Monitoring Stress Using Electrocardiogram Signal

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Abstract

This paper presents a deep learning-based approach to detect mental stress from electrocardiogram (ECG) signals. The proposed method employs data augmentation and a shallow deep learning architecture combined with convolutional neural networks (CNNs) and long short-term memory (LSTM) networks. The model was trained and validated using 132 records collected from 22 healthy subjects. The proposed approach achieves an accuracy of 75%, sensitivity of 70.37%, specificity of 84.62%, precision of 90.48%, and f1-score of 79.17% in detecting mental stress from ECG signals. This study highlights the significance of using a combination of CNN and LSTM networks to achieve ECG-based stress classification. The proposed method has potential applications in the field of mental stress monitoring and management.

1. Introduction

Mental stress is a prevalent health issue that can lead to various health problems, including cardiovascular diseases [1]. Electrocardiography (ECG) is a non-invasive technique that can be used to monitor the electrical activity of the heart and has been shown to be effective in detecting stress-related changes in heart rate variability (HRV) and other ECG parameters [2]. Recent studies have proposed various machine learning [1], [3], [4], [5], [11] and deep learning [2], [8], [9], [10], [10] methods for stress detection. The mental stress of college students and its correlation with exam pressure and internet usage were assessed using four classification algorithms to evaluate performance in [1]. Kang et al. [4] proposed a method for classifying ECG data into four emotional states based on stress levels using support vector machine and naive Bayes algorithms. The proposed model improved the accuracy by 8.7% compared to the previous stress classification algorithm. The study showed that quantifying stress signals experienced by people can facilitate more effective management of their mental state. In another study [10], the author proposed a pre- and post-processing technique to reduce the negative effects of invalid inter-beat intervals in cardiac signals, improving the accuracy of HRV features for mental workload assessment. In [5], author utilized machine learning models to classify stress levels based on various physiological sensor data, the random forest classifier outperformed other models for both binary and multi-class classifications. In [11], Huang et al. suggested a k-nearest neighbor (KNN) based model that utilized HRV features for detecting the state of mental fatigue. They achieved an accuracy of 75.5% in identifying the mental fatigue state. ML-based techniques in stress detection from ECG signals are often considered less efficient due to the manual extraction of features, which has inherent limitations. The process of selecting the most important features becomes challenging, as various studies have shown that the significance of features can vary across different datasets and models.

Behinaein et al. [2] proposed a deep neural network based on convolutional neural network (CNN) and the transformer mechanism for detecting stress using ECG signals. This model was validated using two publicly available datasets, it required a small amount of data for calibration for the generalization to detect the unseen subjects. Two studies [8], [9] proposed multimodal fusion approaches using CNNs for subject-independent stress detection using ECG and electrodermal activity (EDA) signals, achieving higher accuracy than existing models. Kuttala et al. [5] proposed a multimodal hierarchical CNN feature fusion approach for stress detection using ECG and EDA signals. This approach fused low, mid, and high-level features automated extracted from CNN to obtain a comprehensive feature representation. The multimodal transfer module also used for multimodal fusion. It outperformed the existing models on four benchmark datasets by 1-2% and showed that the hierarchical feature set from all three levels were the most effective feature to distinguish stresses. Most of the above approaches used multiple physiological signal such as ECG and EDA.

In this work, we propose a CNN and LSTM based shallow architecture to detect stress using only ECG signal. To reduce the data imbalance, the data augmentation technique was employed to minority class to reduce the data imbalance and improve the model's performance.

 ISSN: 2325-887X DOI: 10.22489/CinC.2023.204

2. Materials and Methods

2.1. Data description

We have used publicly available Mental Arithmetic Stress Dataset (MAUS) [12] in this work. The data were recorded using Procomp Infiniti device with a focus on collecting different physiological signals under different mental stressed conditions. The dataset contains 132 recordings of ECG, PPG, ACM, and EDA signals collected from 22 individuals each for a duration of 35 minutes. Among them we have used ECG signals for stress monitoring. The N-back task was used to elicit different mental workload to the participants. In this task, participants were asked to memorize a sequence of one-digit number and respond by pressing the space bar when a stimulus matched the n-th number preceding it. The task difficulty was increased by adjusting n, stimulating different levels of mental workload. The 2- and 3-back tasks were considered high mental workload states, while the 0-back tasks were evaluated as low mental workload states. The ECG signals were sampled at a sampling rate of 256 Hz. The detailed information of the dataset is demonstrated in Table 1.

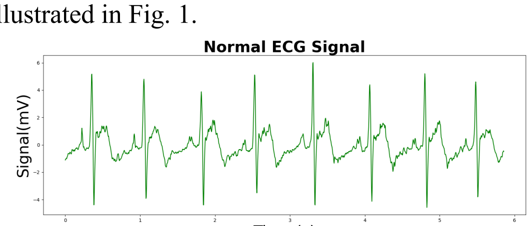
Table 1. The demographic information of MAUS dataset.

Variable	MAUS
Subjects	22
Gender (Male/Female)	20/02
Age (mean±SD) years	23 ± 1.7
No of trials per subject	6
Total trials	132
Time per trial	5 minutes
Total trials	35 minutes (5 min resting)
Frequency	256 Hz

SD: standard deviation

2.2. Preprocessing

Before the ECG signal analysis, a pre-processing step was applied to the raw data to remove the artefacts, followed by zero mean and unit variance normalisation. An example of pre-processed normal and stressed ECG signals is illustrated in Fig. 1.



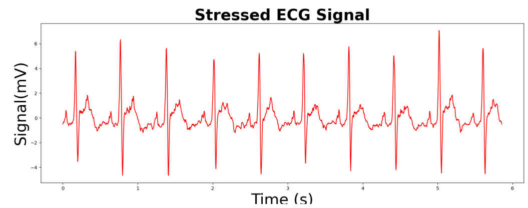


Figure 1. The example of ECG signal recorded at normal (top) and stress condition (bottom).

2.3. Data augmentation

The data augmentation process was utilized to increase the minority classes. A shifting-based approach was applied to augment the data. The data augmentation was deployed only during training the deep learning model to reduce the biases to a specific class by balancing the classes. The details of the data augmentation process are demonstrated in Fig. 2.

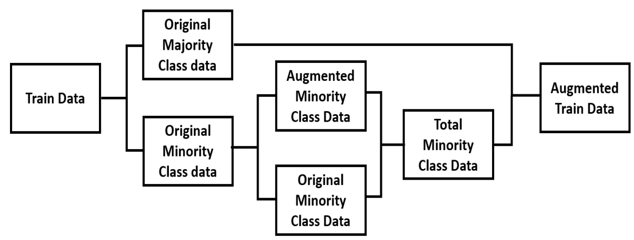


Figure 2. The data augmentation process. The training data was augmented to increase the minority class.

2.4. Deep learning model

The proposed model consists of a series of convolutional and recurrent layers, fully connected layers and a final output layer, as shown in Fig. 3. The first convolutional layer has 32 filters with a kernel size of 5 and ReLU activation function, followed by a max pooling layer with a pool size of 2 and a dropout layer with a rate of 0.3. The second convolutional layer has 64 filters with a kernel size of 5 and ReLU activation function, followed by another max pooling layer with a pool size of 2 and a dropout layer with a rate of 0.35. The third convolutional layer has 128 filters with a kernel size of 5 and ReLU activation function, followed by another max pooling layer with a pool size of 2 and a dropout layer with a rate of 0.4. The subsequent LSTM layer has 64 units with return sequences set to True, followed by a flattened layer. The dense layers have 256 and 128 units, respectively, with ReLU activation function and L2 regularization with a weight decay of 0.01. A dropout layer with a rate of 0.35 follows each dense layer. Finally, the output layer has 1 unit with a sigmoid activation function.

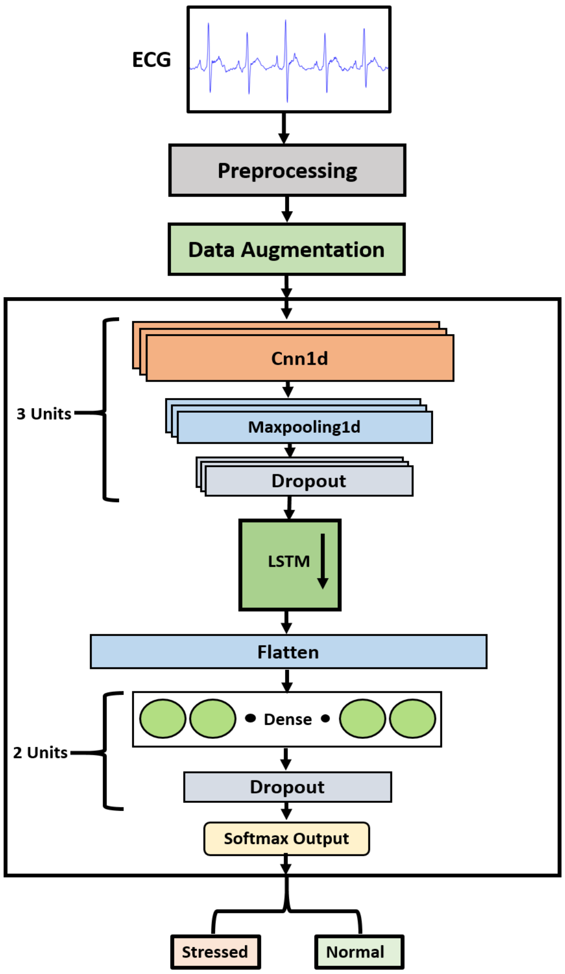


Figure 3. An illustration of the proposed method for stress classification using ECG signal.

2.5. Performance Metrics

We have used 70% of total recordings for training the model and rest of data for testing. The model performance was evaluated using five performance metrics: accuracy, sensitivity, specificity, precision, and F1-score.

3. Results and Discussion

The proposed model showed 70% accuracy, 100% sensitivity, 7.69% specificity, 69.23% precision, and 81.81% F1-score to identify stress using ECG. Since the data were imbalanced, the specificity was very poor, and the model was biased to one class. To reduce the biases of the model, we applied the data augmentation technique before training the model. The data augmentation process significantly improved the specificity from 7.69% to 84.62% as well as the overall classification accuracy from 70% to 75%. In Fig 4 and Fig. 5 the confusion matrix illustrated the performance of the proposed model before and after data augmentation respectively. The performance evaluations of the proposed model before and after data augmentation are demonstrated in Table. 2.

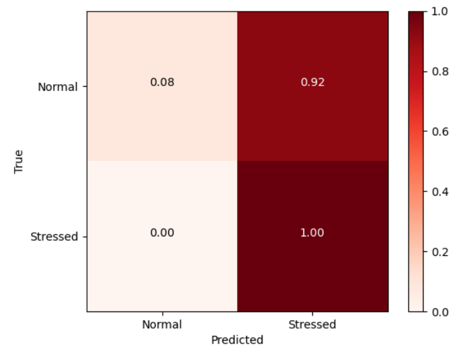


Figure 4. The confusion matrix of the proposed model without data augmentation. The model was highly biased due to data imbalance.

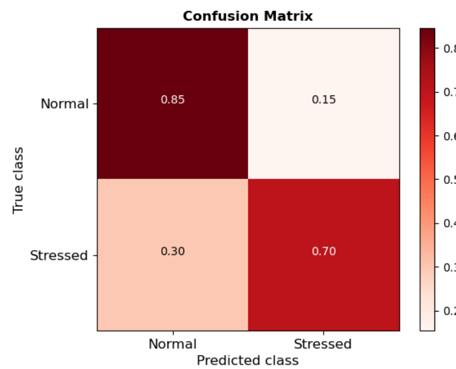


Figure 5. The confusion matrix of the proposed model with data augmentation. The biasness of model with majority class was adjusted using data augmentation.

Table 2. The performance evaluations of the proposed model before and after data augmentation. Here, *Acc*, *Sen*, *Spe*, and *Pre* represent the accuracy, sensitivity, specificity, and precision, respectively.

Augmentation	*Acc*	*Sen*	*Spe*	*Pre*	F1-score
No	70%	100%	7.69%	69.23%	81.81%
Yes	75%	70.37%	84.62%	90.48%	79.17%

The CNN layers helped to learn patterns from the ECG signals such as the shape, frequency, and amplitude of different ECG waveforms like P, Q, R, S and T waves. The CNN layers helped to capture these at different scales and orientations, making the model more robust to variations of input signals. ECG signals are time series data, and there can be variation in the timing, duration, and amplitude of different waveforms due to factors like heart rate, age and health condition. The long-term dependencies and temporal pattern present in the ECG signals captured by LSTM layer, which helped to improve the model performances. The loss vs. epoch curve shown in Fig. 6

illustrates the progressive reduction in the loss function as training epochs increase, indicating the model's enhanced capability to minimize the disparity between predicted and actual values. This displays an initial rapid decline, followed by a more gradual convergence towards a plateau.

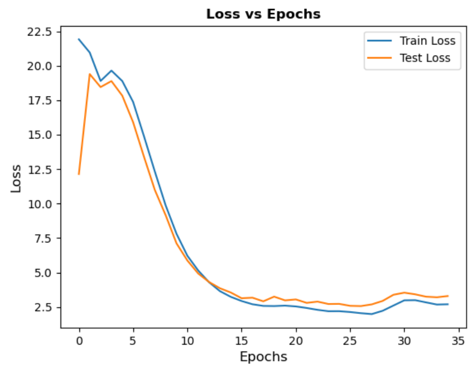


Figure 6. The training and testing loss per epochs. The training and testing losses sharply decreases up to 15 epochs. It became steady state and increases above 25 epochs.

This study observed that increasing the number of CNN layers led to overfitting, while using a lower number of layers resulted in underfitting. The inclusion of LSTM layers played a crucial role in capturing temporal patterns in ECG signals, thereby improving accuracy. Without LSTM layers, the model's performance suffered. Moreover, employing smaller kernel sizes in the initial CNN layers facilitated the capture of local patterns, while larger kernel sizes in subsequent layers enabled the extraction of global patterns, ultimately enhancing overall performance. These findings underscore the importance of carefully selecting the number and type of layers to achieve precise stress detection.

Overall, the proposed model shows promise for identifying stress using ECG signals. However, further optimization and validation on larger datasets are necessary to assess the generalizability and robustness of the proposed model.

4. Conclusion

In this study, a novel approach based on CNN-LSTM based deep learning model has been proposed for the detecting the mental stress using ECG signal. The data augmentation was performed to handle the data imbalance and improve the model performance. The results obtained using the proposed approach demonstrated a robust and promising performance for stress identification. Future work will involve incorporating respiratory signals along with cardiovascular signals to identifying stress and the level of stress.

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