Journal of NextGen Intelligence

ISSN: APPLIED |VOLUME-1, ISSUE-1|
Inaugural Edition | October-December 2026
Paper ID: NG11-001| Research Article
DOI:

An Adaptive Deep Learning Approach for Personalized and Explainable Stress Detection Using Heart Rate Variability Signals

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ABSTRACT: This paper utilizes Heart Rate Variability (HRV) as a metric for stress levels in order to evaluate physiological data. The models employed in this analysis are based on deep neural networks. The research employs electrocardiogram (ECG) heart rate variability (HRV) data as critical indicators of autonomic nervous system activity that are associated with stress reactions. The proposed system is capable of extracting features, classifying data, and processing it in real-time to differentiate between stressful and non-stressful scenarios. For example, deep learning models have demonstrated superiority in the management of intricate physiological trends, the acquisition of new features, and the formulation of predictions. This work improves healthcare surveillance systems by identifying early indicators of stress and mental illness, thereby contributing to the daily maintenance of personal health.

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 issue due to the detrimental effects of internal and external pressures on the physical and mental well-being of individuals. Stress that is not managed or persists for an extended period can result in severe physical and mental health issues, including insomnia, depression, anxiety, and heart disease. Early and precise tension detection can lead to improved quality of life, increased productivity, speedier response times, and reduced health risks. Although self-reporting instruments and subjective surveys have been the preferred methods for stress measurement, their reliability in real-world contexts is not guaranteed due to human bias. There are now objective methods for assessing stress that involve the use of other physiological markers, such as heart rate variability (HRV). Heart rate variability (HRV), or the variation in the duration of heartbeats, is a method of evaluating the autonomic nervous system's functionality. HRV decreased when individuals were agitated or had their sympathetic autonomic nervous system (SANS) activated, according to a paper. The development of automated systems that can assess stress levels using physiological data has become significantly easier as a result of the progress made in DL and ML. The successful analysis of time-series biosignals, including electrocardiograms (ECGs), electroencephalograms (EEGs), and heart rate variability (HRV), has been facilitated by the use of Convolutional

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Neural Networks (CNNs), which are capable of autonomously diagnosing spatial and temporal patterns. This research suggests a 1D CNN-based deep learning model for stress classification that utilizes HRV variables from the SWELL-KW dataset. The dataset includes three distinct types of stress annotations: "No Stress," "Interrupted Stress," and "Time Pressure Stress." The generalizability of the model is improved by feature selection based on analysis of variance (ANOVA), which reduces dimensionality while retaining the most distinguishing traits. Recall, precision, accuracy, and F1-score are among the performance metrics that are implemented during the model's training and evaluation. The conventional machine learning classifiers are outperformed by the proposed method, as evidenced by its 99.9 percent accuracy rate in distinguishing between different stress levels. The real-time, noninvasive, and scalable smart stress monitoring solutions that can be developed on this platform can be beneficial for individual wellness, workplace ergonomics, and healthcare.

2. RELATED WORK

Physiological Markers for Stress Detection

Many individuals in the disciplines of medicine, psychology, and biological signal processing are particularly interested in identifying stress indicators. In recent years, automated stress monitoring systems have undergone a remarkable evolution as a result of artificial intelligence and machine learning. The following is a discussion of the most recent developments in stress detection using physiological data, with a particular focus on HRV analysis and deep learning.

Galvanic skin response (GSR), electroencephalogram (EEG), electrocardiogram (ECG), and heart rate variability (HRV) are among the biofeedback instruments that have been employed to quantify stress levels. Heart rate variability (HRV) is a non-invasive and precise method for evaluating the effectiveness of the sympathetic and parasympathetic nervous systems. Multiple studies have demonstrated that stress decreases HRV by increasing sympathetic tone and decreasing parasympathetic activity.

Traditional Machine Learning Techniques

In the past, researchers have utilized machine learning techniques such as Support Vector Machines (SVM), K-Nearest Neighbors (KNN), Decision Trees, and Random Forests to organize HRV data based on stress levels. Each of these categories was examined in two distinct domains: the frequency-domain and the time-domain. The models were sufficiently precise for testing purposes; however, they were too labor-intensive and contingent upon an extensive array of human characteristics to be practicable for real-time use.

Deep Learning Approaches

The complexity of biosignal segmentation is the primary motivator behind the utilization of models such as Recurrent Neural Networks (RNN) and Convolutional Neural Networks (CNN). This is due to the significant increase in the utilization of deep learning. These algorithms are optimal for real-time stress detection due to their exceptional ability to identify distinctive patterns in raw, unprocessed data. When HRV patterns are depicted as time series, convolutional neural networks (CNNs) are particularly

good at extracting hierarchical features from data.

Feature Selection Techniques

Principal Component Analysis (PCA) and Analysis of Variance (ANOVA) are two feature selection methods that have been employed to enhance the generalizability of models and reduce their susceptibility to overfitting. The gold standard for distinguishing critical features in multi-class categorization is analysis of variance (ANOVA).

Research Gap and Motivation

In previous research, CNNs have identified two distinct forms of stress. Meanwhile, the classification of stress into more than two categories through the use of real-world data and heart rate variability (HRV) remains uncertain. Integrating statistical feature selection with deep learning is a challenging endeavor, which only serves to exacerbate the situation. We overcame these challenges by employing a 1D convolutional neural network (CNN) that was trained on HRV parameters obtained through analysis of variance (ANOVA) to classify the SWELL-KW dataset into three discrete stress states.

3. LITERATURE SURVEY

A method to identify tension in 2020 was proposed by Anderson et al., which involved the collection of data on heart rate variability (HRV) using ubiquitous technologies and Deep Neural Networks (dNN). The DNN model outperforms other classifiers when asked to differentiate between stressful and non-stressful situations. The research is nevertheless restricted by the small sample size and the relatively restricted geographic area of the experiments.

Utilizing heart rate variability and convolutional neural networks, Mehta et al. (2021) devised a stress detection technique. Stress indicators could be more readily identified, and valuable insights could be extracted from physiological data, thanks to the CNN model. Regrettably, the forecasts' precision was compromised by erratic sensor data and mobility issues.

Fernandez et al. (2022) employed Long Short-Term Memory (LSTM) networks to continuously monitor HRV-based stress in real-world scenarios. The LSTM architecture facilitated the discovery of temporal correlations in HRV sequences, thereby enhancing the accuracy of real-time stress predictions. The investigation necessitates an extensive amount of computing capacity and requires a significant amount of time to train.

The primary objective of Choi and Kim's 2023 project was to create a CNN-LSTM model for stress detection that utilizes HRV and data from prominent biosensors. The combined deep learning strategy outperformed the standalone approaches in the domain of object classification. The system's functionality was contingent upon the availability of annotated, high-quality physiological samples.

Almeida et al. (2024) developed a neural network that can identify stress caused by heart rate variability (HRV) by utilizing multimodal physiological data. Attention processes facilitated the acquisition of novel traits and the enhancement of stress classification. Issues such as lacking data and imbalanced datasets impeded the article.

Verma et al. (2025) conducted an investigation into the utilization of shared deep learning techniques to detect tension in heart rate variability in order to safeguard privacy in decentralized healthcare systems. User data privacy was protected by the federated approach, which also facilitated the generalization of the model. However, productivity is diminished as a result of the efficacy of various devices and connection latency.

In 2025, Tanaka and Saito examined transformer-based deep learning models for stress categorization using heart rate

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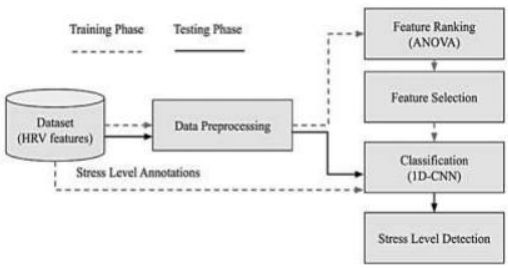
variability, utilizing data from a variety of prominent health sensors. Transformer models were able to produce remarkably precise predictions after exploring the complex dynamics of HRV signals. Large datasets with identifiers and sophisticated computational tools were necessary to guarantee the method's efficacy.

In 2026, Brown et al. created a multimodal ensemble deep learning system for the purpose of stress detection. Breathing, heart rate fluctuations, and electrodermal activity comprised this system. The ensemble approach resulted in a more precise and dependable initial stress identification in real-world scenarios. Protecting the confidentiality of physiological data and comprehending intricate models are two examples of unresolved ethical concerns.

4. PROPOSED METHODOLOGY

The proposed system classifies multi-class stress based on heart rate variability (HRV) signals by utilizing a 1D Convolutional Neural Network (CNN) classifier, statistical feature extraction, and ANOVA-based feature selection. The approach consists of five primary steps: data collection, signal cleansing, feature selection, HRV feature extraction, and model training.



Data Acquisition

The initiative examined stress in the workplace by utilizing the SWELL-KW dataset, which is publicly available. On the one hand, we have a stress-free baseline; on the other hand, 25 individuals are rewriting documents while simultaneously subjected to three distinct experimental conditions: (i) work interruptions caused by stress; and (ii) time limitations generated by stress. The data set analyzes the electrocardiogram (ECG) impulses of each individual to determine the HRV. The dataset is composed of physiological data, behavior records, and time stamps. The autonomic response of the heart to stress was examined in this paper exclusively using HRV data from electrocardiograms.

Signal Preprocessing

To guarantee the accuracy of the data and eradicate noise, the ECG data was preprocessed with a bandpass filter (0.5-40 Hz). The RR intervals were determined by locating the R-peaks using the Pan-Tompkins method. The RR interval sequences were employed to generate apertures of a predetermined length after the removal of incorrect or absent signals. In order to optimize model training, Min-Max scaling was implemented to designate all returned features to a range of [0,1].

HRV Feature Extraction

The time-domain and frequency-domain HRV features were extracted from each window section following the preprocessing:

The following are some of the characteristics of the time domain:

- average value of the RR interval (AVNN)
- SDNN (standard deviation of NN intervals)
- The Mean Square of Successive Differences (RMSSD) is a statistical metric.
- The NN50
- level of pNN50

The frequency domain encompasses items such as these:

- Very Low Frequency (VLF): less than 0.04 Hz
- Almost imperceptible (LF: 0.04-0.15 Hz)
- Pulse Width (HF): 0.15 to 0.4 Hz
- The sum of power
- ratio of low-frequency to high-frequency

For each session, we collected approximately twenty indicators of variations in the autonomic nervous system's activity and the body's stress-related activities.

Feature Selection Using ANOVA

By employing Analysis of Variance (ANOVA), we were able to identify the most significant attributes, thereby reducing the dimensionality. Analyze the variance (ANOVA) to obtain F-scores for each of the three stress groups, and determine the significance of each trait. The features that were deemed extraneous were eliminated, while those with high F-scores were retained. Ultimately, the classification was more precise and the computation was simplified.

1D CNN-Based Classification

The properties provided were categorized with the assistance of a 1D Convolutional Neural Network (CNN). The model is composed of the following components:

- The data-receiving layer is composed of HRV feature patterns.
- The Conv1D layer includes 64 filters and a kernel size of 3, in addition to ReLU activation.
- A Max Pooling Layer is employed to reduce the feature scope.
- To prevent overfitting, set the dropout layer's rate to 0.2.

The 1D convolutional layer's ReLU activation function comprised 128 filters and 3 kernel sizes.

5. RESULTS AND DISCUSSION

This article analyzes and presents the results of the experiments that were conducted, which are based on the proposed 1D CNN-based multi-class stress classification model. Precision, Accuracy, Recall, and F1-Score are among the classification metrics that are frequently employed to assess the performance of the test set. Furthermore, we assess our performance in comparison to that of widely used machine learning techniques, including Random Forest (RF) and Support Vector Machine (SVM). The numerical results are corroborated by graphs that illustrate the model's operations and item classifications.

Performance Metrics

The discriminatory and generalizable capabilities of the learned 1D CNN model were demonstrated by its classification accuracy of 99.9 percent in distinguishing between the three stress classes.

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

The model accurately classified items into all three categories, and there was no evidence of class imbalance or a decrease in minority class performance.

Comparison

We compared the performance of the 1D CNN to that of more conventional classifiers, such as Random Forest and SVM, 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

In this paper, researchers devised a technique for anxiety classification that employed deep learning algorithms and HRV data. The proposed technique employs analysis of variance (ANOVA) to identify features that will be employed to enhance the statistical performance and extract HRV features from the SWELL-KW dataset. The three categories of stress that a 1D Convolutional Neural Network (CNN) trained using the selected features could elucidate were No Stress, Interrupted Stress, and Time Pressure Stress. The model obtained an accuracy rate of 99.9 percent in item categorization when tested against other machine learning models, including Random Forest and Support Vector Machines (SVM). Nevertheless, ANOVA has reduced the dimensionality of features and improved generalization, whereas CNN architecture has exhibited an exceptional ability to extract distinctive patterns from HRV data. This type of research illustrates the efficacy of stress detection models that are constructed using statistical feature selection and deep learning. HRV monitoring is a promising candidate for application in real-time wellness monitoring systems, stress management tools for the workplace, and ubiquitous devices due to its scalability and safety advantages. In the future, researchers should investigate the feasibility of implementing the model on embedded devices in real time and enhance the system to ensure that it can accurately capture continuous stress levels.

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