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MULTI_CLASS STRESS DETECTION THROUGH HEART RATE VARIABILITY

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ABSTRACT

Humans naturally experience stress when facing pressure or demanding situations, especially when these demands are perceived as harmful or overwhelming. Continuous and excessive stress can increase the risk of both mental and physical health problems. Long-term exposure to stress may lead to issues such as anxiety, depression, and sleep disorders. One common method used to evaluate stress is the analysis of physiological signals such as Heart Rate Variability (HRV). However, achieving very high accuracy in stress detection using HRV data remains a challenging task. HRV is different from heart rate; heart rate represents the average number of heartbeats per minute, whereas HRV measures the variation in the time interval between consecutive heartbeats. HRV is calculated from the variation in RR intervals, where RR represents the time between two successive peaks in a heartbeat signal. In this study, a machine learning model is developed for multi-class stress detection by analyzing HRV parameters as biological indicators of stress. Specifically, a convolutional neural network (CNN) model is used to classify three types of stress conditions: no stress, interruption stress, and time pressure stress. The model utilizes both time-domain and frequency-domain features of HRV signals for accurate classification. Experimental results using the publicly available SWELL-KW dataset demonstrate that the proposed model achieves very high performance, reaching an accuracy of 99.9% with Precision = 1, Recall = 1, F1-score = 1, and MCC = 0.99. In addition, the study shows that Analysis of Variance (ANOVA) is an effective feature selection technique for identifying important HRV parameters related to stress detection.

I.INTRODUCTION

In today's fast-paced world, stress has become a prevalent issue affecting individuals' well-being and productivity. The ability to accurately detect and manage stress levels is crucial for

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promoting mental health and preventing adverse health outcomes. Heart Rate Variability (HRV) has emerged as a promising biomarker for quantifying the autonomic nervous system's response to stress. Through advanced computational techniques, particularly deep learning, HRV analysis can be harnessed to develop robust and efficient stress detection systems.

The "Multi-Class Stress Detection Through Heart Rate Variability: A Deep Neural Network Based Study" project addresses this pressing need by leveraging the power of deep neural networks (DNNs) to classify stress levels from HRV signals. Traditional methods often struggle with the complexity and variability of stress responses across different individuals and contexts. However, deep learning models excel in learning intricate patterns and extracting relevant features from raw data, making them well-suited for this task.

II. EXISTING SYSTEM

For HRV data quality, a detailed review on data received from ECG and IoMT devices such as Elite HRV, H7, Polar, and Motorola Droid can be found in [18]. 23 studies indicated minor errors when comparing the HRV values obtained from commercially available IoMT devices with ECG instrument based measurements. In practice, such a small-scale error in HRV measurements is reasonable, as getting HRVs using portable IoMT devices is more practical, cost-effective, and no laboratory/clinical equipment is required [18], [19].

On the other hand, there have been a lot of recent research efforts on ECG data analysis to classify stress through ML and DL algorithms [20], [21], [22], [23]. Existing algorithms have focused mainly on binary (stress versus nonstress) and multi-class stress classifications. For instance, the authors in [4] classified HRV data into stressed and normal physiological states. The authors compared different ML approaches for classifying stress, such as naive Bayes, knearest neighbour (KNN), support vector machine (SVM), MLP, random forest, and gradient boosting. The best recall score they achieved was 80%. A similar comparison study was performed in [27], where the authors showed that SVM with radial basis function (RBF) provided an accuracy score of 83.33% and 66.66% respectively, using the time-domain and frequency-domain features ofHRV. Moreover, dimension reduction techniques have been applied to select best temporal and frequency domain features in HRV [24]. Binary classification, i.e., stressed versus not stressed, was performed using CNN in [25] through which the authors achieved an accuracy score of 98.4%. Another study, StressClick [26], employed a random forest algorithm to classify stressed versus not stressed based on mouse-click events, i.e., the gaze-click pattern collected from the commercial computer webcam and mouse.

In [14], tasks for multi-class stress classification (e.g., no stress, interruption stress, and time pressure stress) were performed using SVM based on the SWELL−KW dataset. The highest accuracy they achieved was 90%. Furthermore, another publicly available dataset, WESAD, was used in [27] for multi-class (amusement versus baseline versus stress) and binary (stress versus non-stress) classifications. In their investigations, ML algorithms achieved accuracy scores up to 81.65% for three-class categorization.

The authors also checked the performance of deep learning algorithms, where they achieved an accuracy level of 84.32% for three-class stress classification. Furthermore, it is worth mentioning that novel deep learning techniques, such as genetic deep learning convolutional neural networks (GDCNNs) [38], [39], have appeared as a powerful tool for two-dimensional data classification tasks. To apply GDCNN to 1D data, however, comprehensive modifications or adaptations are required and such a topic is beyond the scope of this paper.

Disadvantages

- Adaptive moment estimation (ADAM) optimizer as it is computationally efficient and claims less memory.
- Distinctive features are not considered from the new test samples, and the class label is resolved using all classification parameters estimated in training.

III. PROPOSED SYSTEM

• We have developed a novel 1D CNN model to detect multi-class stress status with outstanding performance, achieving 99.9% accuracy with a *Precision, F1-score*, and *Recall* score of 1.0 respectively and a *Matthews correlation coefficient (MCC)* score of 99.9%. We believe this is the first study that achieves such a high score of

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accuracy for multi-class stress classification.

• Furthermore, we reveal that not all 34 HRV features are necessary to accurately classify multi-class stress. We have performed feature optimization to select an optimized feature set to train a 1D CNN classifier, achieving a performance score that beats the existing classification models based on the SWELL-KW dataset.

• Our model with selected top-ranked HRV features does not require resource-intensive computation and it achieves also excellent accuracy without sacrificing critical information.

Advantages

- 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.
- Data are preprocessed to fit into the feature ranking algorithm. In this study, ANOVA F-tests and forward sequential feature selection are employed for feature ranking and selection respectively.

- 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.

IV. MODULES:

Service provider

In this module, the service provider has to login by using valid user name and password.

After login successful he can do some operations such as Login, browse water data sets and train & test, view trained and tested data sets accuracy in bar chart,

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view trained and tested data sets accuracy results,

view predicted detection type, Find type ratio,

download predicted data sets, View water quality detection ratio results, view all remote users.

View and authorize users

In this module, the admin can view the list of users who all registered. In this, the admin can view the user's details such as, user name, email, address and admin authorizes the users.

Remote user

In this module, there are n numbers of users are present. User should register before doing any operations.

Once user registers, their details will be stored to the database. After registration successful, he has to login by using authorized user name and password. Once login is successful user will do some operations like register and login, predict detection type,

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view your profile.

V. CONCLUSION

Finally, the areas of stress detection and mental health monitoring have made great strides ahead with the "Multi-Class Stress Detection Through Heart Rate Variability: A Deep Neural Network Based Study" project. We have created a strong and effective system that can correctly identify stress levels in various situations by combining deep learning with HRV analysis.

We have shown that deep neural networks can effectively and efficiently identify multi-class stress from HRV signals via extensive data collecting and careful model training. Not only can our model assess stress levels with excellent accuracy, but it also provides insights into the physiological systems that contribute to stress reactions. Numerous fields stand to benefit from this study's findings, including healthcare, wellness initiatives in the workplace, wearable technology, and many more. Our approach has the ability to improve mental health outcomes and general well-being by giving people personalised therapies and real-time feedback on their stress levels. A future where stress detection technologies are effortlessly incorporated into everyday living, helping people to lead healthier, more balanced lives, is our goal as we continue to develop and build upon this work.

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Heart rate variability and depression in children and adolescents

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