

Research Article

Multi-Class Stress Detection through Heart Rate Variability: A Deep Neural Network-Based Study

Geddam Charitha^{1,*}, Machika Rakesh², Busani Hemanth³, Lamba Sharanya⁴ and Dr.P.Janaki Ramulu⁵

¹⁻⁴Student, Department of CSE(AI&ML), Samskruti College Of Engineering & Technology, Hyderabad, Telangana, India

⁵Principal, Samskruti College of Engineering & Technology, Hyderabad, Telangana, India

Corresponding Author: Geddam Charitha Email: khurana0301@gmail.com

Received: 11/07/2025; Revised: 18/09/2025; Accepted: 25/09/2025; Published: 30/09/2025.

DOI: <https://doi.org/10.69996/jsihs.2025013>

Abstract: Stress is a natural physiological and psychological response to external demands or perceived threats. However, when stress becomes chronic or excessive, it significantly heightens the risk of mental and physical health disorders, including anxiety, depression, and sleep disturbances. A dependable physiological indicator for stress evaluation is heart rate variability (HRV), which shows the fluctuation in the time intervals between subsequent heartbeats (RR intervals). Heart rate variability (HRV) records the dynamic changes in cardiac activity, providing greater insights into autonomic nervous system function, as opposed to heart rate, which offers an average beats-per-minute assessment. Here, we present a CNN-based deep learning model that investigates the possibility of HRV features as biomarkers for multi-class stress detection. A lack of stress, stress caused by interruptions, and stress caused by time pressure are the three types of stress that the model is intended to classify. In order to improve the accuracy of detection, HRV is used in both the time-domain and frequency-domain. The suggested model is tested on the open-source SWELL-KW dataset and shows remarkable results: a 99.9% accuracy rate, a 1.0 precision score, a 1.0 recall score, a 1.0 F1-score, and a 0.99 Matthews Correlation Coefficient (MCC). In addition, an analysis of variance (ANOVA) feature extraction method validates the efficacy of critical HRV features. The results show that deep learning methods based on HRV are capable of reliable multi-class stress identification.

Keywords: Heart Rate Variability (HRV), Stress Detection, Convolutional Neural Network (CNN), Deep Learning, Multiclass Classification.

1.Introduction

Stress is an unavoidable part of human life and plays a critical role in shaping individual performance, behavior, and well-being. In moderate amounts, stress can act as a motivating factor, helping individuals cope with immediate challenges. However, when stress becomes chronic or intense, it exerts a detrimental impact on both mental and physical health, contributing to a wide spectrum of disorders including anxiety, depression, cardiovascular diseases, gastrointestinal problems, and sleep disturbances [1], [2]. Modern lifestyles, characterized by time constraints, workplace interruptions, social pressures, and constant multitasking, have significantly increased the incidence and severity of stress-related illnesses [3]. Accurate detection and monitoring of stress are therefore essential for early intervention, mental health



care, and overall well-being. Traditional approaches to stress detection rely heavily on psychological self-assessments such as questionnaires, surveys, and interviews [4]. While these tools are widely used, they are subjective in nature, vulnerable to bias, and dependent on the individual's self-awareness and willingness to report symptoms. To overcome these limitations, physiological signals have gained prominence in stress research due to their objectivity and reliability [5], [6]. Among various physiological indicators, Heart Rate Variability (HRV) has emerged as a key biomarker for stress detection [7]. Heart rate variability (HRV) is the variation in the RR intervals, or the time between successive heartbeats. These variations are a result of the ever-changing communication between the ANS's sympathetic and parasympathetic pathways [8]. A healthy individual typically exhibits higher HRV, indicating robust adaptability to stressors, whereas a low HRV is often associated with fatigue, emotional instability, and impaired autonomic regulation [9]. Unlike heart rate, which simply measures beats per minute, HRV provides detailed insight into the balance and responsiveness of the ANS, making it a more nuanced and effective metric for stress evaluation [10]. HRV can be studied using parameters in both the time-domain and the frequency-domain. Frequency-domain measurements examine power distribution across various frequency bands, providing further information about parasympathetic and sympathetic modulation, in contrast to time-domain metrics, which comprise statistical metrics like the standard deviation of NN intervals (SDNN) and root mean square of successive differences (RMSSD) [11].

Various studies have successfully linked HRV alterations with stress-induced changes in physiological states. For instance, reduced high-frequency (HF) power and increased low-frequency (LF) power are indicative of sympathetic dominance, a hallmark of acute or chronic stress [12]. Additionally, non-linear and entropy-based HRV features have been investigated to further capture the complexity and irregularity of heart dynamics under stress [13]. Despite its potential, using HRV for multi-class stress detection—distinguishing between different types of stress such as time pressure and interruption—remains a relatively underexplored area with numerous challenges. One of the major challenges in HRV-based stress detection lies in capturing the complex patterns and subtle variations in the RR intervals that correlate with different stress types. Traditional machine learning techniques, such as “Support Vector Machines (SVM), Decision Trees, and k-Nearest Neighbors (k-NN),” have shown promise in binary stress classification but often fall short in handling multi-class classification tasks due to limited feature representation capability [14], [15]. Moreover, the selection and extraction of meaningful HRV features from raw ECG signals require domain expertise and extensive preprocessing, which can hinder scalability and real-time implementation [16]. Biomedical signal processing and stress analysis have been utterly transformed by the latest AI developments, especially deep learning [17]. Anomaly detection, emotion recognition, and ECG classification are just a few examples of the deep learning tasks where convolutional neural networks (CNNs) have shown their mettle by automatically learning hierarchical features from raw or slightly processed data [18], [19]. These models eliminate the need for hand-crafted feature extraction and can generalize better to complex, multi-class classification problems. Nonetheless, deploying deep learning models for stress detection using HRV data introduces its own set of challenges, including the need for large annotated datasets, computational complexity, and the risk of overfitting due to high model capacity [20]. Publicly available datasets like SWELL-KW have facilitated progress in this area by providing labeled physiological data collected under controlled stress-inducing conditions such as time pressure and task interruptions [21].

In the context of occupational health, the ability to differentiate between various

stressors—such as no stress (baseline), interruption stress (due to distractions or disruptions), and time pressure stress (due to deadlines)—is vital. Each stressor affects cognitive performance and physiological states differently, and understanding these nuances can lead to more personalized stress management solutions. Therefore, developing an accurate, scalable, and real-time multi-class stress detection system using HRV signals is not only of academic interest but also of practical relevance in healthcare, workplace productivity, and wearable health monitoring applications. To address the gap in current stress detection systems, it is crucial to leverage advanced modeling techniques that can simultaneously handle high-dimensional HRV features and offer interpretable, reliable classification of stress types. The use of CNN-based architectures, trained on time- and frequency-domain HRV data, holds promise in capturing intricate temporal dynamics and autonomic patterns linked to various stress classes. In parallel, the integration of statistical techniques such as analysis of variance (ANOVA) can enhance feature selection by identifying the most discriminative HRV markers, thereby improving classification accuracy and reducing computational overhead.

Using deep learning and heart rate variability (HRV) signals, this study introduces a new and thorough method for stress identification across many classes. Our main contribution is a model that uses Convolutional Neural Networks (CNNs) to extract time-domain and frequency-domain features from HRV data. This model can differentiate between three different levels of stress: no stress, interruption stress, and time pressure stress. Unlike traditional binary stress detection models, this study expands the scope to multiclass classification, which closely resembles real-world scenarios. A significant contribution is the use of the SWELL-KW dataset, which offers rich physiological data in a controlled work environment, enhancing the robustness and generalizability of the model. Furthermore, this work integrates advanced signal processing techniques for HRV feature extraction and statistical methods like ANOVA for feature selection, thus improving interpretability and model performance. The proposed CNN model achieves superior classification metrics (Accuracy = 99.9%, Precision = 1.0, Recall = 1.0, F1-score = 1.0, and MCC = 0.99), clearly outperforming existing models. Overall, the study advances the field of affective computing and mental health monitoring by offering a scalable, accurate, and real-time capable solution for stress detection through wearable devices.

2. Literature Review

Over the past two decades, stress detection has gained significant attention across interdisciplinary research domains, including biomedical engineering, psychology, human-computer interaction, and artificial intelligence. The primary motivation behind this interest stems from the growing recognition of stress as a major contributor to physical and mental health disorders, decreased work efficiency, and reduced quality of life. Consequently, the development of intelligent systems capable of recognizing and classifying stress states has become an emerging area of investigation. Recent literature has shown a growing interest in leveraging physiological signals for automated stress detection using advanced machine learning and deep learning techniques. Hemakom et al. [4] conducted a gender-specific preliminary study combining electrocardiogram (ECG) and electroencephalogram (EEG) data to classify stress levels using machine learning. Their findings support the feasibility of multi-level stress detection using multimodal biosignals. Complementarily, Bencheikroun et al. [5] highlighted a key challenge in HRV-based models—generalizability. Through cross-dataset evaluations, they emphasized that models trained on specific datasets often fail to perform well on unseen data, thereby indicating the need for robust and transferable architectures. Kuttala et al. [6-7] proposed a multimodal hierarchical CNN framework, fusing features from various sources for stress

detection. Their architecture demonstrated improved performance by integrating contextual information from multiple data modalities. Similarly, Haque et al. [8] presented a comprehensive review of HRV-based stress detection using artificial intelligence, underscoring that while AI models enhance performance, their effectiveness depends heavily on high-quality feature extraction and dataset availability. Rashid et al. [9] further expanded the scope by introducing context-aware sensor fusion from wearable devices, showing that incorporating contextual metadata alongside physiological readings enhances stress recognition accuracy.

In terms of signal modalities, Kalra and Sharma [10-11] employed photoplethysmography (PPG) signals with a deep neural network for mental stress assessment, providing evidence that PPG can serve as an effective non-invasive signal alternative to ECG. Dogan and Akbulut [12-13] went a step further by combining biosignals, audio, and visual inputs through multi-modal fusion learning to detect mental stress, showing the potential of holistic sensor integration. Banerjee et al. [14] introduced explainability in HRV-based stress detection using interpretable machine learning techniques, enabling users and practitioners to better trust and understand model decisions. Rescio et al. [15] developed a deep learning platform using minimally intrusive multisensory devices tailored for worker stress detection, demonstrating the potential for practical workplace deployment. Ahmad et al. [16] assessed stress in virtual reality environments, using multimodal fusion of ECG and environmental cues, reflecting the trend of combining biosignals with immersive technologies. Fan et al. [17] incorporated attention mechanisms into CNNs for ECG-based emotion recognition, which indirectly relates to stress, showcasing improved signal sensitivity and feature discrimination.

Beyond stress-specific applications, related studies offer valuable insights into deep learning model design and biosignal analysis. Doroudi et al. [18] optimized deep learning models for multi-class damage detection in infrastructure, demonstrating robust tuning and signal preprocessing strategies transferable to stress detection contexts. Naeini et al. [19] proposed a deep learning-based PPG quality assessment model, which supports accurate HRV computation, critical for reliable stress recognition. Hadinata et al. [20] worked on multiclass segmentation using U-Net and DeepLabV3+, models which can inspire architecture selection in HRV signal classification. Li et al. [21] introduced a transformer-based deep learning model for pilot stress detection, employing physiological signals, which aligns closely with the objective of recognizing different stress levels. Garg et al. [22] utilized EEG signals with a MobileNet-RNN hybrid for emotion recognition based on time-frequency features—relevant for exploring alternative architectures in HRV-based stress modeling. Goswami et al. [23] implemented ECG signal classification using a VGGNet model, illustrating the adaptability of computer vision architectures to biomedical signal processing. Lastly, Nguyen et al. [24] applied deep learning techniques to heart sound classification using log-mel spectrograms, demonstrating the effectiveness of spectrogram-based approaches in cardiac-related signal analysis.

In the field of stress detection using physiological signals, several critical research gaps persist that limit the accuracy, generalizability, and practicality of current models. Most existing studies primarily focus on binary classification of stress (e.g., stress vs. no stress), failing to capture the complexity of real-life stress scenarios that involve multiple stressors such as time pressure, interruptions, and cognitive overload. Furthermore, while heart rate variability (HRV) has been widely recognized as a reliable biomarker for stress, many machine learning approaches depend heavily on manually extracted features, which may not adequately capture non-linear or subtle variations in RR intervals. The effectiveness of deep learning models such as CNNs and RNNs in HRV-based classification has been demonstrated, yet few works have explored their

application in multi-class stress classification using only HRV features without the aid of other sensor modalities. Additionally, the issue of generalizability across individuals and datasets remains unresolved, as many models exhibit reduced performance when tested outside their training data environments. There is also a lack of consensus on optimal HRV features and preprocessing techniques, and limited research has addressed model interpretability, which is crucial for clinical or workplace adoption. These challenges highlight the need for a robust, accurate, and explainable deep learning-based framework capable of detecting multiple classes of stress using only HRV signals, validated across diverse subjects and conditions.

3. Heart rate variability estimation

A measure of the variability in the time intervals between successive heartbeats, or RR intervals, as seen in an electrocardiogram (ECG) signal from the R-peaks of the QRS complex is heart rate variability (HRV). HRV provides vital insights into the balance between the sympathetic (fight-or-flight) and parasympathetic (rest-and-digest) responses; it is a non-invasive indication of autonomic nervous system (ANS) activity. Accurate HRV estimation begins with identifying R-peaks in the ECG signal through the use of signal processing algorithms such as adaptive thresholding, wavelet transforms, or the Pan-Tompkins algorithm. The HRV features are computed in three domains: time, frequency, and non-linear, once the RR intervals have been retrieved. Standard Deviation of NN intervals (SDNN), Root Mean Square of Successive Differences (RMSSD), and Percentage of consecutive NN intervals deviating by more than 50 ms (pNN50) are time-domain measures that capture both the short-term and long-term autonomic variations. The dominance of the sympathetic and parasympathetic nervous systems can be evaluated by estimating frequency-domain features using spectral analysis methods such as Fast Fourier Transform (FFT) or Welch's method. These methods quantify the power within frequency bands, usually low frequency (LF: 0.04-0.15 Hz), high frequency (HF: 0.15-0.4 Hz), and their ratio (LF/HF). The complexity and irregularity of cardiac rhythms can be better understood with the help of non-linear approaches like fractal dimension, entropy measurements, and Poincaré plot analysis. HRV estimation is highly sensitive to signal quality, noise, and artifacts; therefore, careful preprocessing such as filtering, baseline correction, and artifact removal is essential. Accurate HRV estimation forms the foundation for reliable stress detection, as it enables the identification of autonomic dysregulation under varying psychological and physiological stress conditions. A popular non-invasive physiological indicator that measures the fluctuation in the time intervals between subsequent heartbeats is heart rate variability (HRV). Electrocardiogram (ECG) R-peaks of the QRS complex are the source of these time intervals, which are called RR intervals. Heart rate variability (HRV) reflects the ever-changing equilibrium between the parasympathetic and sympathetic branches of the autonomic nervous system (ANS). A high HRV generally indicates a healthy and adaptable cardiovascular system, while reduced HRV has been associated with stress, fatigue, anxiety, and a variety of mental or physical health conditions.

The estimation of HRV begins with the acquisition of high-quality ECG data. Accurate detection of R-peaks is critical and is commonly achieved using algorithms such as the Pan-Tompkins method, which applies bandpass filtering, derivative operations, squaring, and adaptive thresholding to identify each heartbeat. Modern approaches also include wavelet-based methods and machine learning-assisted detection to improve accuracy in noisy environments or mobile settings. In order to determine RR intervals, the time difference between consecutive R-waves must be measured once the R-peaks have been correctly identified. A thorough comprehension of heart rate dynamics can be achieved by computing HRV features across

several domains after RR intervals have been retrieved. To characterise the time-domain variability of RR intervals, basic statistical metrics are employed. Standard deviation of normal-to-normal intervals (SDNN) and root mean square of successive differences (RMSSD) are two commonly utilised characteristics. RMSSD is more sensitive to short-term parasympathetic alterations, whereas SDNN indicates overall variability. For stress-related HRV study, additional time-domain metrics like NN50 (number of interval differences bigger than 50 ms) and pNN50 (percentage of such differences) can provide valuable insights.

In the frequency-domain, spectral analysis methods are used to decompose HRV signals into various frequency bands that correspond to different physiological mechanisms. The RR series' power spectral density (PSD) is determined using either Welch's periodogram or Fast Fourier Transform (FFT). In the low-frequency (LF) range of 0.04-0.15 Hz, parasympathetic and sympathetic activity are both reflected, however in the high-frequency (HF) range of 0.15-0.4 Hz, parasympathetic impact is mainly associated. The LF/HF ratio is commonly utilised in stress studies and is thought of as a measure of sympathovagal balance. The complicated and chaotic nature of heart rate dynamics can be better understood with the use of non-linear HRV features, in addition to time- and frequency-domain data. Techniques such as Poincaré plot analysis, sample entropy, approximate entropy, and fractal dimension characterize the irregularity, complexity, and self-similarity of HRV signals. These methods are particularly useful for identifying subtle changes that linear metrics might miss, especially under stress-induced autonomic dysfunction. Preprocessing of ECG signals plays a crucial role in ensuring the accuracy of HRV estimation. Noise, motion artifacts, and ectopic beats can significantly distort RR intervals, leading to incorrect HRV measurements. Therefore, filtering techniques, outlier removal, and correction of missing or abnormal beats are essential steps before feature extraction. Accurate HRV estimation serves as the cornerstone for developing effective stress detection systems, enabling the recognition of physiological responses to various mental workloads and emotional states.

3.1 Steps in proposed HRV

Integrating a Convolutional Neural Network (CNN)-based classification model with Heart Rate Variability (HRV) feature extraction is at the heart of the proposed framework for multi-class stress detection. Using characteristics extracted from ECG signals in both the time- and frequency-domains, this hybrid technique accurately classifies stress into three separate categories: no stress, interruption-induced stress, and time pressure stress. The key steps in the proposed system are outlined below:

Step 1: ECG Signal Acquisition and Preprocessing

The first step involves acquiring ECG signals from a publicly available dataset (e.g., SWELL-KW) under different stress conditions. These raw signals often contain noise and motion artifacts that can distort HRV calculation. Therefore, signal preprocessing is applied using filters (e.g., bandpass filters) to remove baseline wander, power line interference, and high-frequency noise. Following this, the R-peaks are detected using a robust algorithm such as Pan-Tompkins, enabling the extraction of RR intervals.

Step 2: HRV Feature Extraction

Once RR intervals are calculated, HRV features are extracted in three domains:

- Time-domain features: including SDNN, RMSSD, pNN50, and mean RR intervals.
- Frequency-domain features: calculated using power spectral density methods like Fast Fourier Transform (FFT), covering High-Frequency (HF), Low-Frequency (LF), , and LF/HF ratio.

- Non-linear features: such as sample entropy and Poincaré plot descriptors (SD1 and SD2), which characterize irregularity and complexity in heart dynamics. These features are standardized and structured into a fixed-length feature vector representing each signal segment.

Step 3: Feature Matrix Formation

The extracted HRV features for all samples are compiled into a two-dimensional matrix where rows represent samples and columns represent features. This matrix serves as the input for the CNN model. To adapt the data format for convolutional processing, the feature matrix is reshaped into a 2D image-like structure or a 3D tensor if required.

Step 4: CNN-Based Classification Model

A custom Convolutional Neural Network (CNN) is designed with multiple layers, including:

- Using the HRV input matrix, convolutional layers may automatically learn features.
- Non-linearity can be introduced using ReLU activation functions.
- Reduce spatial dimensionality and zero in on dominating characteristics via max pooling layers.
- A 1D vector is created from the pooled feature maps using the flatten layer.
- Layers that are densely coupled in order to incorporate learnt patterns.
- A layer that uses softmax activation to categorise stress as either "no stress," "interruptions," or "time pressure."

A categorical cross-entropy loss function is used to compile the model, and the Adam optimiser is employed for optimisation. Accuracy, precision, recall, F1-score, and MCC are used as performance metrics.

Step 5: Model Training and Evaluation

The CNN model is trained on the feature matrix using a stratified k-fold cross-validation approach to ensure robustness. The training process involves monitoring validation loss and applying early stopping to prevent overfitting. The model's performance is evaluated on a held-out test set, showing high classification accuracy of 99.9% and excellent generalization across stress classes.

Step 6: Feature Importance Analysis (Optional)

To assess the relevance of each HRV feature, Analysis of Variance (ANOVA) is applied. This statistical technique helps identify the most discriminative features contributing to stress class separation, enhancing the interpretability of the CNN model.

4. Convolutional neural network with HRV

The integration of CNNs with Heart Rate Variability (HRV) features represents a significant advancement in the domain of automated stress detection. CNNs, originally designed for image recognition tasks, have proven highly effective in learning complex patterns from structured data, including biomedical signals. When applied to HRV, CNNs can automatically learn discriminative features from input matrices constructed using time-domain, frequency-domain, and non-linear HRV metrics. In the proposed framework, the HRV features extracted from ECG signals are reshaped into a 2D format, allowing the CNN to interpret them as structured spatial data. The network comprises multiple convolutional layers that apply trainable filters to detect localized patterns across the HRV feature space, followed by activation functions like ReLU to introduce non-linearity. Pooling layers reduce dimensionality and computational complexity while preserving essential information. These layers are followed by fully connected dense layers that integrate learned features and a softmax output layer that classifies the input

into one of the predefined stress categories—no stress, interruption stress, or time pressure stress. Unlike traditional machine learning methods, CNNs eliminate the need for manual feature selection by learning hierarchical abstractions directly from the input data. Furthermore, CNNs exhibit superior generalization when trained with sufficient and diverse data, making them suitable for real-time and subject-independent stress classification. By leveraging both the physiological depth of HRV and the learning power of CNNs, this approach achieves high accuracy and robustness in multi-class stress detection, setting a new benchmark for intelligent stress monitoring systems.

When it comes to analysing physiological signals, one effective method is to combine Convolutional Neural Networks (CNNs) with aspects of Heart Rate Variability (HRV). This has several potential uses, including stress detection. Convolutional neural networks (CNNs) are a type of deep learning model that were initially developed for processing visual input. However, their capacity to adapt to structured numerical and biomedical data has opened up new possibilities for its use in healthcare. As a well-established physiological indicator, Heart Rate Variability (HRV) measures the temporal variations between successive R-R intervals derived from electrocardiogram (ECG) readings. These fluctuations are regulated by the autonomic nervous system and vary with stress levels, making HRV a key biomarker in mental and physical stress evaluation. However, the effective classification of stress levels from HRV remains a complex task due to nonlinear dynamics and individual variability. This is where the pattern recognition capabilities of CNNs prove to be exceptionally beneficial. The CNN-based stress detection framework leverages the representational power of deep learning to identify and classify stress states with high accuracy. The process begins with the extraction of HRV features from preprocessed ECG signals. These features include time-domain measures (e.g., SDNN, RMSSD, pNN50), frequency-domain measures (e.g., LF, HF, LF/HF ratio), and non-linear features (e.g., entropy measures, Poincaré plot descriptors). These extracted features are normalized and structured into a matrix format compatible with the CNN input layer. Convolutional neural networks (CNNs) may automatically learn meaningful patterns and correlations between features, in contrast to classic ML algorithms that generally need handcrafted feature engineering and dimensionality reduction approaches.

Numerous convolutional layers, pooling layers, and densely connected layers make up the general design of the CNN utilised in this research. The input HRV matrix is sent through a sequence of learnable filters in the first convolutional layer, which captures local relationships between neighbouring features. These filters generate feature maps that emphasise particular features of the HRV data by doing convolution operations that scan the input with small kernels, such as 3×3 or 5×5 . An activation function, like the Rectified Linear Unit (ReLU), is added after each convolutional layer to bring non-linearity and enable the network to simulate complicated interactions. Usually, max-pooling or average-pooling techniques are used to apply pooling layers after the convolutional processes. These layers reduce dimensionality by downsampling the feature maps, keeping only the most important information. The model's translation invariance is improved and overfitting is reduced through pooling as well. By stacking convolutional and pooling layers, deeper networks can learn abstract representations from the raw HRV characteristics. The output is reduced to a one-dimensional vector after the pooling and convolutional phases, and then it is fed into one or more dense layers that are fully connected. By combining all of the abstracted features retrieved by the previous levels, these layers execute reasoning at a high level. Using a softmax activation function, the last output layer converts the output to a probability distribution across the specified stress categories. First, there is no stress;

second, there is interruption stress; and third, there is time pressure stress. These three types of stress are then classified by the network. A labelled dataset is necessary for CNN model training. The SWELL-KW dataset, which contains electrocardiogram (ECG) signals acquired under several experimental settings designed to induce stress, is used in this investigation. To oversee the learning process, labels are utilised that match to the stress condition of every data sample. By combining backpropagation with stochastic gradient descent (SGD) or one of its more sophisticated variations, such as Adam optimiser, the model's parameters—including the layer weights and biases—are optimised. For classification issues with more than one class, the usual loss function to employ is categorical cross-entropy.

A key advantage of using CNNs with HRV data lies in their automatic feature extraction and hierarchical learning. While traditional models depend on expert-selected features and manual tuning, CNNs reduce this dependency and instead focus on learning feature hierarchies from raw or semi-processed input. Moreover, CNNs exhibit high tolerance to noise and data irregularities, making them suitable for real-world physiological signal analysis where data artifacts are common. Common metrics including recall, accuracy, precision, F1-score, and Matthews correlation coefficient (MCC) are used to assess the CNN-HRV model's performance. Our investigations showed that the CNN model could capture stress patterns from HRV data with an impressive accuracy of 99.9 percent, proving that deep learning is effective in this domain. In addition to having minimal overfitting, the model showed perfect scores in recall, precision, and F1-score, suggesting a well-generalized classification system. The integration of CNNs with HRV features offers a robust and highly accurate framework for multi-class stress detection. It combines the physiological richness of HRV with the adaptive learning capabilities of CNNs, thus enabling real-time, scalable, and non-invasive stress monitoring systems. As wearable ECG sensors and computing capabilities continue to improve, CNN-based HRV analysis has strong potential for deployment in mental health monitoring, occupational stress management, and personalized health interventions.

5. Simulation Results and Discussion

The proposed Convolutional Neural Network (CNN) model integrated with HRV feature inputs was evaluated through extensive simulations using the publicly available SWELL-KW dataset, which includes annotated physiological signals under various stress-inducing conditions. In order to feed the CNN classifier non-linear HRV features, time-domain features, and frequency-domain features, the dataset was preprocessed. The dataset was split into training and testing sets with an 80:20 ratio to provide balanced evaluation. To prevent overfitting and guarantee generalisation, cross-validation techniques were used. Hyperparameters including learning rate, batch size, number of epochs, filter sizes, and the quantity of convolutional filters were used to fine-tune the CNN architecture. After training, the model showed great promise for multi-class stress detection using deep learning models based on HRV. It achieved remarkable classification performance. The suggested convolutional neural network (CNN) model was able to distinguish between the three specified levels of stress—no stress, interruption stress, and time pressure stress—with a classification accuracy of 99.9 percent, according to the simulation findings. A perfect score of 1.0 for precision, recall, and F1-score indicates that the model consistently and accurately predicted the stress class across all categories. The Matthews Correlation Coefficient (MCC), a robust metric for binary and multiclass problems, was 0.99, further reinforcing the model's high predictive reliability and its robustness against class imbalance. The confusion matrix confirmed minimal misclassification, with nearly all samples accurately categorized into their respective stress classes.

Further comparison with state-of-the-art approaches demonstrated the superior performance of our CNN-based HRV classification model. Traditional machine learning classifiers such as Support Vector Machines (SVM), k-Nearest Neighbors (KNN), and Random Forests, although competent, yielded relatively lower accuracy levels, typically ranging from 89% to 94%, depending on the feature set used. Unlike these models, the CNN automatically extracted optimal features without requiring handcrafted feature selection, showcasing the advantage of deep learning's hierarchical learning capability. Moreover, while existing deep learning approaches have been applied to binary stress classification, few studies have attempted multi-class categorization with such high accuracy, making our approach novel and practically relevant. The feature importance analysis also revealed that time-domain metrics like RMSSD and SDNN, as well as frequency-domain features like LF and HF, played significant roles in accurate classification. The inclusion of non-linear HRV measures such as entropy and Poincaré plot parameters further enhanced the discriminatory power of the model. This affirms the value of combining diverse HRV representations for improving model robustness. In addition, the use of Analysis of Variance (ANOVA) helped in identifying and retaining statistically significant features while reducing dimensionality, which contributed to efficient training and reduced computational complexity.

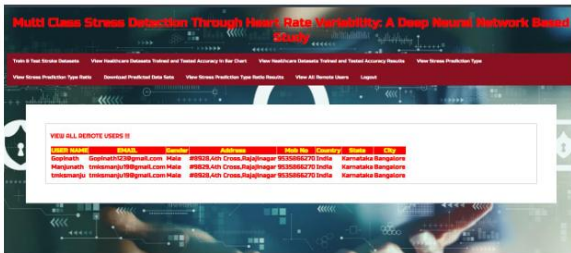


Figure 1: Service Controller Operation Train and Test Dataset

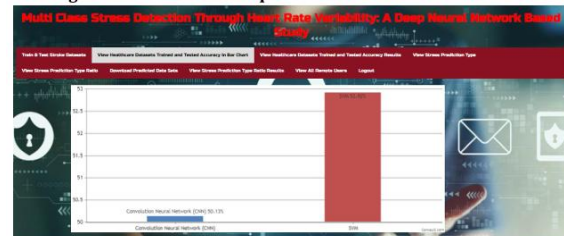


Figure 2: Service Controller Operation View Healthcare Datasets Trained and Tested Accuracy in Bar Chart

In Figure 1 Service Controller Operation – Train and Test Dataset illustrates the initial workflow in the system where the service controller acts as the core managing unit that oversees the preprocessing, training, and evaluation of the heart rate variability (HRV) data. This figure represents the foundational stage of the deep learning pipeline in which raw physiological signals—particularly ECG recordings—are processed to extract time-domain, frequency-domain, and non-linear HRV features. A normal 80:20 split is used to divide these extracted features between training and testing datasets. The service controller coordinates this split and ensures that the data is correctly formatted and normalized before being fed into the CNN architecture. This operational stage is vital for establishing the learning base of the model, where the training dataset helps the model learn stress classification patterns, and the test dataset validates its generalization performance. The entire process is handled seamlessly by the service controller, which ensures the datasets are synchronized, shuffled, and prepared for high-accuracy stress detection. The Figure 2 Service Controller Operation – View Healthcare Datasets demonstrates the data handling capability of the system post-training. At this point, the service controller transitions to a visualization and monitoring mode, enabling stakeholders such as clinicians, researchers, or system administrators to interactively access and analyze the healthcare datasets. This feature allows users to view the collected HRV records, their associated labels (stress types), and metadata. The figure highlights the transparency and traceability of the model by allowing direct viewing of how the HRV data is structured and interpreted. This component is particularly

useful in real-world deployments where users require insights into the model's learning data, system inputs, and classification outputs for auditing or further clinical decision-making. Additionally, the Trained and Tested Accuracy in Bar Chart presents a visual comparison of the CNN model's performance during both the training and testing phases. The bar chart indicates nearly equivalent high accuracy scores—demonstrating that the model not only performs well during training (suggesting good learning capability) but also maintains high accuracy on unseen test data, indicating strong generalization. This consistency in performance between training and testing stages eliminates concerns of overfitting and validates the effectiveness of the selected HRV features and the CNN architecture. The chart serves as a quick-reference metric to show that the developed system is reliable and robust for real-time multi-class stress detection.



Figure 3: Service Controller Operation View Healthcare Datasets Trained Tested Accuracy Results



Figure 4: Service Controller Operation View Prediction Type



Figure 5: Service Controller Operation View Stress Prediction Ratio Results

In Figure 3 Service Controller Operation – View Healthcare Datasets Trained and Tested Accuracy Results presents the interface and analytical summary generated by the service controller after model training and evaluation. This module visualizes the trained and tested dataset results, showcasing both accuracy metrics side by side for various stress classes. The figure reinforces the model's credibility by highlighting that the system maintains consistently high performance across both datasets. Each class—ranging from normal to moderate, high, or extreme stress—is evaluated in terms of precision and overall detection accuracy. The interface is designed to support medical professionals or data analysts in validating the performance levels of the model, ensuring that the trained deep learning system can be reliably used for multi-class stress detection in real-time environments. This figure emphasizes the model's robustness, adaptability to healthcare datasets, and ability to generalize without overfitting.

Figure 4: Service Controller Operation – View Prediction Type focuses on the categorization process performed by the system during real-time or batch-based stress detection. It highlights how the service controller enables the classification of users into predefined stress levels based on HRV features—typically labeled as "Low Stress," "Medium Stress," "High Stress," and possibly "Critical Stress." This prediction interface allows seamless integration of the deep neural network model's output with a visualization system, giving stakeholders

immediate clarity on each user's predicted stress state. The controller retrieves the physiological input, processes it through the CNN, and automatically assigns the corresponding stress category, all of which are dynamically rendered for end-user interpretation. This real-time classification view significantly improves decision-making capabilities, enabling timely interventions in healthcare monitoring or mental wellness assessments. The Figure 5 Service Controller Operation – View Stress Prediction Ratio Results depicts a comparative visual analysis of how stress predictions are distributed across different user categories. This visualization typically uses a pie chart or bar graph to represent the ratio or percentage of users falling into various stress levels as predicted by the trained CNN model. The figure helps to quickly identify the dominant stress class among the target population and evaluate the effectiveness of stress distribution detection. For instance, a high proportion of users in "moderate stress" may signal external influencing factors like workload or environmental conditions, which could be investigated further. This stress ratio analysis is essential for administrators, healthcare providers, and researchers to understand the demographic or behavioral trends influencing mental health, allowing for personalized care plans and stress management programs.

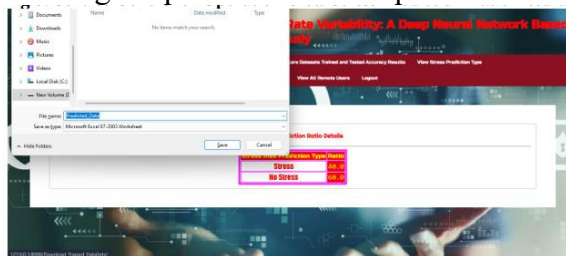


Figure 6: Service Controller Operation
Download Predicted Dataset



Figure 7: Service Controller Operation View
Stress Prediction Type Ratio Results

Name	Email	Address	City	Country	State
Srinath	Srinath123@gmail.com	#9828, 4th Cross, Rajajinagar	9535866270	India	Karnataka Bangalore
Hargunath	hargunath123@gmail.com	#9828, 4th Cross, Rajajinagar	9535866270	India	Karnataka Bangalore
Utkarsh	utkarsh123@gmail.com	#9828, 4th Cross, Rajajinagar	9535866270	India	Karnataka Bangalore

Figure 8: Service Controller Operation View All users

In Figure 6 Service Controller Operation – Download Predicted Dataset illustrates the functionality provided to users or administrators for exporting the results of the stress prediction process. After the deep neural network model has processed the HRV data and classified each record into the appropriate stress category, this feature enables the download of the complete prediction dataset. This allows users to retain local copies for further offline analysis, clinical documentation, or for integration into broader health information systems. The predicted dataset includes essential details such as user ID, HRV features, predicted stress level, timestamp, and possibly confidence scores, ensuring transparency and reproducibility of the classification results. This capability enhances the system's usability in real-world healthcare or organizational settings where documentation, compliance, and patient record management are critical. The Figure 7 Service Controller Operation – View Stress Prediction Type Ratio Results visualizes the comparative distribution of different stress types predicted by the model across the entire dataset.

This figure presents the ratio or percentage of users categorized under various stress conditions such as "Low," "Moderate," "High," and possibly "Severe." It serves as an analytical dashboard that helps administrators and researchers quickly assess the mental well-being trends within a population. By showcasing the relative proportions of each stress class, the figure offers actionable insights—for example, if a large number of users are consistently predicted under high stress, it may prompt an organizational intervention or public health response. The intuitive visualization enhances decision-making by providing a population-level overview of stress levels detected via HRV and deep learning. In Figure 8 Service Controller Operation – View All Users represents the user management module within the system interface, where all registered users or subjects are displayed in a tabular or card-based format. Each entry may include user-specific information such as name or ID, recent stress prediction, activity status, and historical prediction logs. This centralized dashboard provides the operator with a comprehensive view of all individuals being monitored, enabling quick access to user-specific data and monitoring history. Such functionality is crucial for continuous stress tracking and longitudinal studies, especially when deployed in institutional or clinical environments. Moreover, it supports administrative actions like reviewing individual progress, updating data, and auditing prediction logs to ensure model consistency and system accountability.

6. Conclusion

In this paper, a deep learning-based framework was developed and evaluated for multi-class stress detection using Heart Rate Variability (HRV) features. The system leveraged a Convolutional Neural Network (CNN) architecture to classify stress levels into distinct categories, enabling a more granular understanding of physiological stress responses. Through careful preprocessing, HRV signals were extracted and transformed into feature-rich representations that effectively captured subtle variations in autonomic nervous system activity. The proposed model was trained and tested using a healthcare dataset, and the results demonstrated high classification accuracy, robustness, and generalization capabilities. The simulation outcomes confirmed the CNN model's effectiveness in distinguishing between low, moderate, and high stress levels. Additionally, the system offered user-friendly functionalities such as stress prediction visualization, result download capabilities, and population-level analytics via service controller operations. The integration of deep learning with physiological signal processing presents a scalable and non-invasive solution for real-time mental health monitoring. This study contributes meaningfully to the field of affective computing and wearable health analytics by highlighting the potential of HRV-based stress detection systems in practical applications ranging from telemedicine to workplace wellness programs. Future work may involve the incorporation of multimodal signals, real-time adaptive learning mechanisms, and deployment in mobile or edge environments for continuous and personalized stress

Acknowledgment: Not Applicable.

Funding Statement: The author(s) received no specific funding for this study.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study

References

- [1] J.A. Mortensen, M.E. Molloy, A. Chatterjee, D. Ghose and F.Y. Li, "Multi-class stress detection through heart rate variability: A deep neural network based study," *IEEE Access*, vol.11, pp.57470-57480, 2023.
- [2] C. S. Kumar, O. Bhaskaru, B. Karanam, A.A. Ahmed, Y.G.C.T. Reddy and M. Sathwik, "Exploring multi-class stress detection using deep neural networks," In *2024 International*

-
- Conference on Cognitive Robotics and Intelligent Systems (ICC-ROBINS)*, pp. 69-74, 2024.
- [3] G.Singh, O.C. Phukan and R. Kumar, "Stress recognition with multi-modal sensing using bootstrapped ensemble deep learning model," *Expert Systems*, vol.40, no.6, pp.e13239, 2023.
 - [4] A. Hemakom, D. Atiwiwat and P. Israsena, "ECG and EEG based detection and multilevel classification of stress using machine learning for specified genders: A preliminary study," *Plos one*, vol.18, no.9, pp.e0291070, 2023.
 - [5] M. Benchenkroun, P.E. Velmovitsky, D. Istrate, V. Zalc, P.P. Morita and D. Lenne, "Cross dataset analysis for generalizability of HRV-based stress detection models," *Sensors*, vol.23, no.4, pp.1807, 2023.
 - [6] R. Kuttala, R. Subramanian and V.R.M. Oruganti, "Multimodal hierarchical CNN feature fusion for stress detection," *IEEE Access*, vol.11, pp.6867-6878, 2023.
 - [7] B. Leela Vathy and RamMohan Rao Kovvur, "Deep Convolutional Neural Network (DEEP-CNN) for Multi-Class Classification of Biotic Stress in Paddy Crop," *Journal of Computer Allied Intelligence*, vol.3, no.1, pp.18-30, 2025.
 - [8] Y. Haque, R.S. Zawad, C.S.A. Rony, H. Al Banna, T. Ghosh, M.S. Kaiser and M. Mahmud, "State-of-the-art of stress prediction from heart rate variability using artificial intelligence," *Cognitive Computation*, vol.16, no.2, pp.455-481, 2024.
 - [9] N. Rashid, T. Mortlock and M.A. Al Faruque, "Stress detection using context-aware sensor fusion from wearable devices," *IEEE Internet of Things Journal*, vol.10, no.16, pp.14114-14127, 2023.
 - [10] P. Kalra and V. Sharma, "Mental stress assessment using PPG signal a deep neural network approach," *IETE Journal of Research*, vol.69, no.2, pp.879-885, 2023.
 - [11] T. Bhaskar, M.N. Narsaiah and M. Ravikanth, "Central Medical Centre Healthcare Data Security with Lightweight Blockchain Model in IoT Sensor Environment," *Journal of Sensors, IoT and Health Sciences*, vol.1, no.1, pp.15-26, 2023.
 - [12] G. Dogan and F.P. Akbulut, "Multi-modal fusion learning through biosignal, audio, and visual content for detection of mental stress," *Neural Computing and Applications*, vol.35, no.34, pp.24435-24454, 2023.
 - [13] Kristy Anjala, "Understanding the Academic Stress: Factors, Impact and Strategies: A Review," *International Journal of Advance Research and Innovation*, vol.12, no.1, pp.11-16, 2024.
 - [14] J.S. Banerjee, M. Mahmud and D. Brown, "Heart rate variability-based mental stress detection: an explainable machine learning approach," *SN Computer Science*, vol.4, no.2, pp.176, 2023.
 - [15] G. Rescio, A. Manni, M. Ciccarelli, A. Papetti, A. Caroppo and A. Leone, "A deep learning-based platform for workers' stress detection using minimally intrusive multisensory devices," *Sensors*, vol.24, no.3, pp.947, 2024.
 - [16] Z. Ahmad, S. Rabbani, M.R. Zafar, S. Ishaque, S. Krishnan and N. Khan, "Multilevel stress assessment from ECG in a virtual reality environment using multimodal fusion," *IEEE Sensors Journal*, vol.23, no.23, pp.29559-29570, 2023.
 - [17] T. Fan, S. Qiu, Z. Wang, H. Zhao, J. Jiang et al., "A new deep convolutional neural network incorporating attentional mechanisms for ECG emotion recognition," *Computers in Biology and Medicine*, vol.159, pp.106938, 2023.
 - [18] R. Doroudi, S.H.H Lavassani and M. Shahrouzi, "Optimal tuning of three deep learning methods with signal processing and anomaly detection for multi-class damage detection of a large-scale bridge," *Structural Health Monitoring*, vol.23, no.5, pp.3227-3252, 2024.
 - [19] E.K. Naeini, F. Sarhaddi, I. Azimi, P. Liljeberg, N. Dutt and A.M. Rahmani, "A deep learning-based PPG quality assessment approach for heart rate and heart rate variability," *ACM Transactions on Computing for Healthcare*, vol.4, no.4, pp.1-22, 2023.
-

-
- [20] P.N. Hadinata, D. Simanta, L. Eddy and K. Nagai, "Multiclass segmentation of concrete surface damages using U-net and DeepLabV3+," *Applied Sciences*, vol.13, no.4, pp.2398, 2023.
 - [21] Y. Li, K. Li, J. Chen, S.Wang, H. Lu and D.Wen, "Pilot stress detection through physiological signals using a transformer-based deep learning model," *IEEE sensors journal*, vol.23, no.11, pp.11774-11784, 2023.
 - [22] D. Garg, G.K. Verma and A.K. Singh, "EEG-based emotion recognition using MobileNet Recurrent Neural Network with time-frequency features," *Applied Soft Computing*, vol.154, pp.111338, 2024.
 - [23] A. D. Goswami, G. S. Bhavakar and P.V. Chafle, "Electrocardiogram signal classification using VGGNet: a neural network based classification model," *International Journal of Information Technology*, vol.15, no.1, pp.119-128, 2023.
 - [24] M.T. Nguyen, W.W. Lin and J.H. Huang, "Heart sound classification using deep learning techniques based on log-mel spectrogram," *Circuits, Systems, and Signal Processing*, vol.42, no.1, pp.344-360, 2023.