Psychological Detection of Emotions from EEG Brainwave Signals Using Different Deep Learning Models

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Abstract:- Mental anguish has become a social problem and may lead to functional impairment in routine and regular work. In this paper, an electrophysiological signal called the electroencephalogram is used to suggest a method for measuring mental stress. It analyses and records the electrical activity in the brain, and by processing it and further it may be studied to look into various mental illnesses. In order to improve human wellness, this paper presents a study that identifies stress in order to detect and improve mental health. The objective of this study is to detect stress from electroencephalograph signals (EEG) with improved accuracy by testing various Deep Learning Models. By comparing their accuracy, it can be concluded that the deep learning models Convolution Neural Network (CNN) and Model with Deep Neural Network (DNN) give Mental anguish better accuracy results that is 97.65% for CNN and 97.94% for DNN on the EEG brain-waves Dataset's for the categorization of human stress level. As a result, the use of deep learning algorithms in clinical evaluation serves as a baseline for analyzing different neurological illnesses, and a highly trustworthy system may be further used to achieve important advancements in this sector.

***Keywords**: Electroencephalogram, EEG signals, deep learning, CNN, DNN, LSTM .*

1. Introduction

One of the major issues facing contemporary civilization is stress. If it is not addressed in the early stages, it can progress to several serious conditions, including depression and cardiovascular disease. It can also cause cognitive issues. Chronic stress can make the human immune system and healing mechanisms less effective. Stress has an impact on people's daily lives and work performance in addition to their physical health. Also, it has been noted that employee stress levels have an impact on business performance, which may have an impact on the financial burden placed on society. Hence, stress management is crucial for both the general prosperity of society and the health of each individual. On the other side, stress can also be thought of as a typical mood condition that can lead to enduring depressive sensations, memory issues, and a loss of interest in activities. More than 300 million people worldwide suffer from depression, and more than 8 million people die each year from stress, according to data from the World Health Organization (WHO) [1].

By 2025, stress is anticipated to overtake heart disease as the second most prevalent ailment in contemporary culture. Hence, keeping track of someone's stress at an early stage might be beneficial to him and treatable. Consequently, the purpose of the current effort is to use electroencephalogram (EEG) signal analysis to early detect and monitor a person's stress. Assessing and keeping track of a person's stress level is one of the most difficult duties since different people react to stress in various ways. These days, it is possible to observe the symptoms and indicators of stress using a variety of medical tests, bio signals, and psychoanalytic methods. Nonetheless, there are certain common signs, like headaches, high levels of stress, tight muscles, sleeplessness, and quick pulse. Currently, there are several wearable gadgets for assessing stress levels, such Olive, Spire, and Gizmodo, which are combined with various biosensors and provide decent accuracy. For the clinical diagnosis of several neurological illnesses, including Alzheimer's disease, epilepsy, brain stroke, tumors, and many others, electroencephalogram signals are now often employed. Many bioengineering applications also make use of it [2].

Several brain-computer interface applications, including autonomous wheelchair mobility, game theory, and many more, utilize EEG-based analytic techniques. The human scalp's EEG signal is a recording of the electrical activity of brain neurons. EEG signals have a natural rhythm and are unplanned. As they are spontaneous, they are also non-stationary and challenging to study. Hans Berger made the initial discovery of EEG signals in 1926, using them to study and comprehend the connection between normal brain activity and mental illnesses. According to a recent study, EEG signals may be used to detect the majority of psychological processes and cognitive behavior. EEG signals can show changes in an emotional state in real-time since it is strongly tied to brain activity and the emotional state of a person. Cole and Ray emphasized that cognitive activities and emotional states are related to EEG signals obtained from the parietal lobe of the human brain. So, it is clear that EEG signals are essential for examining human brain activity and tracking stress [3].

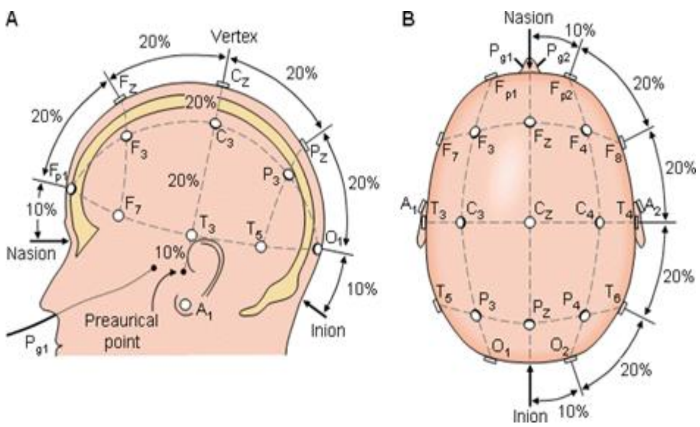

Figure 1 : The international 10/20 electrode placement system

As indicated previously, current research on EEG analysis is utilized to comprehend the mechanisms relating to brain activity, cognitive processes, and the diagnosis of neurological disorders. EEG provides higher temporal resolution, greater time resolution, and reduced maintenance costs when compared to other methods like Computed Tomography (CT) and Magnetic Resonance Imaging (MRI). In order to analyze cognitive behaviour, insomnia, and sleep problems, EEG signals were employed as a psychological tool for gathering data. Five frequency bands are used to group the EEG signal: Theta wave (4–8 Hz), often discovered when someone is drowsy, alpha (8–14 Hz), typically found when somebody is calm, beta (14–30 Hz), occurs while actively thinking state, and gamma wave (30–50 Hz), emerge during meditation. The delta band (0.5–4Hz) arises in the slow wave sleep of an individual [4]. In essence, EEG signals are captured by applying electrodes to the scalp of the human brain in accordance with the International 10-20 system advised by the American EEG Society as shown in Figure 1.

In this paper, a system for tracking people's levels of stress is proposed by analyzing the EEG signals and a comparative study is made by classifying them using multiple Deep Learning models such as CNN, LSTM, GRU, DNN, CNN+LSTM and CNN+GRU.

2. Literature Survey

Sağbaş et al., [1] studied the keyboard typing habits and user stress levels using smartphone touchscreen panels, gyroscope, and accelerometer sensors. Due to a straightforward mobile interface, sensor data from Android-powered smartphones was gathered, and a special data set was created. Cross validation methods and gain ratio feature selection were employed to assess classification accuracy. It was shown that traditional machine learning techniques including Bayesian networks, KNN, and C4.5 decision trees produced effective outcomes in the identification of stress. KNN approach was the most effective classification technique. The study's findings demonstrated that by utilizing smartphone motion sensor data, it is possible to ascertain if a user is under stress or not.

Palacios et al., [2] intended to study the theory that stress in voice may be produced by self-congruent versus contradictory discourse, and investigate the potential of employing ICA paired with PCA to differentiate stressed from non-stressed speech via SVM binary classifiers. The detection of speech stress is fraught with issues. The absence of a common benchmark and a trustworthy data set validated by the scientific community to evaluate emotional detection is the first issue. Most databases are either private or very specialized and are therefore useless for wider study.

P.Sunitha et al., [3] in their project, Stress is identified through physiological indicators such as breathing rate, heart rate, and facial expressions. Traditional methods classify individuals as under stress or as normal based on information gathered from perceptive people like themselves, physiological specialists, and outside observers, which is a biased categorization. In this study, data were gathered through sensors such as the Microsoft Kinect Xbox 360 for respiration rate, the pulse sensor for pulse rate, and the camera for facial expressions in order to prevent data bias. The naive Bayes algorithm, which is powerful to categorize depending on the situation, is used to determine if the person is stressed or normal. Respiration rate and pulse rate (bpm) are taken into account as conditional probabilities in the data set age, whereas the outcome of the facial expression model is taken into account as a class probability. This model achieves an accuracy of 75%. Three different interfaces are used for the manual combination of sensor data.

Manzar et al., [4] proposed a 10-item questionnaire called the PSS is used to gauge respondents' self-reported levels of stress by examining their feelings and thoughts during the previous month. The overall score of the scale ranges from 0 to 40, with each item receiving a value between 0 (never) and 5 (very often). Higher scores on this scale represent a higher degree of stress. The PSS- 10 consists of six items that assess stress and four that assess coping mechanisms. The PSS-4 is a quick instrument that was adapted from the PSS-10. It has 4 items, of which 2 assess stress and 2 assess coping mechanisms.

Avik Sarkar et al., [5] compares and examines the effectiveness of four neural network-based deep learning architectures, namely MLP, CNN, RNN, and RNN with LSTM, as well as two supervised machine learning approaches, SVM and LR, to detect mental sadness using EEG data. With the RNN Model, they were able to achieve a high accuracy of 96.50%.

L. Malviya et al., [6] proposed a novel method Fast Fourier Transform (FFT) for band power selection from EEG channels which is used in the analysis of stress levels in humans. They also used different machine learning classification algorithms for stress analysis including Random Forest (RF), Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). They have achieved an accuracy of 78.6% using Random Forest Classifier.

P. D. Purnamasari et al., [7] utilized Fast Fourier Transform (FFT) to extract features, and K-Nearest Neighbor (KNN) was employed to categorise the features and determine whether or not the subject was under stress from the EEG signals. They achieved an accuracy of 80% using the KNN classifier with the k-value 3.

A. A. Rahman et al., [8] done a comparative study using multiple machine learning models like Support Vector Machine (SVM), Gradient Boosting (GrB), K-Nearest Neighbors (KNN) and XGBoost (XGB) for analyzing the mental state of a person using EEG signals. The highest accuracy of 95.36% was obtained by using the SVM classifier in detecting the state of mind of the humans from the EEG signals.

R. K. Jeevan et al., [9] uses EEG brain waves for emotion identification. They used LSTM (Long short term memory) recurrent neural networks for emotion categorization from the EEG brain waves and they have achieved a classification accuracy of 64.36%.

P. Nagar et al., [10] identifies stress levels using the Electroencephalography (EEG) Signals. They used Support Vector Machine and K-Nearest Neighbour machine learning algorithms for performing the stress level classification task. They achieved the highest average classification accuracy of 74.43 % using the KNN algorithm.

As shown in Table 1, many papers were published for stress monitoring using different machine learning and deep learning models and the highest accuracy got a maximum 96.5%.

Table 1: Existing Works with Machine Learning Models and its accuracy

Existing Work	ML/DL Models	Accuracy (%)
Avik Sarkar et al., [5]	RNN	**96.50**
L. Malviya et al., [6]	Random Forest	78.6
R. D. Purnamasari et al., [7]	KNN	80
A. A. Rahman et al., [8]	SVM	95.26
R. K. Jeevan et al., [9]	LSTM	64.36
P. Nagar et al., [10]	KNN	74.43

3. Methodologies

A method for measuring a person's level of stress using their EEG brainwaves, in which data from the EEG signals is fed into a deep learning framework to discover various patterns and categorize them accordingly. The Deep learning techniques are suggested in order to meet clinical performance criteria. The proposed Architecture is shown in figure 2.

EEG Datasets

The emotional state data set is based on whether a person was feeling positive, neutral, or negative emotions. This Emotional State Data set is available in kaggle [11]. Two people, each aged 21±1, were monitored for six minutes in each state, yielding a total of 36 minutes of data on brainwave activity. Data from the TP9, AF7, AF8, and TP10 extra-cranial electrodes were collected using the experimental configuration of the Muse headset in a prior work can be seen in Figure 3. An example of unprocessed data obtained from the headband can be seen in Figure 4.

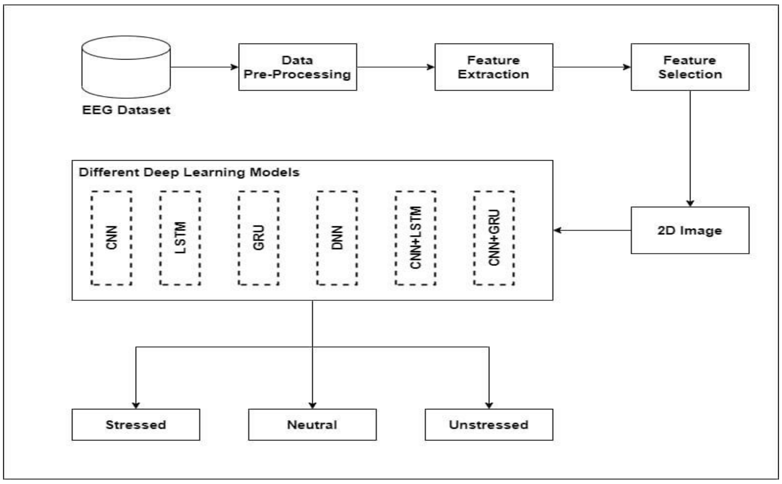

Figure 2 : Architecture of the Proposed System

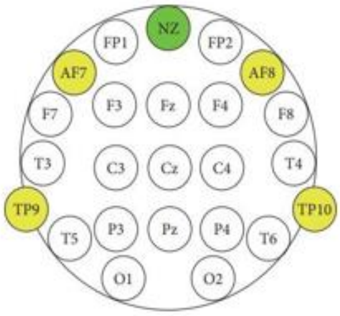

Figure 3 : EEG sensors TP9, AF7, AF8, and TP10 of the Muse headband on the international standard EEG placement system

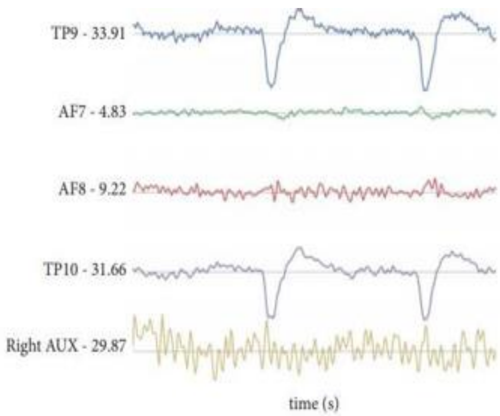

Figure 4 : An example of the raw data retrieved from the headband

Data Pre-processing

To lessen the computational load, the EEG signals were down-sampled to a sampling rate of 200 Hz. Second, the EEG data's time waves were examined visually. The electromyogram (EMG) and electrooculogram recordings that were significantly polluted were manually deleted. Finally, overlapping time frames were used to separate each channel of the EEG data into epochs. The sliding time frames with an overlap of 0.5 seconds are taken into consideration. In other words, windows run from [0s - 1s), [1.5s - 2.5s), [2s - 3s), [2.5s - 3s), and so on until the experiment is complete [12].

4. Deep Learning Models

CNN: For the EEG BrainWave Classification, 3 pairs of convolution layers [13] of filter size 32, 64 and 128 with max pooling layer of size 2x2 were used. Then this pair of convolution and max pooling layers is followed by the Flatten Layer and a Dense Layer with the Soft-max activation function for the classification of stressed, unstressed and neural feelings. The proposed CNN Layer Architecture is shown in Figure 5.

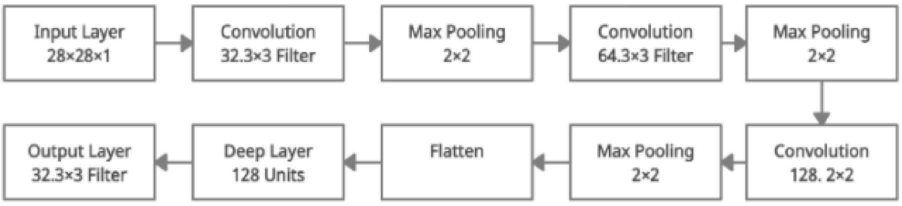

Figure 5 : Proposed CNN Layer Architecture

LSTM: For the EEG BrainWave Classification, 256 units of LSTM [14] with tanh [15] activation were used. The LSTM layer followed by the Flatten Layer and a Dense Layer with the Soft-max activation function for the classification of stressed, unstressed and neural feelings. The proposed LSTM Layer Architecture is shown in Figure 6.

GRU: For the EEG BrainWave Classification, 256 units of GRU [16] with tanh activation were used. The GRU layer is followed by the Flatten Layer and a Dense Layer with the Soft-max activation function for the classification of stressed, unstressed and neural feelings. Figure 7 represents the Proposed Architecture of GRU Layers.

DNN: For the EEG BrainWave Classification, 4 dense layers [17] with 2548, 3822, 5096, 3822 and 2548 units respectively. These 4 dense layers are followed by the 3 units output layer with the Soft-max activation function for the classification of stressed, unstressed and neural feelings. Batch Normalization [18] and Dropout layers [19] are used to avoid the Over-fitting. The Proposed Architecture of DNN Layer is shown in Figure 8.

For the EEG BrainWave Classification, 2 Convolution layers with 16 units for each were used together with the flatten layer. The output of the Flatten Layer was fed into the LSTM of 256 units and 3 units of dense layer with softmax activation function was used for the final Categorization. Figure 9 represents the Proposed Architecture of the fused CNN and LSTM Layers [20].

CNN + GRU: For the EEG BrainWave Classification, 2 Convolution layers with 16 units for each were used together with the flatten layer. The output of the Flatten Layer was fed into the GRU of 256 units and 3 units of the dense layer with soft-max activation function [21] was used for the final Classification. The Architectural design of the proposed CNN+GRU Layers [22] is given in Figure 10.

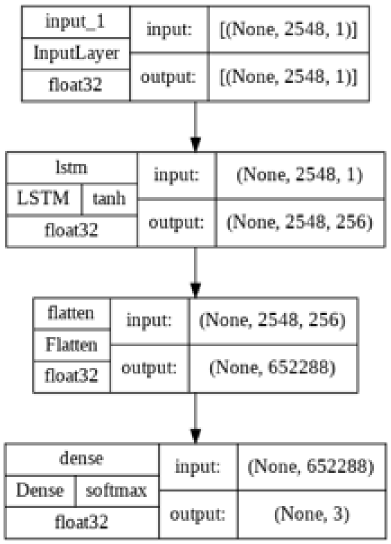

Figure 6 : Proposed LSTM Layer Architecture

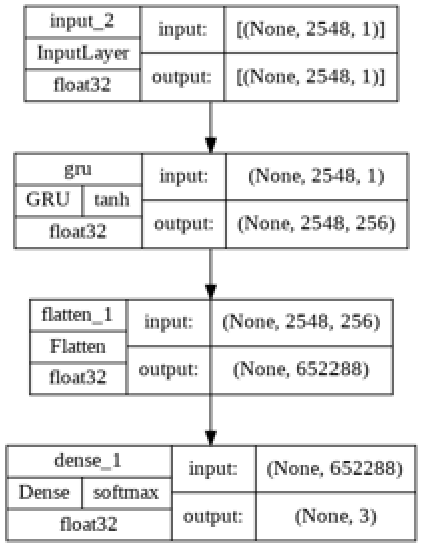

Figure 7 : Proposed GRU Layer Architecture

```
Layer (type)                Output Shape              Param #
=================================================================
input_3 (InputLayer)        [(None, 2548)]            0

dense_2 (Dense)             (None, 2548)              6494852

batch_normalization (BatchN  (None, 2548)             10192
ormalization)

dropout (Dropout)           (None, 2548)              0

dense_3 (Dense)             (None, 3822)              9742278

batch_normalization_1 (Batc  (None, 3822)             15288
hNormalization)

dropout_1 (Dropout)         (None, 3822)              0

dense_4 (Dense)             (None, 5096)              19482008

batch_normalization_2 (Batc  (None, 5096)             20384
hNormalization)

dropout_2 (Dropout)         (None, 5096)              0

dense_5 (Dense)             (None, 3822)              19480734

batch_normalization_3 (Batc  (None, 3822)             15288
hNormalization)

dropout_3 (Dropout)         (None, 3822)              0

dense_6 (Dense)             (None, 2548)              9741804

batch_normalization_4 (Batc  (None, 2548)             10192
hNormalization)

dropout_4 (Dropout)         (None, 2548)              0

dense_7 (Dense)             (None, 3)                 7647

=================================================================
Total params: 65,019,867
Trainable params: 64,984,195
Non-trainable params: 35,672
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Figure 8: Proposed Architecture of DNN Layers

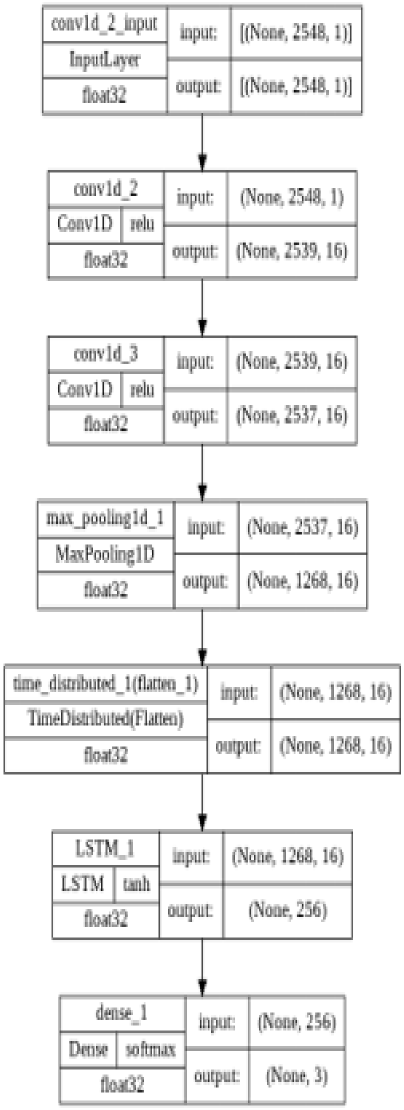


Figure 9: Proposed Architecture of CNN+LSTM Layers

5. The Experimental Results

The accuracy assessment determines whether a person is classified as stressed, unstressed, or neutral. A confusion matrix was used to compute and examine the classification accuracy.

CNN: Using the proposed CNN an accuracy of 97.65% was obtained. The Accuracy Graph for the Proposed CNN model was shown in Figure 11.

LSTM: Using the proposed LSTM an accuracy of 96.87% was obtained. The Accuracy Graph for the Proposed LSTM model was shown in Figure 12.

GRU: Using the proposed GRU an accuracy of 95.46% was obtained. The Accuracy Graph for the Proposed GRU model was shown in Figure 13.

DNN: Using the proposed DNN an accuracy of 97.65% was obtained. The Accuracy Graph for the Proposed DNN model was shown in Figure 14.

CNN + LSTM: Using the proposed CNN+LSTM an accuracy of 95.93% was obtained. The Accuracy Graph for the Proposed CNN+LSTM model was shown in Figure 15.

CNN + GRU: Using the proposed CNN+GRU an accuracy of 94.53% was obtained. The Accuracy Graph for the Proposed CNN+GRU model was shown in Figure 16.

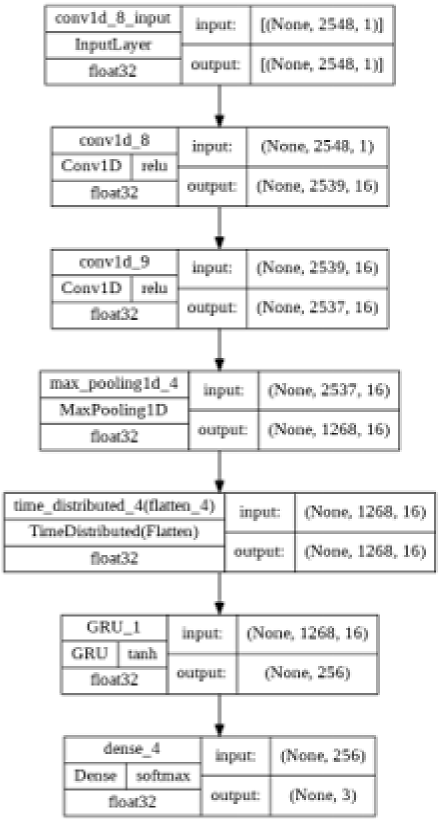


Figure 10: Proposed Architecture of CNN+GRU Layers

Figure 11: Accuracy Loss Graph for Proposed CNN Model

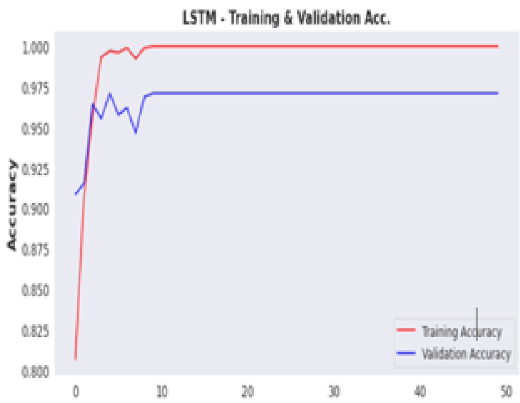


Figure 12 : Accuracy Graph for Proposed LSTM Model

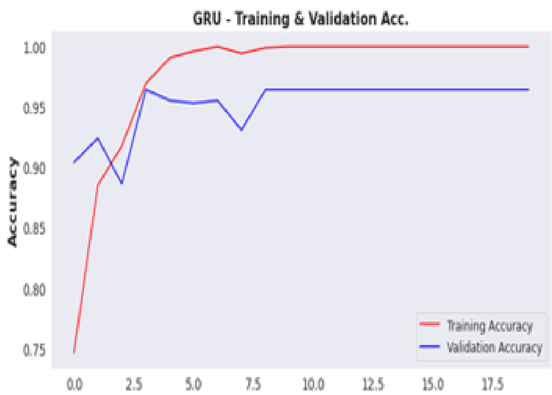
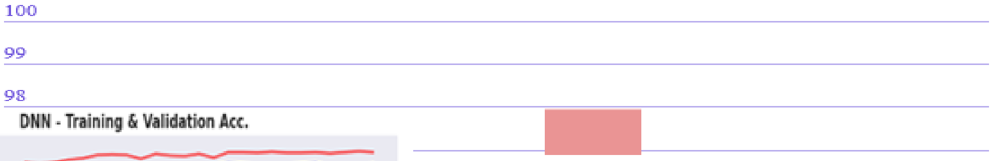


Figure 13 : Accuracy and Loss Graph for Proposed GRU Model



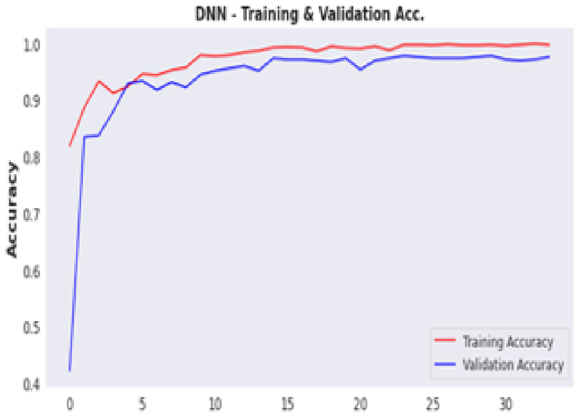


Figure 14 : Accuracy and Loss Graph for Proposed DNN Model

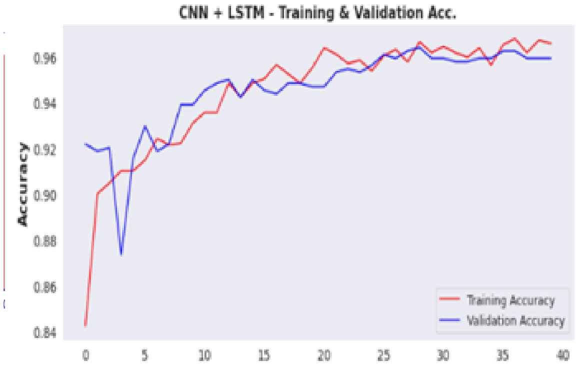


Figure 15 : Accuracy and Loss Graph for Proposed CNN+LSTM Model

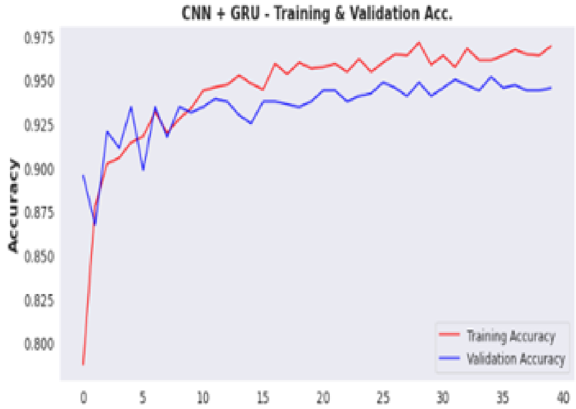


Figure 16 : Accuracy Graph for Proposed CNN+GRU Model

Table 2: Number of Layers and Accuracy Score for the Proposed DL Models

Models	#Layers	Accuracy
CNN	**10**	**97.65%**
LSTM	4	96.87%
GRU	4	95.46%
DNN	**17**	**97.94%**
CNN+LSTM	7	95.93%
CNN+GRU	7	94.53%

The number of layers used, and the accuracy scores of our proposed deep learning models are tabulated as shown in Table 2. The Comparison Graph for our proposed DL models are plotted in Figure 17. The Proposed CNN and DNN yield better results than all other models as number of layers used are more in these models. A Deep Neural Network (DNN) arranges learning algorithm in such a way that it can make accurate decisions on its own, in contrast to a Machine Learning model that makes decisions based on what it has learned from the data. Therefore, even if models that use machine learning can learn from training data, they may need some human assistance in the beginning. However, DNN does not require human intervention. DNN is thus able to learn features that are even beyond human prediction. DNN therefore produce high accuracy when compared to other current models.

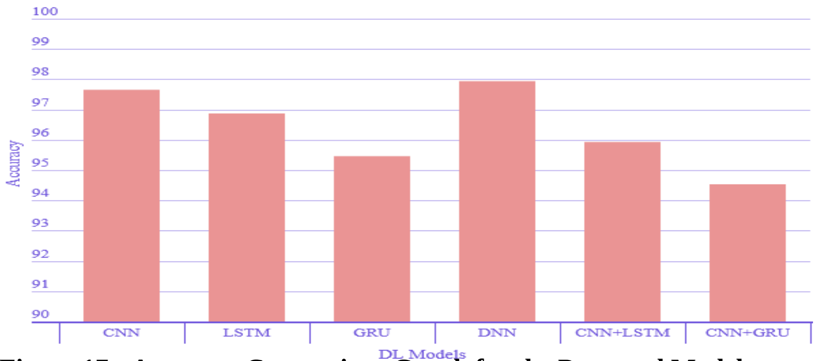


Figure 17 : Accuracy Comparison Graph for the Proposed Models

6. Conclusion

It is crucial to accurately and consistently identify stress, which calls for a dependable experimental approach and analytic framework. This study's key contribution is the creation of an experimental paradigm for successfully creating stress at various levels as well as a framework using EEG data processing for identifying stress at various levels. In order to identify stress early on and stop its negative long-term effects, it is crucial to regularly monitor stress levels. The idea of stress detection emerged from the need to manage chronic stress in persons. The suggested method is an excellent place to start when trying to identify stress in order to enhance the quality of life. In order to categorize three different states—neutral, stressed, and unstressed—this project provides research on the categorization of mental states based on EEG signals. It suggests a set of characteristics utilizing a short-term windowing retrieved from five signals from an EEG sensor. Data from five participants collected across one-minute sessions for each state were used to construct a data set.

This paper main objective is to evaluate various deep learning classification models that perform on the data set with acceptable accuracy and can be beneficial for clinical applications. A method for monitoring stress is suggested in this study effort, which is built utilizing EEG signals and a deep learning framework, after comparing and examining the prior work. Hence, it's possible to demonstrate that deep learning algorithms can boost diagnosis capabilities while resolving typical machine learning techniques' limitations. The method for stress monitoring that is suggested in the current study work uses a deep learning framework to interpret EEG signals, and it offers a high accuracy of above 97.6% for the proposed CNN and DNN models. With regard to performance indices like accuracy, sensitivity, and precision, we can infer that a deep learning framework will meet the norms of clinical performance and be approved as a dependable approach. As future research, we can try different pre-trained deep learning models to improve the accuracy for the stress detection and classification using EEG brainwave signals.

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