Multi Class Stress Detection Through Heart Rate Variability A Deep Neural Network Based Study

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 hasreached 99.9% (*Precision*=*1*, *Recall*=*1*, *F1*−*score*=*1*, and *MCC*=*0.99*), thus outperforming the existingmethods in the literature. In addition, this study demonstrates the effectiveness of essential HRV features forstress detection using a feature extraction technique, i.e., analysis of variance.

**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.

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.

**SYSTEM REQUIREMENTS**

➢ **H/W System Configuration:-**

➢ Processor - Pentium –IV

➢ RAM - 4 GB (min)

➢ Hard Disk - 20 GB

➢ Key Board - Standard Windows Keyboard

➢ Mouse - Two or Three Button Mouse

➢ Monitor - SVGA

**SOFTWARE REQUIREMENTS:**

* **Operating system :** Windows 7 Ultimate.
* **Coding Language :** Python.
* **Front-End :** Python.
* **Back-End :** Django-ORM
* **Designing :** Html, css, javascript.
* **Data Base :** MySQL (WAMP Server).