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

[1]MR.S.MANIVANNAN, [2]MOGILI HARSHITHA, [3]MVARSHINI, [4]AMMULA JOSEPH, [5]HANIEL NISSI M

[1]Assistant Professor, Department of CSE-AI&ML, Malla Reddy College of Engineering,secunderabad Hyderabad

[2,3,4,5]UG Students,Department of CSE-AI&ML, Malla Reddy College of Engineering,secunderabad Hyderabad

ABSTRACT

Stress is a natural human reaction to demands or pressure, usually when perceived as harmful or/and toxic. When stress becomes constantly overwhelmed and prolonged, it increases the risk of mental health and physiological uneasiness. Furthermore, chronic stress raises the likelihood of mental health plagues such as anxiety, depression, and sleep disorder. Although measuring stress using physiological parameters such as heart rate variability (HRV) is a common approach, how to achieve ultra-high accuracy based on HRV measurements remains as a challenging task. HRV is not equivalent to heart rate. While heart rate is the average value of heartbeats per minute, HRV represents the variation of the time interval between successive heartbeats. The HRV measurements are related to the variance of RR intervals which stand for the time between successive R peaks. In this study, we investigate the role of HRV features as stress detection bio-markers and develop a machine learning-based model for multi-class stress detection. More specifically,

a convolution neural network (CNN) based model is developed to detect multi-class stress, namely, *no stress, interruption stress, and time pressure stress*, based on both time- and frequency-domain features of HRV. Validated through a publicly available dataset, SWELL−KW, the achieved accuracy score of our model has reached 99.9% (*Precision=1*, *Recall=1*, *F1−score=1*, and *MCC=0.99*), thus outperforming the existing methods in the literature. In addition, this study demonstrates the effectiveness of essential HRV features for stress detection using a feature extraction technique, i.e., analysis of variance.

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Vol. 17, Issue 2, 2024

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 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

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Vol. 17, Issue 2, 2024

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

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Vol. 17, Issue 2, 2024

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 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.

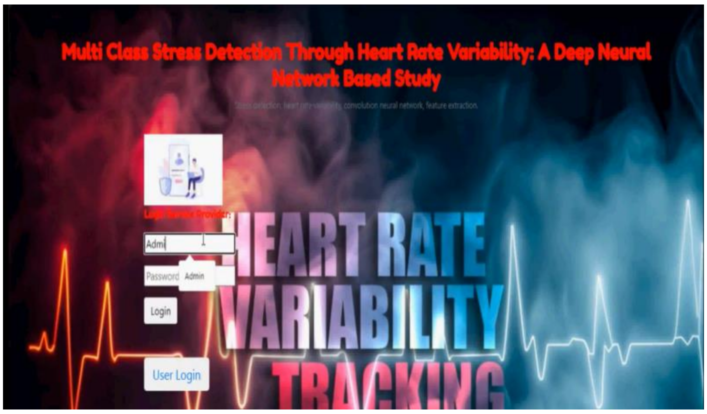
Advantages

- ➢ 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,

International Journal of Engineering Research and Science & Technology

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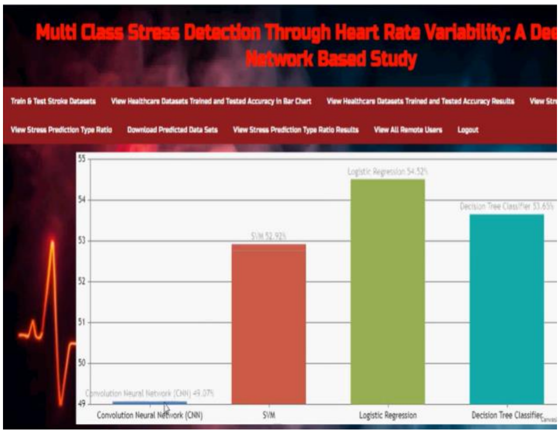
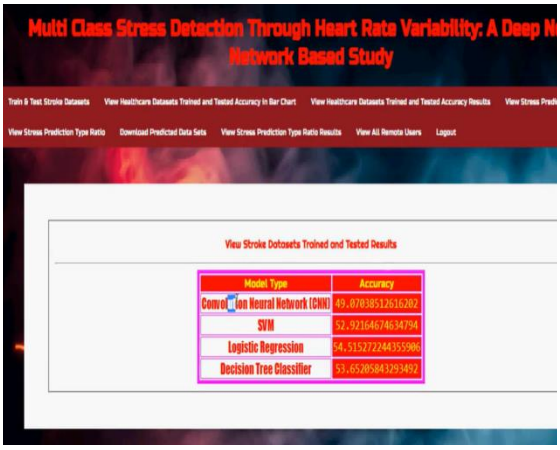
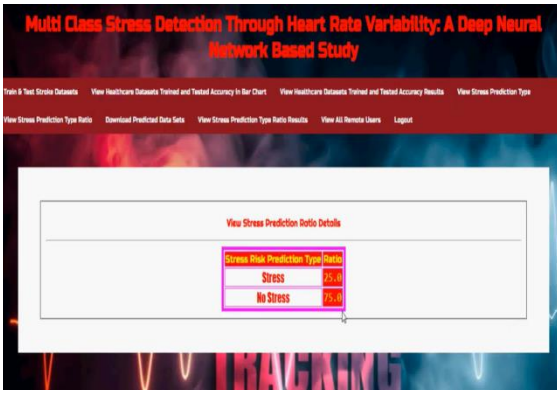
Vol. 17, Issue 2, 2024



view trained and tested data sets accuracy results,



view predicted detection type, Find type ratio,



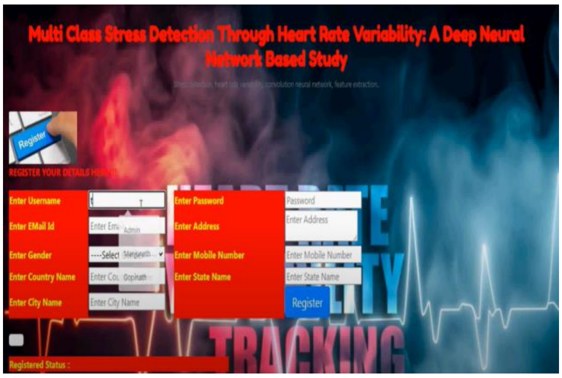
download predicted data sets, View water quality detection ratio results, view all remote users.

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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Vol. 17, Issue 2, 2024

view your profile.

V.CONCLUSION

In conclusion, the "Multi-Class Stress Detection Through Heart Rate Variability: A Deep Neural Network Based Study" project represents a significant step forward in the field of stress detection and mental health monitoring. By harnessing the power of deep learning and HRV analysis, we have developed a robust and efficient system capable of accurately classifying stress levels across diverse scenarios.

Through comprehensive data collection and meticulous model training, we have demonstrated the feasibility and effectiveness of using deep neural networks for multi-class stress detection from HRV signals. Our model not only achieves high accuracy in classifying stress levels but also offers insights into the underlying physiological mechanisms contributing to stress responses. The potential applications of this research are far-reaching, with implications for healthcare, workplace wellness programs, wearable devices, and beyond. By providing individuals with real-time feedback on their stress levels and personalized interventions, our system has the potential to improve mental health outcomes and enhance overall well-being. As we continue to refine and expand upon this work, we envision a future where stress detection systems are seamlessly integrated into daily life, empowering individuals to take proactive steps towards managing their stress and leading healthier, more balanced lives.

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Vol. 17, Issue 2, 2024

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Vol. 17, Issue 2, 2024

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