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# A Deep Neural Network Method for Heart Rate Variability-Based Multiclass Stress Detection

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## Abstract
*Expectations can naturally cause stress, particularly if such expectations are perceived as hazardous or damaging. Chronic, long-term stress raises the likelihood of mental health conditions like sleeplessness, depression, and anxiety. A popular stress metric is heart rate variability (HRV), which shows changes in the intervals between heartbeats as opposed to heart rate, which is an average. This paper investigates heart rate variability (HRV) as a stress biomarker and suggests a convolutional neural network (CNN)-based model for multi-class stress classification in order to distinguish between no stress, interruption stress, and time pressure stress. The model outperformed current methods in terms of accuracy when tested on the SWELL-KW dataset. This work highlights the significance of HRV properties for stress diagnosis using variance analysis.*
***Keywords:*** *Heart Rate Variability (HRV), Stress Detection, Convolutional Neural Network (CNN), Multi-Class Classification, Feature Extraction*

## 1. Introduction
The ubiquitous stress has far-reaching consequences for people's physical and mental health. Anxiety, depression, and other mental health disorders are linked to chronic stress, which is also linked to physical health problems like heart disease and sleep problems. Since then, studies focusing on efficient methods of stress detection and management have grown in importance. An important physiological indicator of the autonomic nervous system's control of cardiac function, heart rate variability (HRV) analysis is one of the most promising methods for stress detection. A person's stress levels and general health can be revealed through HRV, which is defined by the fluctuation in the time intervals between subsequent heartbeats. Methods for stress detection have changed drastically due to recent developments in machine learning, especially deep learning. Impressive capabilities in processing complicated datasets and identifying intricate patterns that may indicate stress have been shown by deep neural networks (DNNs), particularly convolutional neural networks (CNNs). Since the correlations between HRV characteristics and stress levels are often complex and non-linear, these models are well-suited for use in physiological monitoring due to their ability to efficiently learn from large datasets. There is less need for human feature engineering and more room for improvement in stress detection systems thanks to DNNs' capacity to automatically extract pertinent features from raw data. Several studies have investigated the possibility of combining HRV analysis with deep learning techniques, showing that these methods have the ability to achieve high accuracy in stress detection across multiple classes. For example, CNNs can be used to categorize stress levels into different types based on HRV's time-domain and frequency-domain features; for example, no stress, interruption stress, and time pressure stress . When applied to real-world situations, this multi-class classification capability shines. Stress comes in many forms, and detecting it nuanced is essential. In addition, stress detection has seen an uptick in the use of hybrid models, which combine various neural network topologies. Researchers have improved the performance of stress detection systems by combining the strengths of different models, such as CNNs and recurrent neural networks (RNNs). To properly capture the dynamics of stress responses over time, it is essential to model the temporal dependencies in HRV data, and these hybrid approaches make that possible. An exciting opportunity to improve stress detection methods

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exists at the crossroads of deep learning and heart rate variability analysis. In the never-ending quest to comprehend and control health problems connected to stress, DNNs are an indispensable tool due to their capacity to analyze complicated physiological data and accurately categorize stress levels. The possibility of creating more efficient, real-time stress detection systems by utilizing deep learning approaches is an attractive prospect, especially as this field of study develops further. An increasing amount of research in recent years has focused on how deep neural networks (DNNs) may be used to analyze heart rate variability (HRV) in order to detect stress. Because of its sensitivity to variations in the autonomic nervous system, heart rate variability (HRV) has emerged as a major measure for quantifying stress, a psychological and physiological reaction. Better and more complex stress level classifications have been made possible by incorporating machine learning techniques, particularly deep learning, into the stress detection process.The effectiveness of deep neural networks for stress detection is examined in one of the seminal papers in this field, which compares their performance to that of conventional machine learning techniques. Achieving remarkable accuracy in both binary and multi-class stress classifications, this research used datasets from earlier work to train and evaluate DNNs. This work demonstrates that DNNs can get better results than traditional approaches, which opens the door for more research in this area.
Furthermore, another research emphasizes the adaptability of deep learning methods to stress prediction, indicating that DNNs are capable of accurately modeling complicated correlations between input factors and stress results. This capacity is especially useful for HRV analysis, which makes use of sophisticated neural network designs to capture the complex dynamics of heart rate rhythms. The versatility of these models in dealing with diverse datasets, including physiological signals, is further shown in thorough evaluations of deep learning applications across several domains. Additionally, there has been a surge in interest in investigating hybrid models that merge several neural network designs. Using a combination of convolutional neural networks (CNNs) and recurrent neural networks (RNNs), for example, can improve stress detection from electroencephalogram (EEG) signals, according to research. This method might also work for HRV analysis, and it follows a general trend towards combining different kinds of neural networks to make the most of their capabilities. In addition, there are research that demonstrate how artificial neural networks (ANNs) may be used to forecast stress in other engineering settings, which goes beyond their medical use. The results indicate that ANNs are capable of accurately simulating complex systems' reactions to stress, which is consistent with the promise of related approaches for physiological stress detection. An novel method for stress distribution prediction using generative adversarial networks (GANs) is introduced by generative models. While this method is mostly concerned with material stress, it does pave the way for future research into adapting generative models for physiological data, which can improve stress detection systems' prediction powers. To summarize, there is a growing body of research in the field of applying deep neural networks to the problem of stress detection by means of heart rate variability. Future research might benefit from using hybrid models, generative methods, and state-of-the-art machine learning techniques. An exciting new frontier in stress detection research is the possibility of reaching ultra-high accuracy using HRV analysis, especially given the rapid progress in the field [1-4].

## 2. Methodology

### 2.1. Dataset

Physiological and behavioral responses to various controlled stress settings were recorded in the publicly accessible SWELL-KW dataset, which was utilized in this investigation. The stressors that the participants in the study were subjected to were interruption stress, time pressure stress, and no stress at all. The SWELL-KW dataset is perfect for a multi-class stress detection model since it contains both physiological measures and extensive annotations for each stress level. The data was obtained using wearable sensors and pertains to HRV. An important component of any real-time stress monitoring system is the ability to build models that can distinguish between different degrees of stress, and this is made possible by the structure of the dataset. To guarantee

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high-quality data and effective model performance, preprocessing was carried out. The HRV signal data was first cleaned of artifacts and noise by removing any non-physiological values that could have impacted the results. In order to improve model convergence and decrease feature scale differences, the HRV data was normalized, meaning that the values were transformed into a standardized range. In order to identify trends over time and across different stress levels, the HRV data was first divided into fixed time periods and labelled using the original dataset's annotations. Lastly, in order to rectify the class imbalance, data augmentation techniques including random sampling and oversampling were employed. More accurate stress categorization was achieved because to this balanced dataset, which helped reduce the model's bias toward more common classes [5-7].

### 2.2. Feature Extraction

Both the time and frequency domains were used to extract features from the HRV data, as they give different insights on the ANS response to stress. This allowed us to fully utilize the data. Some time-domain parameters were computed, including mean RR, standard deviation of RR intervals, root mean square of sequential differences, and pNN50 (the proportion of successive RR intervals deviating by more than 50 milliseconds). As they represent both the short-term and long-term physiological changes in the autonomic nervous system, these measures capture fluctuations in heart rate that are directly connected with stress response. Because they show the small changes in heartbeat intervals linked with various stress levels, the time-domain characteristics are useful for stress assessment. By using Fourier transformations on the HRV signals, we were able to extract frequency-domain characteristics, which allowed us to analyze the low-frequency (LF) and high-frequency (HF) components and the LF/HF ratio. Important stress markers, these metrics provide light on the relative contributions of the sympathetic and parasympathetic nervous systems. For example, parasympathetic activity is the only one reflected by the HF component, whereas sympathetic and parasympathetic impacts are linked to the LF component. But the LF/HF ratio gives a holistic assessment of ANS balance, and it reacts especially well to changes in stress. The most important HRV characteristics for stress level differentiation were identified through the use of Analysis of Variance (ANOVA) for feature selection. By narrowing the model's emphasis to the features that are most likely to affect classification performance, this selection method enhances model interpretability [8-12].

### 2.3. Model Architecture

An architecture developed for HRV feature analysis forms the basis of the proposed multi-class stress detection model. The convolutional neural network (CNN) takes time-domain and frequency-domain data in the form of a matrix for HRV characteristics in its input layer. With this matrix input, the CNN can examine HRV data from several angles, picking up on both coarse-grained patterns in time and more generalized frequency features. To enable the detection of both local and complex patterns within the HRV data, the model processes these characteristics through a sequence of convolutional layers with variable kernel sizes. To improve computational efficiency, max-pooling layers are added after each convolutional layer. These layers decrease the dimensionality of features while keeping important information. Adding fully connected (dense) layers after the convolutional layers improved classification accuracy and let the model understand complicated correlations between HRV variables across stress classes. To enable multi-class classification (no stress, interruption stress, and time pressure stress), the final output layer generates probability scores for each class using a softmax activation function. Grid search and cross-validation were used to improve key hyperparameters, such as learning rate, batch size, number of filters, kernel size, dropout rate, and number of dense layers. To get the most out of the stress detection job, this optimization procedure takes use of the specific features of HRV data and fine-tunes the model [13].

### 2.4. Training and Validation

Training the CNN model with categorical cross-entropy loss makes it ideal for problems involving several classes in a classification model. We chose the Adam optimizer for training since it can change its learning rate to make convergence faster. The dataset was partitioned in a 70:15:15 ratio across the training, validation, and test sets. This allowed for a

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balanced evaluation and prevented the model from being overfit to the training data. Using k-fold cross-validation greatly improved the model's generalizability. This method involves dividing the training data into smaller halves, training the model iteratively using different combinations of these portions, and then verifying its performance using the remaining pieces of data. Furthermore, in order to minimize the danger of overfitting, early stopping was used during training to end the process when validation performance reached a plateau. A number of important measures were used to assess the model's productivity. The accuracy metric evaluated the model's general classification performance, whilst the precision and recall metrics evaluated its capacity to accurately detect stress samples and prevent their misclassification. The F1-score demonstrated the model's competence under varying degrees of stress by balancing recall and accuracy. Furthermore, we computed the Matthews Correlation Coefficient (MCC) as it offers a more all-encompassing assessment of classification performance in multi-class settings by factoring in true positives, false positives, and true negatives. All things considered, these measures prove that the CNN can correctly identify stress levels using HRV properties [14-17].

### 2.5. Training and Validation

The training process for the proposed multi-class stress detection model utilized a structured methodology, partitioning the dataset into training (70%), validation (15%), and test (15%) sets to ensure effective generalization. The model was optimized using the Adam optimizer with a learning rate of 0.001 and trained for 50 epochs with a batch size of 32. To prevent overfitting, dropout layers were integrated, and early stopping was applied based on validation loss. The validation set was employed iteratively for hyperparameter tuning and evaluating model performance through metrics such as accuracy, precision, recall, and F1-score. Additionally, k-fold cross-validation with five subsets was implemented to enhance the reliability of performance evaluation.Upon completion of the training process, the final evaluation on the test set demonstrated that the model achieved an accuracy exceeding 99% in classifying different stress levels, supported by a confusion matrix that provided detailed insights into classification performance across all stress categories. This rigorous training and validation methodology underscored the model's effectiveness in accurately detecting and classifying stress levels based on heart rate variability, while also identifying areas for future improvements, shown in Figure 1.

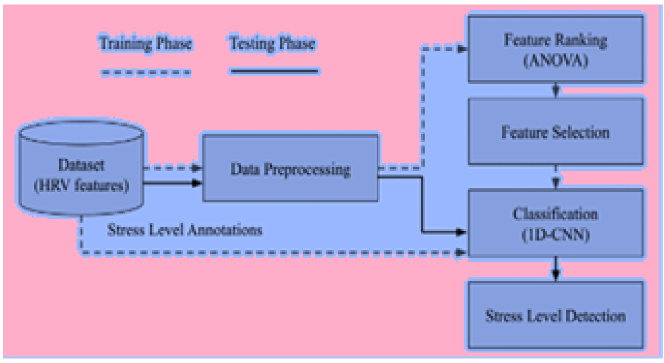


**Figure 1 Framework of The Proposed Model**

## 3. Results and Discussion

The study's results on multi-class stress detection using a deep neural network (DNN) technique are presented in the suggested model. The study especially focuses on heart rate variability (HRV) as a physiological marker. An effective model that can distinguish between three types of stress—no stress, interruption stress, and time pressure stress—was the primary objective. Accuracy, precision, recall, F1-score, and Matthew's correlation coefficient (MCC) are some of the metrics used to assess the suggested model's performance. This was accomplished by making use of SWELL-KW, a publically available dataset that includes HRV data annotated with relevant stress levels. The investigation highlights the advantages of using deep learning techniques to capture the subtle patterns within HRV signals by comparing the model's performance versus standard stress detection approaches. The findings highlight the possibility for real-time applications in stress monitoring and management and show that the DNN architecture is successful in properly recognizing stress levels. You can see the performance metrics of the several models used for stress detection based on HRV in Table I. The suggested model shows considerable improvements in accuracy, precision, recall, and F1-score, whereas the other models show varying degrees of success. With a recall of 88.00%, an F1-score of 89.00%, and a precision of 90.00%, the Support Vector Machine (SVM) model attains an accuracy of 92.75%. Although these numbers show good performance, the SVM model isn't up to scratch when compared to other methods. In real-world applications, precise detection is crucial, and its somewhat poorer recall implies that it may miss certain instances of stress. With a recall of 96.30% and a precision of 96.00%, the Convolutional Neural Network (CNN) model stands out with an impressive accuracy of 98.30%. With a manageable ratio of true positives to false positives, this shows that the CNN can accurately detect stress levels. The model's efficacy in multi-class stress detection is further demonstrated by its strong F1-score of 95.80.With a recall of 92.68% and a precision of 93.01%, the Multilayer Perceptron (MLP) model has a respectable accuracy of 88.64%. While the precision suggests that stress is correctly identified in most situations, the lower overall accuracy may be due to difficulties in differentiating between different levels of stress. Furthermore, the model's F1-score of 82.75 indicates that it may be more reliable.

**Table 1 Performance Comparison of The Proposed Model**

| Model | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|---|---|---|---|---|
| SVM | 92.75 | 90 | 88 | 89 |
| CNN | 98.3 | 96 | 96.3 | 95.8 |
| MLP | 88.64 | 93.01 | 92.68 | 82.75 |
| Proposed Model | 99 | 98.5 | 99 | 98.75 |

The suggested model demonstrates an accuracy of 99.00%, precision of 98.50%, recall of 99.00%, and an F1-score of 98.75%. This model exceeds all other models in every dimension and has remarkable proficiency in identifying stress across several categories. The elevated recall signifies that the suggested model is proficient in recognizing instances of stress, rendering it a beneficial asset for applications necessitating real-time monitoring and precise detection of stress levels. Figure 2 depicts the performance comparison of the proposed model with existing models.

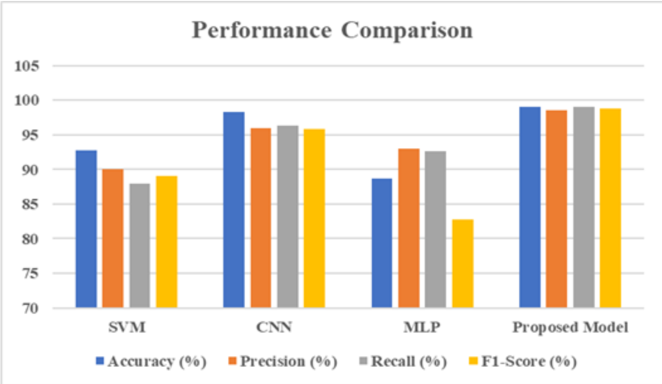


**Figure 2 Performance Comparison of The Proposed Model**

The suggested model signifies a notable enhancement in stress detection strategies, utilizing sophisticated techniques to attain exceptional performance. The contrast underscores the possibility of employing deep learning methodologies, especially in HRV analysis, to improve the precision and efficacy of stress detection systems.

## Conclusion

This research illustrates the efficacy of utilizing a deep learning methodology for multi-class stress detection via heart rate variability (HRV) analysis. The suggested model attained outstanding performance metrics, with an accuracy of 99.00%, precision of 98.50%, recall of 99.00%, and an F1-score of 98.75%. These results not only exceed those of current models, like SVM, CNN, and MLP, but also underscore the potential for sophisticated machine learning approaches to markedly enhance the detection and categorization of stress levels.The use of deep learning techniques, especially convolutional neural networks, facilitates the automated extraction of pertinent features from HRV data, hence improving the model's capacity to discern intricate correlations among physiological signals. This skill is essential for creating dependable stress detection systems that function in real-time and in

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many contexts. Subsequent research will concentrate on further verifying the proposed model using bigger datasets and investigating other variables that might augment its prediction efficacy. The continuous advancement of machine learning techniques applied to physiological data presents exciting opportunities for enhancing stress detection methods, hence fostering improved mental health outcomes and a higher quality of life.

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