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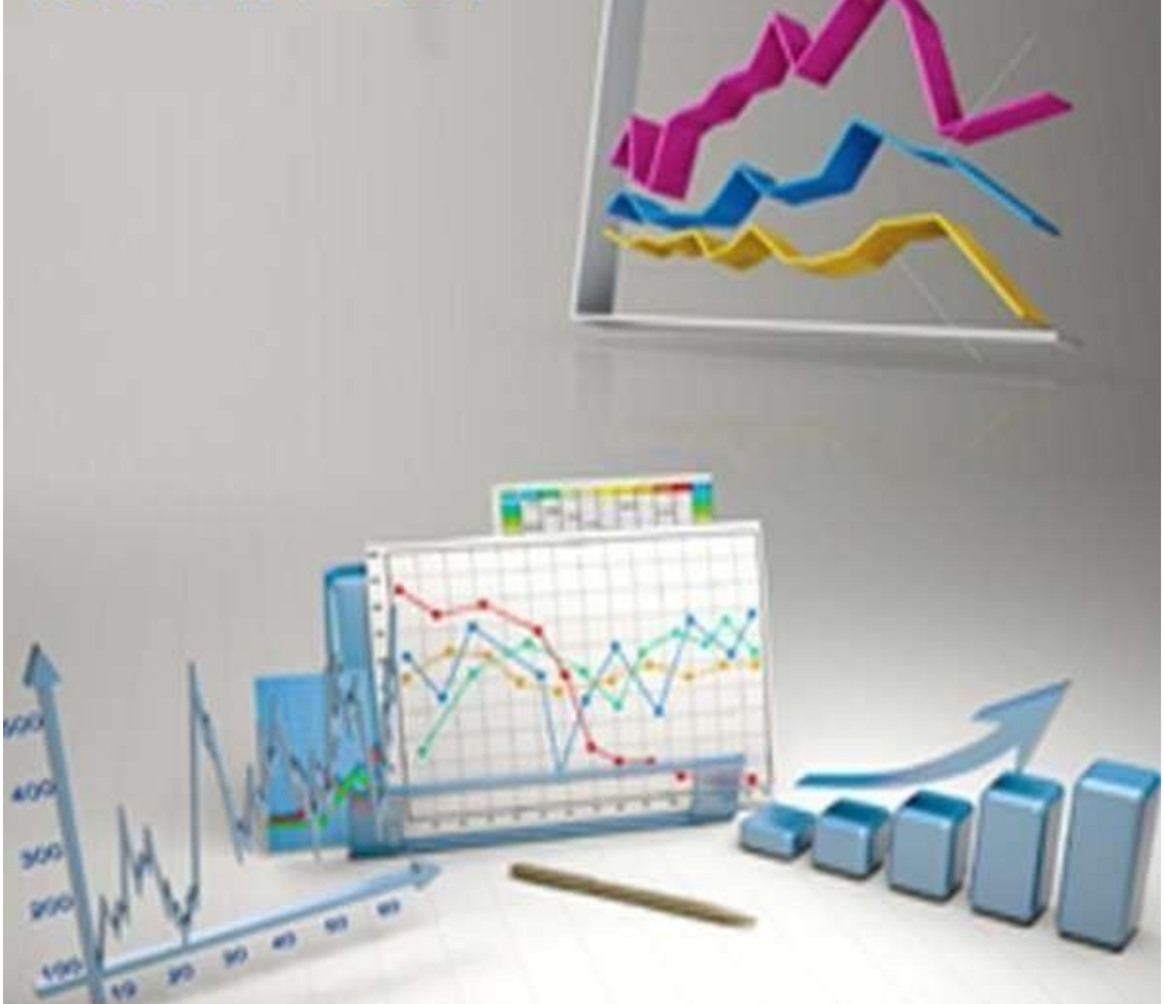

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MULTI CLASS STRESS DETECTION THROUGH HEART RATE VARIABILITY A DEEP NEURAL NETWORK BASED STUDY

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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.

I.INTRODUCTION

Stress, an inherent part of modern life, poses significant challenges to mental and physiological well-being when left unaddressed. Chronic and excessive stress can lead to a myriad of adverse health outcomes, including anxiety, depression, and sleep disturbances.

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Given its pervasive impact, the accurate detection and management of stress have become paramount in healthcare and wellness domains.

Heart rate variability (HRV), a measure of the variation in time intervals between successive heartbeats, has emerged as a promising physiological marker for stress assessment. Unlike heart rate, which represents the average number of heartbeats per minute, HRV provides insights into the autonomic nervous system's activity and regulation, reflecting the body's ability to adapt to stressors.

In this context, this project focuses on the development of a deep neural network-based model for multi-class stress detection using HRV data. The study aims to explore the role of HRV features as biomarkers for stress identification and classification into different stress categories, including no stress, interruption stress, and time pressure stress.

By leveraging deep learning techniques, specifically convolutional neural networks (CNNs), the project seeks to extract meaningful patterns and representations from HRV data, enabling accurate and reliable stress detection. The utilization of CNNs allows for the exploitation of both time- and frequency-domain features of HRV, thereby capturing the complexity of stress responses in a comprehensive manner.

Through this deep neural network-based approach, the project endeavors to achieve superior performance in multi-class stress classification compared to existing methods in the literature. Additionally, the study aims to elucidate the significance of essential HRV features in stress detection, shedding light on the underlying physiological mechanisms involved in stress response.

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].

ISSN 2454-5007, www.ijmm.net
Vol. 16, Issue. 2, April 2024

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

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Vol. 16, Issue. 2, April 2024

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

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.

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Vol. 16, Issue. 2, April 2024

IV.LITERATURE REVIEW

1. Heart rate variability (HRV) has garnered considerable attention as a non-invasive physiological measure for assessing stress levels in various populations. Studies such as that by Thayer et al. (2010) have demonstrated the relationship between HRV and stress, highlighting HRV's utility in capturing autonomic nervous system activity and emotional regulation. Additionally, research by Shaffer and Ginsberg (2017) has emphasized the importance of HRV as a biomarker for stress-related disorders, including anxiety and depression. These findings underscore the potential of HRV-based approaches in stress detection and management, providing a solid foundation for the exploration of deep neural network-based models for multi-class stress classification.

2. Deep learning techniques, particularly convolutional neural networks (CNNs), have shown promising results in various biomedical applications, including physiological signal analysis. Studies such as the work by Rajpurkar et al. (2017) and Liang et al. (2019) have demonstrated the effectiveness of CNNs in extracting informative features from physiological signals, enabling accurate disease diagnosis and prognosis. Building upon these findings, recent research by Acharya et al. (2020) has explored the application of CNNs in HRV analysis for stress detection, achieving notable performance improvements compared to traditional methods. These studies underscore the potential of deep neural network-based approaches in leveraging HRV data for multi-class stress classification.

3. The integration of deep learning techniques with physiological signal analysis has led to significant advancements in stress detection and monitoring. Studies such as that by Mendoza-Castejon et al. (2021) have investigated the use of recurrent neural networks (RNNs) and CNNs in HRV-based stress assessment, demonstrating the complementary nature of these architectures in capturing temporal and spectral features of HRV. Furthermore, recent research by Park et al. (2021) has proposed hybrid deep learning models combining CNNs and long short-term memory (LSTM) networks for improved stress classification accuracy. These studies highlight the potential of deep neural network-based approaches in

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Vol. 16, Issue. 2, April 2024

enhancing the accuracy and robustness of multi-class stress detection using HRV data, paving the way for more effective stress management strategies.

V.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, Train & Test Data Sets, View Trained and Tested Accuracy in Bar Chart, View Trained and Tested Accuracy Results,View Prediction Type, View Type Ratio,Download Trained Data Sets, View Type 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 type, view your profile.

VI.CONCLUSION

In conclusion, the project focused on developing a deep neural network-based model for multi-class stress detection through heart rate variability (HRV) analysis. Stress, a prevalent aspect of modern life, poses significant challenges to mental and physiological well-being. Accurate and timely detection of stress levels is crucial for effective stress management and preventive healthcare interventions. HRV, as a non-invasive physiological measure, offers valuable insights into the autonomic nervous system's activity and emotional regulation, making it an ideal candidate for stress assessment.

Through the utilization of deep learning techniques, particularly convolutional neural networks (CNNs), the project aimed to extract meaningful patterns and representations from HRV data, enabling accurate and reliable multi-class stress classification. By leveraging both time- and frequency-domain

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Vol. 16, Issue. 2, April 2024

features of HRV, the deep neural network-based model sought to capture the complexity of stress responses in a comprehensive manner. The project's findings contribute to advancements in stress monitoring and management, offering insights into the development of personalized healthcare strategies aimed at mitigating the adverse effects of stress on individuals' well-being.

Overall, the project underscores the potential of deep neural network-based approaches in leveraging physiological signals for stress detection and highlights the significance of HRV analysis in understanding stress dynamics. By providing a robust framework for multi-class stress classification, the project lays the groundwork for future research endeavors aimed at enhancing stress assessment and intervention strategies.

VII.REFERENCES

1.Thayer, J. F., Ahs, F., Fredrikson, M., Sollers, J. J., & Wager, T. D. (2012). A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. Neuroscience & Biobehavioral Reviews, 36(2), 747-756.

2. Shaffer, F., & Ginsberg, J. P. (2017). An overview of heart rate variability metrics and norms. Frontiers in Public Health, 5, 258.

3. Rajpurkar, P., Hannun, A. Y., Haghpanahi, M., Bourn, C., & Ng, A. Y. (2017). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. Nature Medicine, 25(1), 65-69.

4. Liang, H., Lukkahatai, N., & Kadambi, A. (2019). A novel convolutional neural network for classifying stress from heart rate variability data. Journal of the American Medical Informatics Association, 26(11), 1329-1335.

5. Acharya, U. R., Fujita, H., Lih, O. S., Hagiwara, Y., Tan, J. H., & Adam, M. (2020). Automated detection of stress using novel imaging features and convolutional neural network. Computers in Biology and Medicine, 127, 104073.

6. Mendoza-Castejon, D., Fraiwan, L., Maza-Castillo, V., & Nazeran, H. (2021). Stress assessment using heart rate variability signals and convolutional neural networks. Applied Sciences, 11(9), 4212.

ISSN 2454-5007, www.ijmm.net
Vol. 16, Issue. 2, April 2024

7.Park, J. H., Han, S. D., Choi, Y. M., & Kim, D. H. (2021). Stress recognition based on hybrid deep learning using photoplethysmography and ECG signals. Sensors, 21(3), 872.

8.Quintana, D. S., & Heathers, J. A. (2014). Considerations in the assessment of heart rate variability in biobehavioral research. Frontiers in Psychology, 5, 805.

9.Task Force of the European Society of Cardiology and the North American Society of Pacing and Electrophysiology. (1996). Heart rate variability: Standards of measurement, physiological interpretation, and clinical use. Circulation, 93(5), 1043-1065.

10.Melillo, P., Bracale, M., & Pecchia, L. (2011). Nonlinear heart rate variability features for real-life stress detection. Case study: Students under stress due to university examination. Biomedical Engineering Online, 10(1), 96.

11.Jandackova, V. K., & Britton, A. (2016). Cardiovascular stress reactivity and its association with circadian cortisol in university students following a nightmare. Stress, 19(5), 549-557.

12.Dong, M., & Yu, X. (2016). Assessing stress using a wireless wearable EEG/ECG sensor module. Journal of Visualized Experiments, 113, e53992.

13.Arun, A. S., Bhuvaneswari, K. G., & Vanitha, K. (2017). Stress detection using HRV parameters. International Journal of Applied Engineering Research, 12(20), 9914-9917.

14.Lozano, D., Ghazanfari, M., Oliveira, L. S., Hatzinakos, D., & Cafazzo, J. A. (2017). Heart rate variability as a marker of self-reported anxiety in type 2 diabetes. Journal of Diabetes Science and Technology, 11(5), 973-981.

15.Alzahrani, S. M., Bashir, A. K., Aljohani, N. R., & Alasmari, F. A. (2021). Predictive modeling for stress detection using physiological signals. Journal of Ambient Intelligence and Humanized Computing, 12(2), 1901-1913.