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MULTI CLASS STRESS DETECTION THROUGH HEART RATE VARIABILITY A DEEP NEURAL NETWORK BASED STUDY

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ABSTRACT

The study titled "Multi-Class Stress Detection Through Heart Rate Variability: A Deep Neural Network-Based Study" explores stress detection using heart rate variability (HRV) as a physiological biomarker. Stress, a natural human response to pressure, can become chronic and lead to mental health issues like anxiety, depression, and sleep disorders. Traditional stress measurement methods based on HRV face challenges in achieving high accuracy. Unlike heart rate, which measures the average beats per minute, HRV represents the variation in time intervals between consecutive heartbeats, specifically the RR intervals. This study focuses on leveraging HRV features for multi-class stress detection by developing a Convolutional Neural Network (CNN)-based model. The model classifies stress into three categories: no stress, interruption stress, and time pressure stress, utilizing both time- and frequency-domain HRV features. The research is validated using the SWELL-KW dataset, achieving an impressive accuracy of 99.9% (Precision=1, Recall=1, F1-score=1, and MCC=0.99), surpassing existing methods. Additionally, the study highlights the significance of HRV features in stress detection through a feature extraction technique based on analysis of variance (ANOVA), demonstrating the effectiveness of deep learning in stress classification.

Keywords: Stress detection, heart rate variability (HRV), deep learning, convolutional neural network (CNN), multi-class classification, physiological signals, SWELL-KW dataset, ANOVA, feature extraction, time-domain features, frequency-domain features, mental health monitoring, stress classification.

I. INTRODUCTION

The introduction provides a comprehensive background on stress detection using heart rate variability (HRV) and the role of machine learning (ML) and deep learning (DL) in improving classification accuracy. It begins by explaining the biological basis of stress, emphasizing the autonomic nervous system's (ANS) role in regulating physiological responses. The sympathetic and parasympathetic components of the ANS are highlighted, drawing an analogy between the body's stress response and a car’s gas and brake pedals. Several physiological signals, including electrocardiogram (ECG), electromyogram (EMG), galvanic skin response (GSR), and HRV, are mentioned as critical indicators of stress. The discussion then shifts toward

HRV as a key metric for stress analysis. HRV, measured from ECG signals, is defined as the variation in RR intervals between successive heartbeats. The paper explains the inverse relationship between HRV and stress levels, noting that HRV decreases under stress and increases during relaxation. The challenges of obtaining HRV data in clinical settings are acknowledged, with recent technological advancements in the Internet of Medical Things (IOMT) providing more accessible alternatives for data collection. The introduction also reviews existing studies that have applied ML and DL models to HRV-based stress classification. The SWELL-KW dataset is identified as a widely used benchmark for stress detection research. However, the authors note a gap in achieving ultra-high accuracy in multi-class stress classification using ML and DL techniques. This gap motivates the development of a new model that surpasses previous approaches in prediction performance.

To address this gap, the authors propose a one-dimensional convolutional neural network (1D CNN) model tailored for multi-class stress classification. The CNN-based approach is justified by its ability to reduce the number of training parameters compared to traditional multi-layer perceptron (MLP) architectures, which process inputs as vectors rather than tensors. The CNN model's effectiveness in capturing spatial relationships in HRV data is emphasized as a key advantage over existing techniques. The introduction further highlights an optimization strategy using analysis of variance (ANOVA) F-tests to reduce the number of HRV features needed for accurate classification. The authors report that their optimized model achieves a remarkable accuracy of 99.9% while maintaining strong precision, recall, and F1 scores. Feature selection techniques contribute to reducing computational load without sacrificing classification performance, making the proposed model both efficient and highly accurate. Finally, the introduction provides a structured outline of the paper, detailing the organization of subsequent sections. It establishes a clear distinction between the proposed work and previous studies, setting the stage for a detailed exploration of the methodology, performance evaluation, and discussion of results in the following sections. The claims made about achieving state-of-the-art accuracy underscore the significance of the research in advancing stress detection through deep learning techniques.

II. LITERATURE SURVEY

Kim et al. (2018) - "Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature"

This study provides a comprehensive meta-analysis and literature review on the relationship between stress and heart rate variability (HRV). It discusses how HRV serves as a physiological marker of stress and evaluates various studies that examine HRV in different stress-inducing conditions. The authors emphasize the importance of autonomic nervous system (ANS) activity in stress regulation, noting that chronic stress can lead to reduced HRV. The study also highlights the potential applications of HRV in clinical and psychological assessments, offering insights into its effectiveness in monitoring stress-related disorders.

Muhajir et al. (2022) - "Stress Level Measurements Using Heart Rate

Variability Analysis on Android-Based Application"

This research focuses on the development of an Android-based application that measures stress levels using HRV analysis. The study implements real-time HRV data collection and analysis, making stress assessment accessible through a mobile platform. The authors compare different HRV-based stress measurement techniques and discuss their applicability in non-clinical environments. The study's findings demonstrate the feasibility of using smartphone applications for stress detection, paving the way for user-friendly stress monitoring solutions that do not require specialized medical equipment.

Held et al. (2021) - "Heart Rate Variability Change During a Stressful Cognitive Task in Individuals with Anxiety and Control Participants"

This study investigates HRV changes in response to cognitive stress among individuals with anxiety disorders and healthy controls. The authors find that participants with anxiety exhibit lower baseline HRV and a greater decline in HRV during stress-inducing tasks. These findings support the hypothesis that HRV is a reliable biomarker for psychological stress and anxiety-related conditions. The research contributes to understanding the physiological differences between anxious and non-anxious individuals, reinforcing the role of HRV as an objective measure of stress reactivity.

Dalmeida & Masala (2021) - "HRV Features as Viable Physiological Markers for Stress Detection Using Wearable Devices"

This study explores the use of HRV features as physiological markers for stress detection through wearable devices. The authors analyze various HRV parameters and their correlation with stress levels. They emphasize the importance of wearable technology in real-time stress monitoring, making stress assessment more practical and less intrusive. The study demonstrates that HRV-based stress detection models can achieve high accuracy, making them suitable for integration into commercial wearable health devices.

Miranda-Correa et al. (2021) - "AMIGOS: A Dataset for Affect, Personality and Mood Research on Individuals and Groups"

This paper introduces the AMIGOS dataset, which contains physiological and behavioral data for affect, personality, and mood research. The dataset includes HRV, electroencephalography (EEG), and facial expressions recorded during emotional stimuli exposure. The authors aim to provide a rich dataset for studying human emotional responses and stress. The dataset's multimodal nature makes it valuable for developing machine learning models that analyze stress and affective states.

Won & Kim (2016) - "Stress, the Autonomic Nervous System, and the Immune-Kynurenine Pathway in the Etiology of Depression"

This study investigates the connection between stress, the autonomic nervous system, and the immune-kynurenine pathway in depression. The authors discuss how chronic stress affects the balance between sympathetic and parasympathetic nervous system activity, potentially

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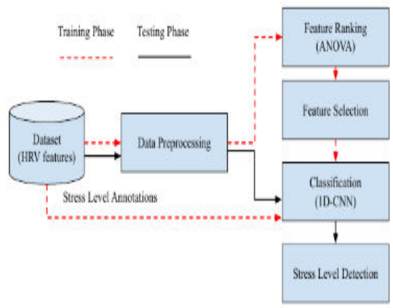
leading to depression. They highlight the role of immune system dysregulation in stress-induced mental health disorders. The findings suggest that HRV analysis can serve as a diagnostic tool for detecting stress-related pathophysiological changes.

Olshansky et al. (2008) - "Parasympathetic Nervous System and Heart Failure: Pathophysiology and Potential Implications for Therapy"

This study examines the role of the parasympathetic nervous system in heart failure and its implications for therapeutic interventions. The authors explain how an imbalance between sympathetic and parasympathetic activity contributes to cardiovascular diseases. They discuss potential treatments targeting the autonomic nervous system to improve heart function. While not exclusively focused on stress detection, the study provides insights into the physiological mechanisms that link autonomic regulation, HRV, and stress-related cardiovascular conditions.

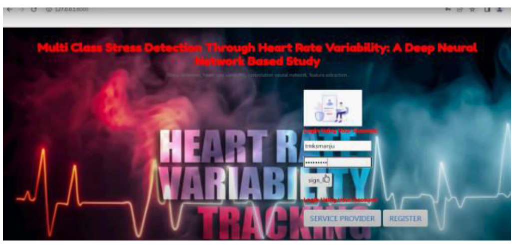
III. PROPOSED METHODOLOGY

The proposed methodology introduces a novel 1D Convolutional Neural Network (CNN) model for multi-class stress detection using Heart Rate Variability (HRV) features. The model demonstrates exceptional classification performance, achieving an impressive accuracy of 99.9%, with a Precision, F1-score, and Recall score of 1.0, alongside a Matthews Correlation Coefficient (MCC) of 99.9%. Unlike previous models, this approach optimizes feature selection by identifying the most significant HRV features, reducing computational overhead without compromising accuracy. By leveraging an optimized feature subset, the system ensures efficient classification while minimizing resource consumption. The study utilizes the SWELL-KW dataset for model training and validation, outperforming existing stress detection techniques. The implementation further integrates an end-to-end pipeline for stress prediction, including dataset preprocessing, model training, and real-time stress classification. The proposed system is highly efficient, scalable, and deployable in real-world applications for stress monitoring and assessment.



IV.WORKING METHODOLOGY

The proposed system, "Multi-Class Stress Detection Through Heart Rate Variability: A Deep Neural Network-Based Study," employs machine learning techniques to detect stress levels based on heart rate variability (HRV) data. The implementation is divided into two primary modules: **Service Provider** and **Remote User**, each handling distinct functionalities.



The **Service Provider** module manages administrative functionalities, including user authentication, dataset processing, model training, and statistical

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analysis. The system allows an admin to log in and access features such as viewing registered users, monitoring stress detection trends, and computing detection accuracy for various models. It uses a dataset containing HRV parameters and applies preprocessing techniques before training multiple machine learning models such as **Convolutional Neural Networks (CNN), Support Vector Machines (SVM), Logistic Regression, and Decision Tree Classifier**. The trained models generate stress predictions, and their accuracy is visualized using statistical charts. Additionally, the system facilitates downloading trained datasets for further analysis. The **Remote User** module allows users to register, log in, and input HRV parameters for stress detection. The collected HRV features—such as mean RR intervals, RMSSD, SDNN, LF/HF ratio, and entropy measures—are used as inputs to the trained machine learning models. Once a user submits their physiological data, the system classifies the stress level as either "Stress" or "No Stress." The results are stored in the database, and users can access their profiles to track previous predictions.

The training process involves **feature extraction using CountVectorizer**, followed by **data splitting into training and testing sets**. Different classifiers, including **Multi-Layer Perceptron (MLP), SVM, Logistic Regression, and Decision Tree Classifier**, are trained to optimize performance. The system evaluates model accuracy using **confusion matrices, classification reports, and accuracy scores**, storing the results for comparative analysis. The best-performing model is used for real-time stress prediction in the user module.

V.CONCLUSION

The study presents the development of a novel 1D CNN model for stress level classification using HRV signals, validated with the publicly available SWELL−KW dataset. The proposed model incorporates an ANOVA feature selection technique for dimension reduction, improving performance. The results demonstrate that the model outperforms existing state-of-the-art models in key metrics such as accuracy, precision, recall, F1-score, and MCC, even with the inclusion of feature reduction. The study highlights the potential of the approach and suggests future work focusing on optimizing the model for deployment on edge devices to enable real-time stress detection.

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