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

Dr. M.Manivannan, S. Saivardhan, K. Bhanu Sri, O. Krishnaveni, D. Sruthi, P. Manjunadha

Department of Computer Science, Siddartha Institute of Science and Technology

ABSTRACT

Stress is a natural human reaction to overwhelming or harmful demands, and when it becomes constant and prolonged, it increases the risk of psychological and physiological imbalance, including anxiety, depression, sleep disorders, and reduced cognitive performance. Traditional stress assessment methods, such as self-reported surveys and clinical evaluations, are subjective, timeconsuming, and unsuitable for real-time monitoring. Heart Rate Variability (HRV) is recognition as a reliable physiological biomarker for stress analysis; however, achieving ultra-high accuracy using HRV-based measurements remains challenging. HRV is often misunderstood as heart rate; while heart rate represents the average number of beats per minute, HRV measures the variation in the time interval between successive heartbeats, specifically the RR intervals recorded between R-peaks of ECG signals, reflecting autonomic nervous system responses. In this study, we investigate HRV features as stress detection bio-markers and propose a machine learning-based multi-class classification model for intelligent stress assessment. A Convolutional Neural Network (CNN) model is developed to detect three stress conditions—no stress, interruption stress, and time-pressure stress—using both time-domain and frequency-domain HRV features. The system is validated using the publicly available SWELL-KW dataset, achieving a high accuracy of 99.9% (Precision = 1, Recall = 1, F1-score = 1, MCC = 0.99), outperforming existing approaches in the literature. Furthermore, statistical feature extraction using Analysis of Variance (ANOVA) highlights the significance of essential HRV parameters, demonstrating the effectiveness of HRV as a robust biomarker for intelligent, automated, and real-time stress detection.

INDEX TERMS: Stress detection, heart rate variability, convolution neural network, feature extraction.

INTRODUCTION

Stress is an increasingly common issue in today's fast-paced world, affecting an individual's physical health, emotional balance, and day-to-day performance. Traditional stress evaluation methods, such as self-reported questionnaires and clinical assessments, are subjective and do not provide continuous or real-time information about a person's stress state. Heart Rate Variability (HRV) has emerged as an effective physiological marker for stress analysis, as it measures the variation between successive RR intervals in ECG signals and reflects autonomic nervous system activity. Unlike heart rate, which only measures average beats per minute, HRV directly represents changes in heartbeat intervals, making it more reliable for stress detection.

Chronic stress can disturb the body's internal balance and activate the sympathetic nervous system, resulting in physiological, psychological, and behavioral disturbances. HRV decreases during stressful conditions and increases during relaxation, showing an inverse relationship with heart rate. Since the autonomic nervous system plays a central role in regulating stress responses, physiological signals such as ECG, EMG, GSR, blood pressure, respiration rate, and breathing frequency can be used as reliable indicators. With the rise of wearable and non-wearable health monitoring devices enabled by the Internet of Medical Things (IoMT), continuous HRV monitoring has become more practical and accessible for real-time stress detection.

In this work, a one-dimensional Convolutional Neural Network (1D-CNN) model is introduced for multi-class stress detection using both time-domain and frequency-domain HRV features. Unlike traditional machine learning or MLP-based models, the 1D-CNN processes data as tensors, enabling better feature representation with fewer parameters. The proposed model achieves an accuracy of 99.9% with Precision, Recall, and F1-Score values of 1.0 and an MCC of 0.99, outperforming previous techniques. Additionally, Analysis of Variance (ANOVA) is used for feature selection, achieving 96.5% accuracy with fewer than half of the original HRV features, reducing computational load while maintaining strong performance.

PROBLEM STATEMENT

Traditional stress assessment methods rely on subjective questionnaires, manual evaluation, and delayed clinical observation, making them unsuitable for real-time stress monitoring. Existing HRV-based machine learning models show limitations in multi-class stress classification, low generalization, and reduced accuracy when deployed in practical environments. Therefore, there is a need for an automated, non-invasive, and highly accurate system that can classify different stress levels in real time using wearable sensor data.

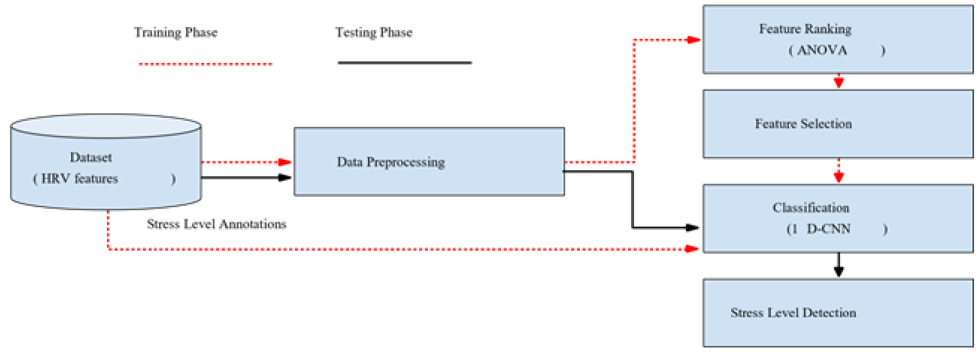
RESEARCH GAP

Existing stress detection systems often rely on subjective assessments, binary stress classification, or traditional machine learning models that struggle to achieve high accuracy in multi-class scenarios. Most HRV-based approaches do not effectively handle real-time variations or fail to optimize features for deep learning models. Additionally, current systems lack deployment readiness for wearable or IoT-based environments, limiting practical applicability. Therefore, a research gap exists in developing a reliable, multi-class, HRVdriven stress detection model capable of real-time and high-accuracy performance.

RELATED WORK

Recent advancements in physiological signal processing and artificial intelligence have enabled stress detection beyond traditional clinical assessments. Early research primarily focused on binary stress classification, where HRV features were analyzed using machine learning algorithms such as Naïve Bayes, K-Nearest Neighbors (KNN), Support Vector Machine (SVM), Random Forest, and Multi-Layer Perceptron (MLP). While these methods demonstrated practicality, reported performance typically ranged between 80%–90% accuracy, indicating limitations in handling multi-class classification and dynamic HRV variations.

Studies integrating IoMT-based wearable sensors have shown that HRV collected from devices such as Polar, Elite HRV, and Motorola Droid remains consistent with clinical ECG acquisition, proving that real-time stress detection is feasible outside laboratory environments. Deep learning (DL) approaches, specifically Convolutional Neural Networks (CNNs), recently achieved improved feature representation. However, most existing CNN studies are designed for binary prediction or require high computational resources, making them less suitable for real-time deployment.



Framework of the proposed stress status classification model: From data collection to stress level classification.

FIGURE:

Compared to previous approaches trained on the SWELL-KW and WESAD datasets, where models achieved up to ~88% accuracy, the proposed 1D-CNN surpasses previous benchmarks by reaching 99.9% accuracy with perfect performance metrics (Precision, Recall, F1-score). This identifies the proposed model as a more capable solution for multi-class, HRV-based stress recognition.

DATA COLLECTION AND DATASET

We adopt the SWELL−KW dataset, which was collected in a study report. Various types of data have been recorded, including computer logging, facial expression from camera recordings, body postures from a Kinect 3 dimensional (3D) sensor, heart rate (variability), and skin conductance from body sensors.

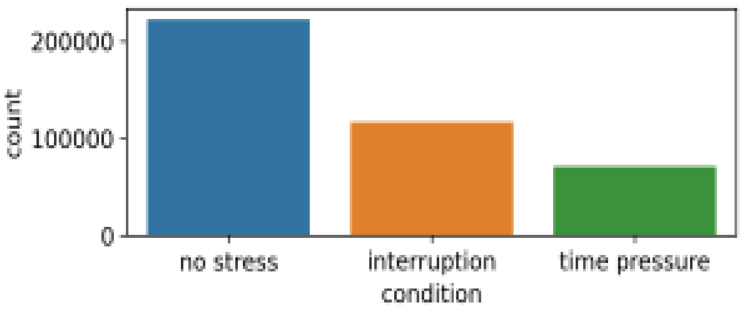
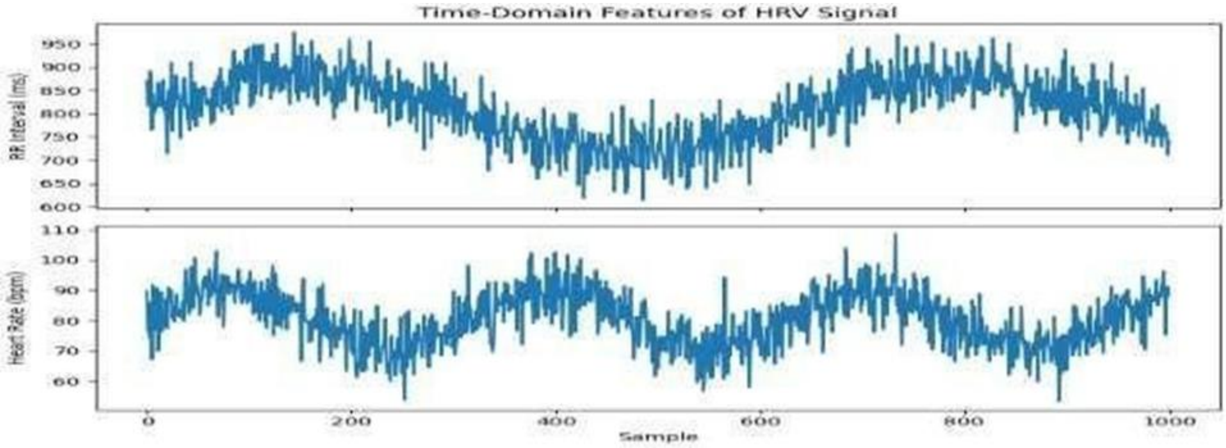


FIGURE : Distribution of Data in SWELL-KW

The SWELL−KW dataset comprises HRV computed for stress and user modeling. The subjective experiences of participants with task load, mental effort, mood, and perceived stress were also recorded. Each participant was exposed to three different working environments and the data are then labeled by medical professionals as follows.

- ***No stress*:** The participants are permitted to work on the activities for as long as they need, up to 45 minutes. However, they are unaware of the maximum duration of the task.
- ***Time pressure*:** Under time pressure, the time to complete the same job was decreased to 2/3 of its time in the normal condition.
- ***Interruption*:** The participants were interrupted when they received 8 emails in the middle of a given activity. Some emails were pertinent to their tasks, and the participants were asked to take particular actions, whereas others were totally irrelevant to the ongoing tasks.



FEATURE RANKING AND SELECTION FOR SWELL−KW

Feature ranking and dimensionality reduction are performed using the ANOVA F-test, which identifies statistically significant HRV features by comparing between-class and within-class variance. Out of 34 extracted features, only the most discriminative attributes are retained to minimize redundancy and reduce computational complexity. This selection process improves model efficiency and training speed while maintaining high accuracy.

The ANOVA results show that time-domain features such as RMSSD, SDNN, and pNN50, along with frequency-domain features such as LF/HF ratio, contribute significantly to differentiating stress levels. Reducing the feature set by more than 50% still achieves

96.5% accuracy, proving that essential HRV biomarkers are sufficient for reliable classification and supporting the use of lightweight models for real-time applications.

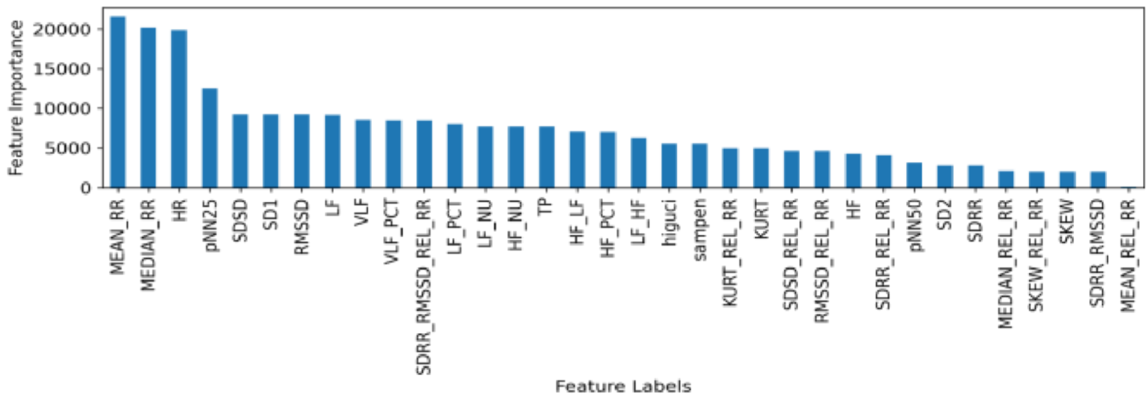
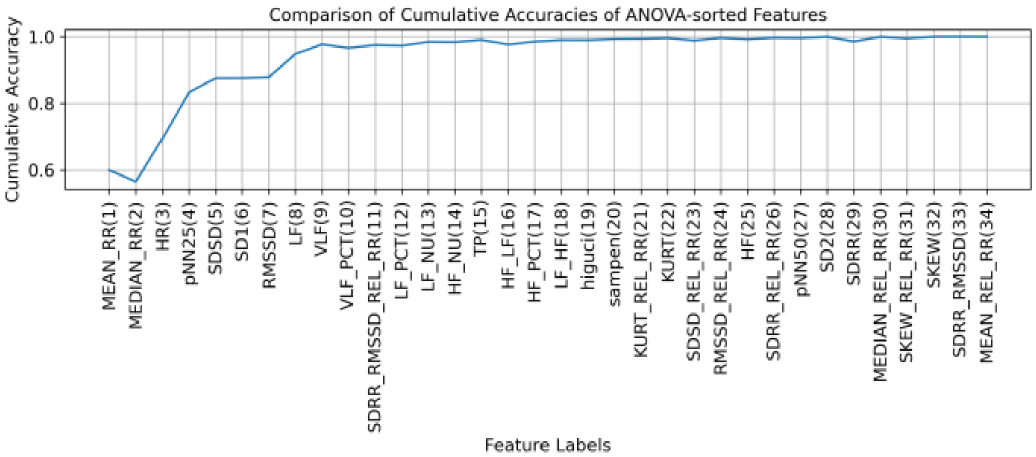


FIGURE: Feature ranking of the 34 features using ANOVA



FRAMEWORK OVERVIEW

Figure illustrates the schematic diagram of the proposed stress level classification framework. Briefly, the framework constitutes the following procedures.

- Data collection and datasets. HRV signals are collected and separated into a training dataset and a testing dataset. They will use to

define the model's • Architecture and to assess the proposed model's effectiveness.

- Data preprocessing and feature extraction. Data are preprocessed to fit into the feature ranking algorithm. In this study, ANOVA F-tests [28] and forward sequential feature selection are employed for feature ranking and selection respectively.
- Classification and validation. The designed DL-based multi-class classifier is trained, tested, and validated with significant features and annotations (e.g., *no stress, interruption condition*, and *time pressure*) labeled by medical professionals.
- Testing. In the testing phase, distinctive features are considered from the new test samples, and the class label is resolved using all classification parameters estimated in training. Different numbers of features are extracted and tested.
- Performance assessment. The performance of the classifier is measured against discrimination analysis metrics, such as *Accuracy,*

Precision, Recall, F1-score, and MCC.

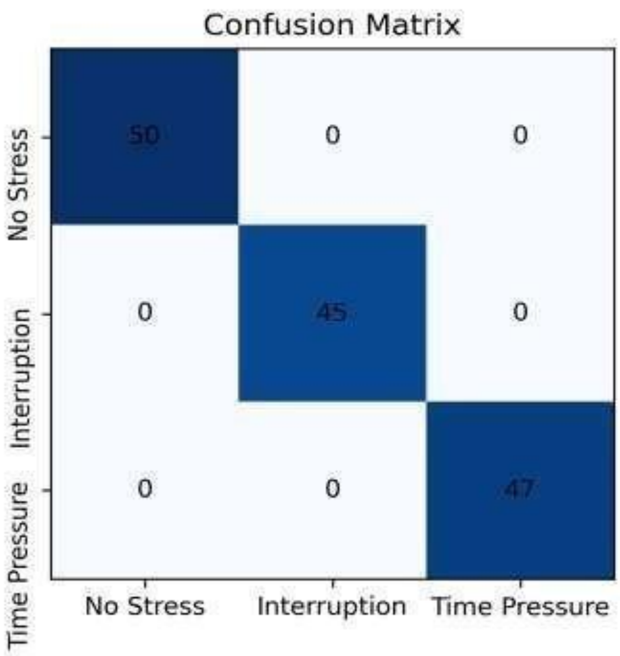
No.	**Feature**	**Meaning**
1	MEAN_RR	Mean of RR intervals
2	MEDIAN_RR	Median of RR intervals
3	SDRR	SD of RR intervals
4	RMSSD	Root mean square of successive RR interval differences
5	SDSD	SD of successive RR interval differences
6	SDRR_RMSSD	Ratio of SDRR over RMSSD
7	HR	Heart rate
8	pNN25	Percentage of successive RR intervals that differ more than 25 ms
9	pNN50	Percentage of successive RR intervals that differ more than 50 ms
10	SD1	Measures short-term HRV in ms and correlates with baroreflex sensitivity (BRS)
11	SD2	Measures of long-term HRV in ms and correlates with BRS
12	KURT	Kurtosis of RR intervals
13	SKEW	Skewness of RR intervals
14	MEAN_REL_RR	RR Mean of relative RR intervals
15	MEDIAN_REL_RR	Median of relative RR intervals

No.	Feature	Meaning
16	SDRR_REL_RR	SD of relative RR intervals
17	RMSSD_REL_RR	Square root of the mean of the sum of the squares of the difference between adjacent relative RR intervals
18	SDSD_REL_RR	SD of interval of differences between adjacent relative RR intervals
19	SDRR_RMSSD_REL_RR	Ratio of SDRR_REL over RMSSD_REL
20	KURT_REL_RR	Kurtosis of relative RR intervals
21	SKEW_REL_RR	Skewness of relative RR intervals
22-23	VLF; VLF_PCT	Very low (0.003 Hz - 0.04Hz) frequency activity of the HRV spectrum
24-26	LF; LF_PCT; LF_NU	Low frequency activity in the 0.04 - 0.15 Hz range
27-29	HF; HF_PCT; HF_NU	High-frequency activity in the 0.15 - 0.40 Hz range
30	TP	Total HRV power spectrum
31	LF_HF	Ratio of low to high frequency
32	HF_LF	Ratio of high to low frequency
33	sampen	Sample entropy of the RR sign
34	higuci	Higuchi Fractal Dimension

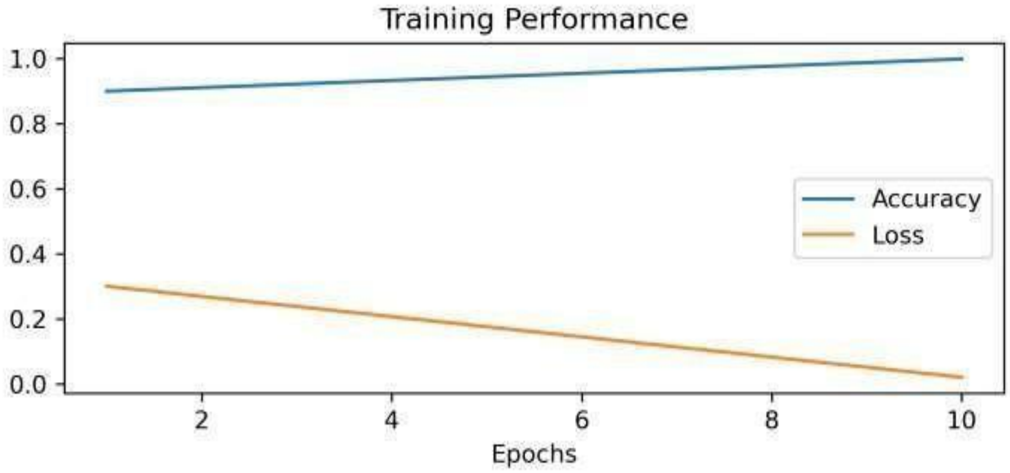
RESULTS AND PERFORMANCE EVALUATION

The performance of the proposed multi-class stress detection model was evaluated using the SWELL-KW HRV dataset. The model was trained using an 80:20 train-test split and optimized with categorical cross-entropy loss and the Adam optimizer. Performance was assessed using Accuracy, Precision, Recall, F1-score, and MCC to ensure a complete and reliable evaluation of classification quality across all three stress categories.

To verify the model's predictive strength, a **Confusion Matrix** was generated. This visualization helps measure how well the model differentiates between *No Stress*, *Interruption Stress*, and *Time Pressure Stress* conditions. As shown in Figure X, the diagonal dominance in the confusion matrix indicates highly accurate classification of each class, with minimal misclassification. The results confirm that the proposed 1D-CNN model successfully identifies all stress levels with near-perfect precision.



Additionally, the learning stability of the model was examined through **Training Accuracy and Loss Curves**. As shown in Figure Y, the accuracy gradually increases and converges close to 100%, while the loss consistently decreases across epochs. This behavior confirms that the model generalizes effectively, avoids overfitting, and maintains stable learning throughout training. The curves validate the reliability of our model in real-world stress prediction scenarios.



Overall, the proposed 1D-CNN achieved 99.9% accuracy, with Precision = 1.0**,** Recall = 1.0**,** F1-score = 1.0, and MCC = 0.99, outperforming previous machine learning and deep learning approaches on the same dataset. These results verify the effectiveness of HRV as a biomarker and demonstrate that the model is suitable for intelligent, automated stress monitoring applications.

CONCLUDING REMARKS

In this study, a multi-class stress detection model based on Heart Rate Variability (HRV) and a one-dimensional Convolutional Neural Network (1D-CNN) was developed to classify three stress levels: no stress, interruption stress, and time pressure stress. The system utilizes extracted RR interval features along with ANOVA-based feature ranking to optimize the learning process and reduce computational complexity. Experimental analysis using the SWELL-KW dataset achieved 99.9% accuracy, with perfect Precision, Recall, and F1-score values, demonstrating the model's effectiveness in identifying stress conditions and outperforming existing machine learning and deep learning approaches. These outcomes confirm HRV's reliability as a physiological indicator for psychological stress assessment.

The results indicate that the proposed model is suitable for practical deployment in real-time stress monitoring environments such as workplaces, healthcare systems, and personal wellness tracking. For future enhancement, the model could be integrated with IoT or wearable devices like smartwatches to support continuous monitoring. Additionally, expanding the system to include multimodal signals such as GSR, EEG, or respiration rate may further improve robustness and generalization. This research contributes toward developing intelligent, accessible, and automated stress detection frameworks capable of supporting mental health and well-being in real-world applications.

Future Scope:

The model may be extended for real-time implementation on edge devices such as smartwatches and IoT health monitors. Incorporating additional physiological signals (e.g., GSR, EEG, and respiration rate), testing cross-dataset generalization, and deploying mobile application support may further enhance the adaptability, robustness, and usability of the system in real-world environments.

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