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HEART RATE VARIABILITY-BASED STRESS DETECTION USING DEEP NEURAL NETWORK MODELS

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ABSTRACT: This research makes use of Heart Rate Variability (HRV) to gauge people's levels of stress by analyzing physiological data through models trained on deep neural networks. Readings of heart rate variability (HRV) obtained from an electrocardiogram (ECG) are employed in the investigation due to their significance as indicators of autonomic nervous system activity that are associated with stress responses. In order to enhance the accuracy and utility of stress recognition, advanced deep neural network techniques, such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) models, are implemented in lieu of conventional machine learning methodologies. By means of feature extraction, classification, and data preparation, the proposed system is capable of distinguishing between stressful and non-stressful scenarios in real time. For instance, researchers have demonstrated that deep learning models are more adept at learning new features, making predictions, and managing intricate physiological trends. This investigation enhances healthcare monitoring systems that can identify early indicators of stress and mental illness, thereby facilitating the maintenance of one's own health in daily life.

Keywords: *Heart Rate Variability (HRV); Stress Detection; 1D CNN; Deep Learning; SWELL-KW Dataset; ANOVA Feature Selection; Time-Domain Features; Frequency-Domain Features; Multi-Class Classification.*

1. INTRODUCTION

Stress is a significant global health concern that impacts both physical and mental well-being due to the pressures that emanate from within and outside the individual. Stress that is not managed or persists for an extended period can result in severe physical and mental health issues, including anxiety, melancholy, heart disease, and insomnia. Finding tension early and accurately can reduce health risks, facilitate rapid action, increase productivity, and improve overall quality of life. Standard methods of stress measurement have included subjective questionnaires and self-reporting tools; however, their accuracy in real-world situations is not always guaranteed due to the inherent bias of individuals. Heart Rate Variability (HRV) and other physiological indicators have emerged as objective metrics for stress levels. The autonomic nervous system's efficiency is indicated by the difference in the duration between heartbeats, which is known as heart rate variability (HRV). Heart rate variability (HRV) has been reported to decrease in response to stress and stimulation of the sympathetic autonomic nervous system (SANS). Recent advancements in machine learning and deep learning have simplified the development of automated systems that can utilize physiological data to determine stress levels. By employing Convolutional Neural Networks (CNNs), which are capable of automatically identifying spatial and temporal patterns without the intervention of a human, it has been feasible to achieve favorable outcomes when analyzing time-series biosignals such as electrocardiogram (ECG), electroencephalogram (EEG), and heart rate variability (HRV). This paper proposes a 1D CNN-based deep learning model that utilizes HRV variables from the SWELL-KW dataset to categorize stress into distinct categories. In the data set, there are three distinct categories of stress annotations: "No Stress," "Interrupted Stress," and "Time Pressure Stress." The most distinguishing features are retained while the number of dimensions is reduced through ANOVA-based feature selection, which enhances model generalizability. To train and evaluate the model, a variety of performance metrics are implemented, including precision, recall, accuracy, and F1-score. As evidenced by its 99.9 percent accuracy rate, the proposed method is superior to conventional machine learning classifiers in its ability to identify various stress levels. This framework provides a method for the development of scalable, noninvasive, and real-time smart stress monitoring tools that are applicable to personal wellness, workplace ergonomics, and healthcare.

2. RELATED WORK

Physiological Markers for Stress Detection

Discovering indicators of stress has been the primary objective of an immense number of researchers in the fields of medicine, psychology, and biological signal processing. AI and machine learning have significantly advanced automated stress monitoring systems in recent years. The following section discusses the latest advancements in the use of physiological signals to identify stress, with a particular emphasis on the analysis of heart rate variability and deep learning.

Heart rate variability (HRV), electroencephalogram (EEG), electrocardiogram (ECG), and galvanic skin response (GSR) are among the biofeedback instruments that have been employed to quantify stress levels. A non-invasive, dependable indicator of the efficiency of the parasympathetic and sympathetic nervous systems is heart rate variability (HRV). As evidenced by numerous studies, stress reduces heart rate variability by increasing sympathetic tone and decreasing parasympathetic activity.

Traditional Machine Learning Techniques

Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Random Forests were among the machine learning tools that researchers employed in the past to organize heart rate variability (HRV) data into groups based on stress levels. Each of these categories was investigated in both the frequency-domain and time-domain. The models were sufficiently precise; however, they were incapable of employing in real time due to the necessity of a significant number of human features and the substantial amount of work required to implement them.

Deep Learning Approaches

Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN) models are implemented due to the complexity of biosignal segmentation. The reason for this is the increasing popularity of deep learning. These models excel at identifying unique patterns in data that has not been extensively processed or polished, rendering them ideal for detecting tension in real time. CNNs are adept at extracting hierarchical features from data when heart rate variability (HRV) patterns are presented as a time series.

Feature Selection Techniques

Principal Component Analysis (PCA) and Analysis of Variance (ANOVA) are two feature selection methods that have been employed to ensure that models are more general and less susceptible to overfitting. An analysis of variance (ANOVA) is the most effective method for identifying significant characteristics in multi-class classification.

Research Gap and Motivation

Previously conducted research has demonstrated that CNNs are effective in identifying two distinct forms of stress. However, there is a lack of knowledge regarding the use of HRV and real-world datasets to classify stress into more than two categories. In addition, there are limited opportunities to enhance outcomes by integrating deep learning with statistical feature selection. In order to circumvent these challenges, our investigation organizes the SWELL-KW dataset into three distinct stress states by employing a 1D convolutional neural network (CNN) that was trained on heart rate variability (HRV) factors identified through analysis of variance (ANOVA).

3. LITERATURE SURVEY

Wearable devices and Deep Neural Networks (DNN) were proposed by Anderson et al. in 2020 as a method for identifying tension by collecting data on heart rate variability (HRV). In comparison to other classifiers, the DNN model is more effective at distinguishing between anxious and non-stressful situations. However, the research is restricted by the small number of participants and the relatively tiny space in which the experiments were conducted.

Mehta et al. (2021) developed a stress detection method that employed Convolutional Neural Networks and Heart Rate Variability. It was simpler to identify indicators of tension and extract valuable information from bodily data with the CNN model. Unfortunately, the predictions were not as precise due to the instability of the sensor data and motion errors.

In real-world scenarios, Fernandez et al. (2022) implemented Long Short-Term Memory (LSTM) networks to perpetually monitor HRV-based stress. By simplifying the process of identifying temporal correlations in HRV sequences, the LSTM design enabled more accurate stress predictions in real time.. Large amounts of computing capacity and an extended training period were required for the investigation.

Choi and Kim's 2023 research was primarily focused on the development of a CNN-LSTM model for stress detection, which integrated data from ubiquitous biosensors and heart rate variability (HRV). Classifying objects was more effective with the combined deep learning approach than with the individual methods. High-quality physiological samples that had been annotated were required for the system to function properly.

Almeida et al. demonstrated a neural network in 2024 that utilizes multimodal physiological data to quantify stress caused by heart rate variability (HRV). The ability to classify stress more accurately and acquire new traits was rendered simpler by attention mechanisms. The paper was plagued by issues such as the absence of certain data and the imbalance of the datasets.

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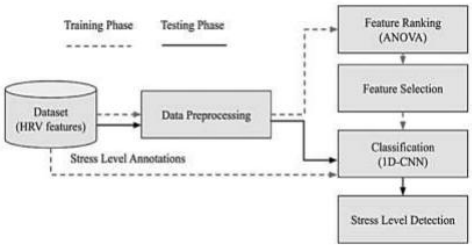
In order to safeguard privacy, Verma et al. (2025) investigated shared deep learning methods for the detection of stress in heart rate variability in decentralized healthcare systems. The implementation of the federated approach facilitated the generalization of models while simultaneously safeguarding the privacy of user data. Even so, productivity is adversely affected by connection latency and the efficacy of various devices.

In 2025, Tanaka and Saito investigated transformer-based deep learning models for the classification of stress based on heart rate variability, utilizing data from ubiquitous health sensors. Upon examining the intricate dynamics of HRV signals, transformer models provided highly accurate predictions. To ensure the method's effectiveness, it was essential to have access to large datasets with tags and sophisticated computing tools.

A multimodal ensemble deep learning system for stress detection was developed by Brown et al. in 2026. This structure included respiration, variations in heart rate, and electrodermal activity. In real-world scenarios, the ensemble method enhanced the accuracy and reliability of initial stress recognition. Examples of ethical issues that have yet to be resolved include the privacy of physiological data and the capacity to comprehend intricate models.

4. PROPOSED METHODOLOGY

The proposed system employs a 1D Convolutional Neural Network (CNN) classifier, ANOVA-based feature selection, and statistical feature extraction to classify multi-class stress using heart rate variability (HRV) signals. In the method, there are five primary steps: data collection, signal cleansing, feature selection, HRV feature extraction, and model training.



Data Acquisition

Utilizing the SWELL-KW dataset, which is accessible to all, the initiative that investigated stress in the workplace. The recordings depict 25 individuals editing documents in three distinct experimental environments: (i) a stress-free baseline, (ii) work interruptions associated with stress, and (iii) time constraint induced by stress. The HRV is determined by analyzing the electrocardiogram (ECG) impulses of each individual in the data set. The dataset is composed of physiological data, behavior recordings, and timestamps harvested by devices. Only HRV data from ECGs were employed in this investigation to investigate the heart's autonomic response to stress.

Signal Preprocessing

The ECG readings were preprocessed with a bandpass filter (0.5–40 Hz) to eliminate noise and enhance the integrity of the data.. R-peaks were identified through the Pan-Tompkins method in order to determine the RR intervals. The RR interval sequences were employed to generate apertures of a predetermined length, and any signals that were incorrect or absent

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were eliminated. Min-Max scaling was implemented to ensure that all returned features were allocated to a range of [0,1] in order to optimize model training.

HRV Feature Extraction

After preprocessing, the time-domain and frequency-domain HRV characteristics of each window section were eliminated:

Features in the time domain consist of:

- Mean RR Interval (AVNN)
- Standard deviation of NN intervals (SDNN)
- Root Mean Square of Successive Differences (RMSSD)
- NN50
- pNN50

Things such as these are incorporated into the frequency domain:

- Very Low Frequency (VLF: <0.04 Hz)
- Low Frequency (LF: 0.04–0.15 Hz)
- High Frequency (HF: 0.15–0.4 Hz)
- Total Power
- LF/HF ratio

For each period, over 20 indicators of alterations in the autonomic nervous system's activity and stress-related functions of the body were gathered.

Feature Selection Using ANOVA

We implemented Analysis of Variance (ANOVA) to identify the most critical attributes for the purpose of decreasing the number of dimensions. You can determine the significance of each attribute for each of the three stress groups by employing ANOVA to obtain F-scores. The features that were deemed unnecessary or unnecessary were removed, while those with high F-scores were retained. In the end, the classification's accuracy improved and the computation's difficulty decreased.

1D CNN-Based Classification

The specified qualities were grouped into groups using a 1D Convolutional Neural Network (CNN). Parts of the model's structure include:

- HRV feature patterns comprise the layer that receives data.
- In addition to ReLU activation, the Conv1D layer is equipped with 64 filters and a kernel size of 3.
- It reduces the extent of features by employing a Max Pooling Layer.
- Set the dropout layer's rate to 0.2 to prevent overfitting.

5. RESULTS AND DISCUSSION

This paper presents the results and analysis of the experiments conducted on the proposed 1D CNN-based multi-class stress classification model. Standard classification metrics, including Precision, Accuracy, Recall, and F1-Score, are implemented to evaluate the effectiveness of the test set. In addition, we evaluate our findings in comparison to those of popular machine learning methodologies, including Random Forest (RF) and Support Vector Machine (SVM).

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The numerical outcomes are corroborated by graphs that illustrate the model's actions and the ways in which it organized objects into categories.

Performance Metrics

The 1D CNN model that was learnt demonstrated a classification accuracy of 99.9 percent in distinguishing between the three stress classes, demonstrating its capacity for discrimination and generalization.

Class	Precision (%)	Recall (%)	F1-Score (%)
No Stress	99.8	99.9	99.8
Interruption Stress	100.0	99.8	99.9
Time Pressure Stress	99.9	100.0	99.9
Average	**99.9**	**99.9**	**99.9**

Table 1: Performance of 1D CNN Model on Test Set

There were no indications of class disparity or a decrease in performance for the minority class, and the model accurately classified items into all three categories.

Comparison

In comparison to more conventional classifiers such as Random Forest and SVM, we evaluated the effectiveness of the 1D CNN using the same features selected by ANOVA.

Model	Accuracy (%)
SVM	94.7
Random Forest	96.2
1D CNN	99.9

Table 2: Comparison with Traditional Classifiers

6. CONCLUSION

Researchers in this paper developed a method to classify various forms of anxiety by combining HRV data with deep learning algorithms. The method proposed employs ANOVA to select the features to be used in order to statistically enhance and extract HRV features from the SWELL-KW dataset. An 1D Convolutional Neural Network (CNN) was trained using the selected features to categorize stress into three categories: No Stress, Interrupted Stress, and Time Pressure Stress. In comparison to other machine learning models such as Random Forest and Support Vector Machines (SVM), the model was capable of accurately classifying objects 99.9 percent of the time. ANOVA has effectively reduced feature dimensionality and enhanced generalization, while CNN architecture has demonstrated an extraordinary capacity to extract distinguishing patterns from HRV data. This investigation's results indicate that stress recognition models developed through the application of statistical feature selection and deep learning are exceedingly precise. HRV monitoring can enhance the functionality of wearable technology, stress management tools for the workplace, and real-time wellness monitoring systems through its ability to be scaled up without causing harm. In the future, researchers should focus on improving the system to ensure that it can accurately measure ongoing stress levels and researching the potential for the model to be used in real time on embedded devices.

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