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Stress Detection and Prediction Using CNNs from Electrocardiogram Signals

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Stress prediction is a crucial aspect of mental health monitoring, with consequences for both psychological well- being and productivity. This work presents a unique way for stress prediction that uses binary and multiclass classification models. Through extensive experimentations with different durations and frequencies of Electrocardiogram Signal (ECG) signals, we identified a 5-second dataset sampled at 200Hz as the optimal configuration for our model. Moreover, we introduced an innovative feature i.e., the prediction of stress scores ranging from 0 to 100, providing nuanced insights into stress levels, where 0 represents no stress and 100 indicates high stress levels. The model obtains 95.04% accuracy, 95.27% precision, 94.95% F1 score, 86.69% sensitivity, and 99.44% specificity for the binary classification. With "Fun" added to the list of stress categories in addition to "Base" and "TSST," the model continues to perform well in the multiclass classification scenario, with accuracy of 88.10%, precision of 87.60%, F1 score of 87.35%, sensitivity of 95.97%, and specificity of 79.23%. These findings highlight how well this applied strategy predicts stress levels, providing important information for mental health and stress management strategies.

Keywords: Stress Detection, Stress Score, ECG Signals, Stress Levels, CNNs.

Introduction:

People become increasingly stressed as societies expand because of the increased competition. This stress can have negative consequences for work, relationships, and safety. Our rapid and demanding society has made mental stress a widespread problem that has an impact on people's productivity and general well-being. Uncontrolled chronic stress can cause a variety of health issues, such as cardiovascular disease, depression, and anxiety [1]. Long- term stress can lead to depression, addiction, and heart and brain disorders [2]. Emotional stress is currently a major issue for both physical and mental health. Thus, creating efficient techniques for stress evaluation and management is essential to preserving public health. Stress is a physiological reaction to challenging events. It is distinguished by a sequence of physical and emotional changes, such as elevated heart rate, muscle tension, and anxiety. While acute stress can help mobilize resources to deal with urgent dangers, chronic stress, when extended, can be harmful to both physical and mental health. The neurological system in our bodies responds differently when we are under stress. Stress stimulates the sympathetic nervous system (SNS), which regulates heart rate and breathing. After stress, the parasympathetic nervous system (PNS) takes over to calm things down. We can detect stress by observing changes in parameters such as heart rate. Researchers have been looking into how electrocardiogram (ECG) signals, which assess heart activity, can help detect stress. Traditionally, they used five minutes of ECG data, which is too long for real-time monitoring [3]. Some studies have successfully detected stress using only one minute of ECG data, but this is still not ideal because it requires wearing uncomfortable equipment and is too slow for real-time monitoring.

Healthcare is one of the many industries that artificial intelligence (AI) has changed. AI has shown great promise in the field of stress assessment as a means of detecting stress patterns and forecasting stress levels. Complex patterns can be extracted and analyzed from a variety of data sources, such as physiological signals, behavioral data, and self-reported assessments, by AI models, especially deep learning algorithms. Because ECG signals are constant, freely accessible, and non-invasive, they have become more important in AI-based stress evaluation. ECG signals are the electrical activity of the heart [4]. Rich information on physiological changes linked to stress can be found in ECG signals, including heart rate variability (HRV), heart rate (HR), and signal complexity. These minute variations in ECG signals can be examined by AI models to precisely identify and categorize stress levels. Traditional approaches for assessing stress from ECG signals typically rely on hand- crafted time or frequency domain features [5]. These approaches, however, may be limited in their ability to capture complex patterns and correlations within ECG signals

We've developed a new method for detecting mental stress and predicting stress scores based on a Convolutional Neural Networks (CNN) architecture. Our method entails obtaining ECG signals, cleaning them using a bandpass filter to reduce noise, and altering the frequency from 700Hz to 100Hz. These preprocessed signals are then sent into a CNN, which extracts unique stress patterns from the temporal data of ECG signals. We trained two models: one for binary classification, which distinguishes between stressed and non-stressed individuals, and another for multiclass stress prediction. The binary classification technique has produced ground- breaking results in predicting stress levels. We use the obtained information to reliably diagnose stress levels and predict stress scores.

Literature Review:

In this article [6], the author investigated the analysis of ECG Raw Signal and Spectrogram pictures, using a dual method combining Raw ECG with 1D CNN and Spectrograms with ResNet-18 architecture. Their analysis produced complex results, with an accuracy of 66.6%, precision of 67.6%, and recall of 66.6% across three unique categories: neutral, tension, and amusement. This extensive study combined Leave-One-Subject-Out (LOSO) methods with chest-worn ECG data. Furthermore, the study expanded its investigation to the RML dataset, where deep learning models showed notable performance measures, including an accuracy of 72.7%, precision of 76.6%, and recall of 72.7%. Notably, this study used datasets from LESO, RML, and WESAD, allowing for both binary and three-class classification. In [5] emphasis is on the use of raw ECG signal data, which was analyzed using CNN and Bidirectional Long Short-Term Memory (BiLSTM) architecture. The results of this investigation were positive, with an overall accuracy of 86.5% and a specificity of 92.8%. Furthermore, the study carefully classified stress levels into three categories: low (91.3%), moderate (89.4%), and high (79.8%). These conclusions are based on locally acquired data, demonstrating the study's relevance and applicability. Article [7] analyzed ECG and HRV data using CNN for categorization purposes. Their investigation produced remarkable performance measures, including 97% accuracy, precision, recall, and F1-Score. Notably, the study got its data locally, which ensured the dataset's validity and dependability. Furthermore, the categorization assignment had three unique classes, which provided insights into subtle changes in the dataset. In the [8] raw ECG data is used, which was classified using CNN and VGG-inspired architectures. The study produced strong results, with claimed accuracies of 83.55% for three classes and 93.77% for two classes. Notable is the use of the Drive DB and Arachnophobia datasets, using a VGG-inspired architecture for binary classification and a 1D CNN for categorization into three classes. This strategic approach demonstrated the flexibility and versatility of the approaches used across a variety of datasets. The [9] performed a detailed investigation of ECG and HRV features using K-Nearest Neighbors (KNN) and Probabilistic Neural Network (PNN) classifiers. The study found impressive accuracies of 91.66% (ECG) and 94.66% (HRV), along with thorough specificity and sensitivity data for both modalities. The use of locally obtained data is significant since it increases the study's relevance and application to real-world circumstances. Furthermore, the study's emphasis on binary categorization highlighted its practical applications in the healthcare domain. The study described in [10] included the integration of ECG and EEG data using a Radial Basis Function Support Vector Machine (RBF-SVM) and KNN classifiers. The results showed significant accuracies ranging from 86.13% to 87.75% across various stress characteristics, as defined in the Kaggle dataset. This extensive research enabled binary categorization scenarios, revealing light on different stress levels and their physiological manifestations. The study's thorough approach to feature integration and categorization has shown its importance in the field of stress detection and management.

In [11], the authors conducted a thorough study of ECG plot pictures, investigating both time and frequency domains using CNN and Long Short-Term Memory (LSTM) architectures. The study revealed appealing performance data, including accuracies of 94.8% in the time domain and 98.3% in the frequency domain. Notable is the precise characterization of accuracy, sensitivity, and specificity measurements for each domain, which provides insight into the efficacy of the approaches used. The study's focus on binary classification tasks, which used the ST Change and WESAD datasets [12], emphasized its practical applications in healthcare and diagnostic contexts.

Within the scope of [13], the study focused on raw ECG data and used the CNN architecture for classification purposes. The research produced respectable findings, with a stated accuracy of 88.4% and an F1-score of 0.90. Notably, the study used data from the PhysioNet and SWELL databases, which allowed for categorization into three unique groups. This thorough technique demonstrated the resilience and usefulness of the used methodology in detecting small alterations within the dataset.

The study [14] investigated HRV features using Artificial Neural Network (ANN) and Naive Bayes (NB) classifiers. The study revealed impressive performance metrics, including an accuracy of 95.75% on the WESAD and SWELL-KW datasets for binary classification tasks. The full study of HRV characteristics is noteworthy, as it takes advantage of a synergistic method that combines the strengths of both ANN and NB classifiers. This intentional combination highlighted the study's effectiveness in detecting subtle patterns within the dataset, increasing its usefulness in therapeutic and diagnostic contexts. The research conducted [15] focused on the analysis of HRV features using a Support Vector Machine (SVM) classifier. The study provided insights into the dataset, with a reported accuracy of 72.82% on the SWELL-KW dataset [16] for binary classification tasks. Notably, the study's emphasis on HRV characteristics highlighted their importance in detecting minor alterations within the dataset, hence increasing its usefulness in therapeutic and diagnostic situations. Using CNN architecture, a thorough study of HRV Features was initiated in the [17]. On the Spider Fear dataset, the study produced impressive performance metrics: 83.29% accuracy, 85% precision, and 82% recall for classifying the data into three different categories. Of particular note is the careful characterization of the accuracy, recall, and sensitivity measures, which sheds light on how well the used algorithm distinguishes minute differences in the dataset. This thorough analysis highlighted how important the study was in clarifying subtle patterns in the dataset, which increased its use in diagnostic and clinical contexts.

Methodology:

The methodology includes custom data collection and preprocessing, selection of model architecture, and concluded results as shown in Figure 1.

Data Collection:

The dataset employed in this research comprises raw sensor data recorded using a chest-worn device (RespiBAN) and a wrist-worn device (Empatica E4). Synchronization of these devices was achieved by having subjects perform a double tapping gesture on their chest, creating a characteristic pattern in the acceleration signal. The synchronized raw sensor data and labels were stored in files labeled SX.pkl. The dataset includes various physiological modalities such as ACC (acceleration), ECG, EDA (electrodermal activity), EMG (electromyography), RESP (respiration), TEMP (temperature), and BVP (blood volume pulse). Labels were assigned to different study protocol conditions, with 0 = not defined / transient, 1 = baseline, 2 = stress, 3 = amusement, 4 = meditation, and 5/6/7 = disregarded conditions. Ground truth information was available in SX_quest.csv.

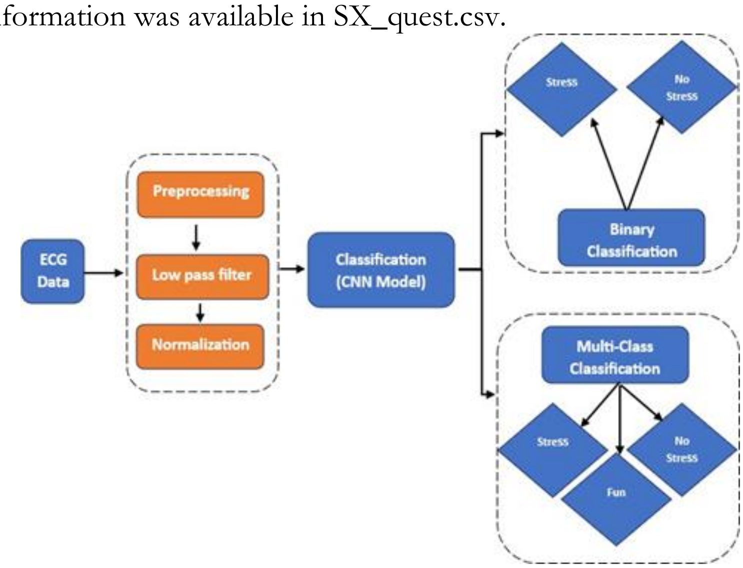

Figure 1: Block Diagram of the used methodology

Data Preprocessing:

Data Extraction:

From ECG recordings the data for binary classification focusing on stress and baseline conditions, and for multiclass classification stress, baseline, and amusement conditions were extracted from the dataset. There are different duration signals for each class then the signal was chunked to specific time durations of 30 seconds, 20 seconds, 15 seconds, 10 seconds, 5 seconds, and 3 seconds, these all are used for creating different datasets of different duration and finding the best time for stress prediction. The WESAD dataset ECG signal frequency is 700Hz this is used as one dataset and then different sampling frequencies 350Hz, 250Hz, 200Hz, and 100Hz were experimented with to find the optimal configuration, and best model using these all datasets.

Removing Noise from Signals:

We implemented a bandpass filter to increase the quality of the ECG data. As shown in Figure 2, this filter was designed to allow frequencies ranging from 0.5Hz to 50Hz while rejecting others. We effectively reduced high-frequency noise from the data, retaining only the desired frequency range for further analysis.

Normalizing Data:

The clean and preprocessed data are then normalized using the following mathematical formula (1) bring the data in the range of 0 to 1 here.

$$x' = \frac{x - min(x)}{max(x) - min(x)} \quad (1)$$

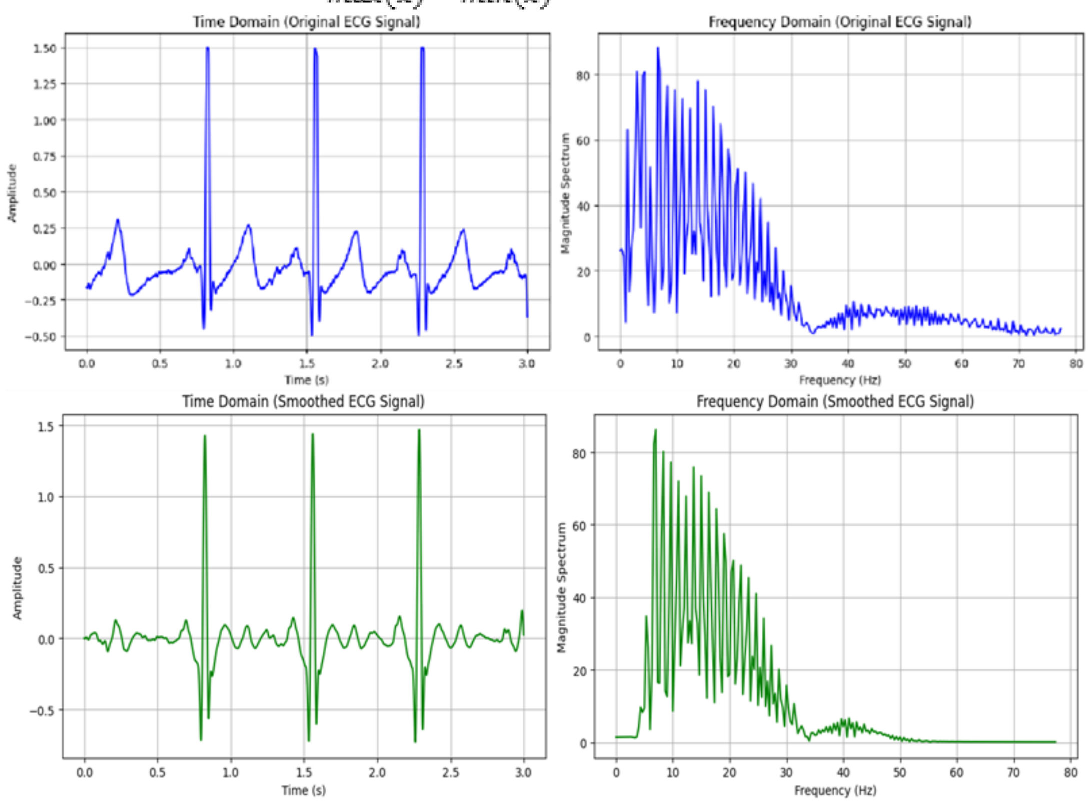

Figure 2: Raw and Filtered ECG signals

Where min and max are the minimum and maximum values in the dataset. This normalized dataset is used as input to the model.

Model Architectures and Selection:

Several neural network architectures were explored, including CNN, Long Short-Term Memory (LSTM) [18], and combinations like ANN with LSTM [19] and CNN with LSTM, Resnet34, and ResNet50 [20]. Each of these models was trained on all datasets, as after preprocessing we get datasets 30 seconds dataset with 700Hz, 350Hz, 250Hz, 200Hz, and 100Hz and the same for 15 seconds, 10 seconds 5 seconds, and 3-second datasets. We have a total of 25 datasets and we applied each model on each dataset to get the best dataset duration and frequency and the best model that is less computational and accurate. And then we have the same datasets for multiclass classification.

For binary classification the selected CNN architecture shown in Figure 3 exhibited superior performance, achieving a training accuracy of 96.07%, a validation accuracy of 95.04%, and a test accuracy of 94.59%. while for multiclass classification the same CNN architecture shown in Figure 4 exhibits the best result 93.38% on training data, 88.67% on validation data, and 87.60% on test data. The complexity of the model depends on the size of the fed input sample size, this 5-second size and 200 Hz frequency selection methodology is 7 times more computationally efficient than the existing methodologies. For stress score prediction the binary model was used as the sigmoid activation function in the output layer was employed to predict stress scores in the range of 0 to 1, then it's multiplied by 100 to ensure a range from 0 to 100. A stress score of 100 means high stress and 0 means no stress.

Result and Discussion:

To detect stress levels in real-time, we created a deep neural network and compared its performance to more traditional methods that rely on manually built features. We proposed a 1D-CNN base model that takes the Raw ECG data of 5 seconds and a frequency of 200Hz. We implement different models for getting the optimal model for the data, the dataset of 30 seconds is used and the ANN model is trained the result of the ANN model for the 30 seconds datasets 700Hz, 350Hz, 250Hz, 200Hz, and 100Hz has accuracy 67.43%, 68.43%, 66.56%, 71.21% and 69.21% respectively. For multiclass classification the accuracy for this dataset of 30 seconds with frequencies of 700Hz, 350Hz, 250Hz, 200Hz, and 100Hz having an accuracy of 57.13%, 59.93%, 61.56%, 62.91%, and 59.01% respectively. All the models were trained in the same way CNN model with 9 layers and with batch normalization of each layer used for all the data the result is for 30 seconds it had the highest accuracy for 250Hz and the accuracy for this was 83.34% for binary and 78.67% for multiclass classification. For 15 seconds dataset, the CNN has the highest accuracy for 200Hz, 82.23% for binary, and 72.39% for multiclass classification, for the dataset of 10 seconds the 200HZ has good results, 90.32% for binary and 82.32% for multiclass classification, for the dataset of 5 second the model has the accuracy of 95.04 for binary and 88.67% for multiclass and the frequency for this result was 200Hz and this is our selected data and model. We also tried 3 second dataset with all frequencies but its result was not good as 5 seconds. The dataset for the 5 seconds contains 6595 examples for binary and 7987 examples are used for multiclass classification. As we have an additional feature in our method which is stress score prediction for that purpose, we used a binary model and the output layer used the sigmoid activation function (2).

$$S(z) = \frac{1}{1+e^{-z}} \qquad (2)$$

This equation gives the value from 0 to 1 range to classify it as no stress or stress the threshold is 0.5 and then predicts the stress score from 0 to 100 using that model output multiplied by 100. The final training and validation accuracy and loss plots are in Figure 5 for binary classification.

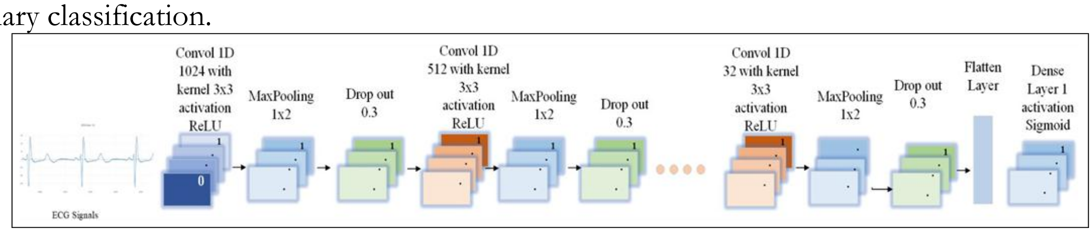

Figure 3: 1-D CNN architecture for binary class classification and prediction.

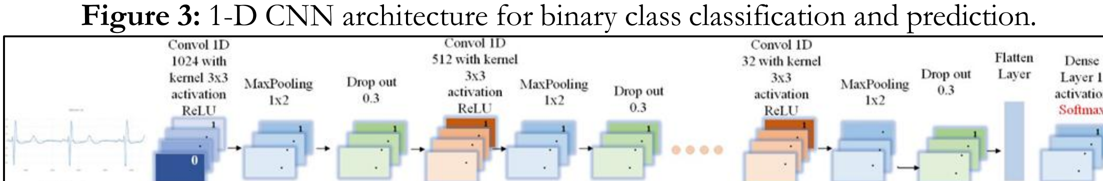

Figure 4: 1-D CNN architecture for multiclass classification and prediction.

The performance of the model is determined by the accuracy (3), precision (4), F1 score (5), sensitivity (6) and specificity (7).

$$Accuray = \frac{TP + TN}{TP + TN + FP + FN} \quad (3)$$

$$Precision = \frac{TP}{TP + FP} \quad (4)$$

$$F1\,Score = 2\,x\,\frac{Recall\,x\,Precision}{Recall + Precision} \quad (5)$$

$$Sensitivity = \frac{TP}{TP + FN} \quad (6)$$

$$Specificity = \frac{TN}{TN + FP} \quad (7)$$

- True positive (TP) = the number of cases accurately identified as stress.
- False positive (FP) = the number of cases wrongly diagnosed as stress.
- True Negative (TN) = the number of instances correctly diagnosed as having no stress.
- False negative (FN) = the number of cases mistakenly categorized as "no stress."
- The performance of the binary and multiclass model in terms of accuracy, precision, F1 score, sensitivity and specificity are mentioned in table 1.
- The confusion matrix of the binary model is on validation test data is shown in the Figure 5.
- Figure 6 shows the multiclass classification model's confusion matrix based on validation and test data.

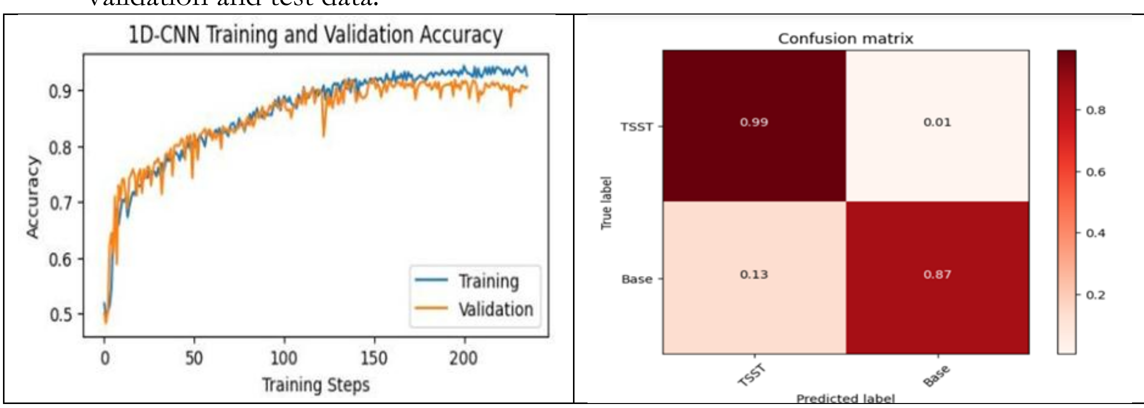

Figure 5: Performance metrics of the binary classification model on 5 seconds 200Hz dataset

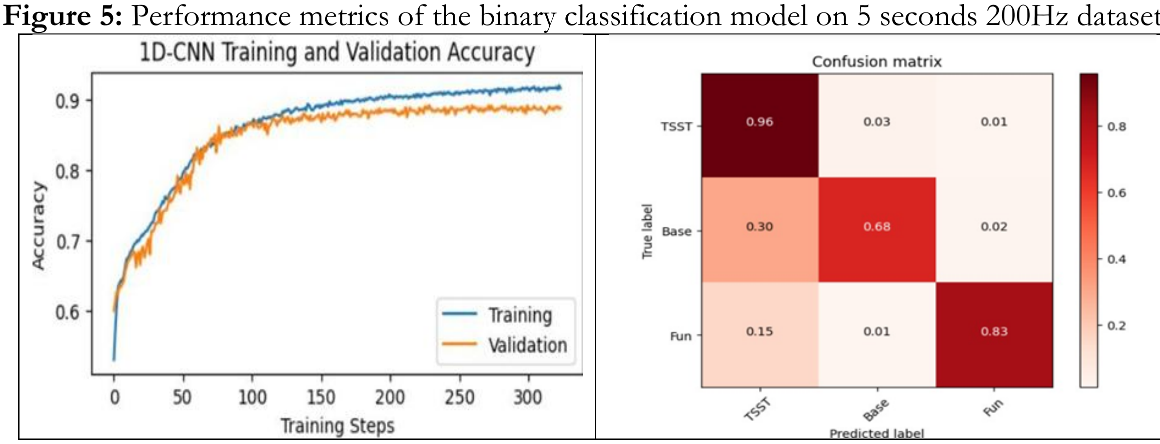

Figure 6: Performance metrics of multiclass classification model on 5 seconds 200Hz dataset.

Table 1: Different evaluation metrics of binary and multiclass model.

Performance Matrices	Binary Model	Multiclass Model
Accuracy	95.04%	88.10%
Precision	95.27%	87.60%
F1 score	94/95%	87.35%
Sensitivity	86.69%	95.97%
Specificity	99.44%	79.23%
PPV	98.96%	85.55%
NPV	93.64%	78.97%

Conclusion:

In this study, we have developed a deep neural network-based approach for real-time stress detection utilizing electrocardiogram (ECG) data. By comparing our proposed 1D-CNN model against traditional methods relying on manually engineered features, we demonstrated superior performance in stress prediction. Our methodology involved rigorous experimentation with different dataset durations and sampling frequencies, aiming to optimize model accuracy and computational efficiency. Through extensive model selection and evaluation, we found that a Simple 1D Convolutional Neural Network architecture yielded the best results for both binary and multiclass stress classification tasks. Specifically, our model achieved notable accuracies across various dataset configurations, with the highest accuracy obtained for a 5-second dataset sampled at 200Hz, demonstrating the effectiveness of our approach in capturing temporal dynamics of stress patterns.

Additionally, we introduced an innovative aspect to our methodology by incorporating stress score prediction, enabling a finer-grained understanding of stress levels ranging from 0 to 100. Leveraging the sigmoid activation function in the output layer of our binary model, we accurately predicted stress scores, further enhancing the utility of our approach for comprehensive stress assessment. Our study underscores the importance of leveraging deep learning techniques for stress detection, offering valuable insights into individuals' well-being and mental health. The ability to predict stress levels in real-time has significant implications for personalized stress management interventions and improving overall quality of life. Moving forward, further research may explore additional physiological modalities and sensor data fusion techniques to enhance the robustness and generalizability of stress detection models in diverse real-world settings.

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