. The evaluation is based on the accuracy rate achieved by the traditional ML-based stress detection models. From the analysis, it is clear that RF [35] attained a better classification accuracy of 99%, whereas CNN [28] attained the second effective performance of 98.11% accuracy. Next, the SVM and QDA [39] and RF and SVM [37] models obtained 94.33% and 94% stress detection accuracy. Lastly, the CNN and BiLSTM [33] model achieved 86.5% accuracy for stress detection. In Figure 1, the analyzed prevailing techniques' graphical representation is presented.

Table 4

Comparative study of existing techniques

Author Name	Techniques	Accuracy (%)
Amin *et al.* [28]	CNN	98.11
Zhang *et al.* [33]	CNN and BiLSTM	86.5
Han *et al.* [34]	RF and SVM	94
Dahal, Bogue-Jimenez, and Doblas [35]	RF	99
Zubair and Yoon [36]	SVM and QDA	94.33

The performance evaluation of the conventional models grounded on the accuracy obtained for stress detection is illustrated in Figure 1. The RF [35] technique achieved a robust performance with 99% stress detection accuracy in the graph analysis. Therefore, from the overall analysis, a significant stress detection model is estimated.

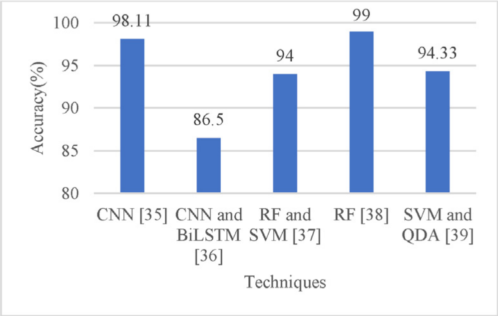

Figure 1

Performance evaluation of the existing techniques

3. Summary of the review

Stress is considered as a major health problem by the WHO, compared to other problems. A person's quality of life is impacted because of mental issues. Stress can occur due to job pressure, social force, life tension. Obesity, cardiovascular, diabetes, gastrointestinal diseases can be caused due to stress. Stress detected at an early level, could be useful for the mental health of a person. Researched have used various ML algorithms to detect stress at an early level by using ECG and other physiological parameters. Thus, this review portrays the motive, development, accomplishments and the disadvantages of the current stress detection models. Hence, from the overall study, it is observed that the ML – based models can detect stress using ECG and various physiological parameters.

4. Conclusion

Here, this review analyzed the detection of stress levels by the ML techniques based on the ECG signals and other physiological signals. Moreover, this study evaluated the diverse models utilized for the stress detection models' evaluation. As per the experimental analysis centered on the standard datasets, the developed stress detection models obtained 99% classification accuracy. Similarly, the existing mental stress detection models attained precision and recall rates of 95.6% and 91.56%, respectively. For detecting stress, the prevailing techniques obtained 96.26% of the F1-score. Thus, the RF technique's robustness in detecting stress is proved by the overall analysis of the conventional stress detection model. Hence, the prevailing stress detection models' purpose, findings, and limitations are effectively described in this review.

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