EEG BASED MENTAL STRESS LEVEL DETECTION

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Abstract **- Today's pupils frequently endure stress in their daily lives. They experience stress from a variety of sources, which is known to impair their performance. As a result of rising standards for academic performance, bad time management, and financial worries, stress has grown pervasive in the academic environment. Their physical and emotional health are both negatively impacted, which has a negative impact on their quality of life. If it goes unnoticed for a longer time, it increases the risk of sadness and suicidal thoughts. A approach that is non-invasive, exact, accurate, and trustworthy is required. The fact that electroencephalography (EEG) is a non-invasive process makes it the ideal tool. Moreover, it gets the feedback from the emotion released stress hormone, making it a gaining truth access tool to measure the stress. This project totally deals with the stress and the stress hormones are analysed and further the stress levels are detected and the students stress is detected. Fast Fourier Transform is being used to extract essential time-frequency characteristics from the EEG recordings after the EEG signal has been pre-processed to remove disturbances (FFT). Utilizing a split of the retrieved attributes, stress levels are determined using Deep Learning Convolution Neural Network (CNN) classifier. This technique is novel in that it modifies the CNN's convolution kernel to accommodate the input of EEG recordings. The classification accuracy of 86.4% is obtained. This system revealed that the efficiency to detect stress level using brain waves datasets .**

Keywords: **Electroencephalogram(EEG), Deep Learning, Convolution Neural Network(CNN)**

I. INTRODUCTION

Emotions are closely related to people's work and life. EEG were first discovered by Hans Berger in 1926 for the study purpose of brain working and mental illness.

Students experience stress in their everyday lives. It is an unavoidable evil that is brought on by physically taxing exercise. It is not always a bad thing to do this process. However, in some situations, it poses a risk to mental health. Stress may develop as a result of pressures on the body or the mind. The sympathetic nervous system is activated when the body experiences physical stressors in order to maintain homeostasis. So, stress detection is the focus of our efforts. The approach that is non-invasive, exact, accurate, and trust-worthy is must.

The fact that electroencephalography (EEG) is a non-invasive process makes it the ideal tool. A significant burden on both humans and society, mental stress is one of the key risk factors for ailments including melancholy, mental illnesses, cardiac arrest, and attacks. As one of the most frequent co-occurring syndromes among children with autism spectrum disorder (ASD), psychological problems make up a significant portion of the population that is especially prone to mental stress, which drastically reduces quality of life overall. Early stress assessment using deep learning (DL) and efficient anxiety reduction using non-pharmacological therapies are crucial for avoiding this.

A physiological signal that may be used to track a person's mental state, such as stress, is the electroencephalograph (EEG). The suggested and developed Stress Detection Application is a software that may be used for stress reduction since it uses EEG to acquire brainwave data. Fast Fourier Transform (FFT) was employed in this system's feature extraction, and Convolution Neural Network (CNN) was utilized to categorize the characteristics and determine whether or not the subject was under stress.

There are Five frequency bands which divides brain signals/data that are – theta , alpha, beta, gamma, delta. The theta waves are from 4-8Hz and detected when someone is drowsy , the alpha waves from 8-14Hz when one is calm , beta waves from 14-30Hz when one is in thinking process/state , gamma from 30-50Hz during meditation process , delta waves from 0.5-4Hz while sleeping position. The most effective feature type for stress identification was the Alpha, beta, theta, and delta waves. Among from this we will be using alpha band wave for determining stress using

CNN classifier. The accuracy attained by this will be 0.8659 i.e. approximately 86-87 percent.

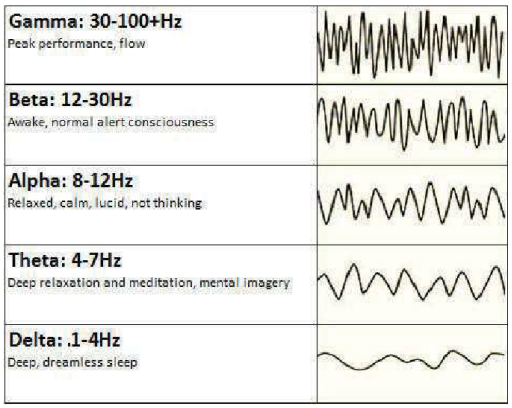

Fig. 1. The waveform of brainwaves [13]

Fig 1: Frequency Band

II. RELATED WORK

The review includes various research papers on the topic, methodology used in the papers, and advantages and limitations of the same.

M Rohini et al. [1] presents a quick overview of the pressures experienced in daily living. The evaluation of emotional strain using current EEG signal analysis techniques is done in this work. Despite the fact that excessive strain is harmful to well being, moderate strain may be beneficial to humans. An examination with five individuals is organised and conducted to validate the computation. A Stroop coloring word experiment is used to apply stress or to provoke five different levels of tension, and the EEG data are captured throughout the test. The investigation and proposal of various component blends and classifiers. Four degrees of stress may be detected with a typical precision of 96.056% by combining fractal aspect and quantifiable components, using Neural organisation (NN) as the assessor, and fractal aspect as the discriminator.

Ahuja R. et al. [2] In this study, we estimate students' psychological anguish one day before the examination and while they are using the web. The database, which included the data of 204 students, was collected from the Jaypee Institute of Information Technology. Responsiveness, selectivity, and correctness are used as evaluation criteria for the four classification methods Linear Regression, Naive Bayes, Random Forest, and SVM. Applying 10-Fold Cross-Validation further improves accuracy and performing of the data. Support Vector Machine had the best accuracy (84.61%).

Joong Woo Ahn et al. [3] In order to allow for constant stress assessment in regular living, an unique wearable device that can concurrently analyze electrocardiograms (ECG) and EEG was developed in this study. The created system has a great noise performance of 0.12 Vrms, is lightweight (42.5 g), and is conveniently worn by hanging from both ears. Using 14 young volunteers, world is changing and frequency aspects of HRV and EEG were discovered under two separate stressors, the Stroop colored name and mental arithmetic tests. Different HRV and EEG feature choices and a support vector machine approach were used to characterize stressful life conditions. The greatest performance was achieved with an accuracy of 87.5% in the five-fold cross-validation findings employing both EEG and HRV characteristics, illustrating the need for simultaneous HRV and EEG measurement.

III. PROBLEM STATEMENT

"To identify Stress Level using deep learning convolution neural network based on EEG dataset."

IV. METHODOLOGY

Multiple learning algorithms are available for classification. The proposed methodology uses CNN Algorithm. Our proposed methodology is such that using deep learning CNN on offline datasets proposes output as the high , medium and low stress detection.

A. Title and Author Details

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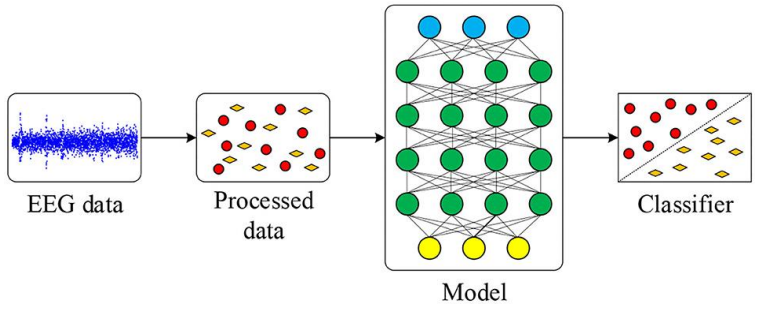


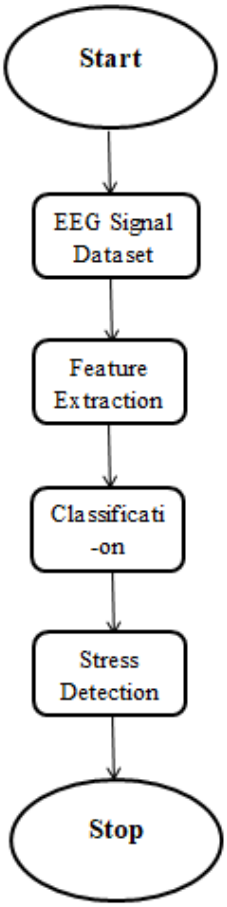
Fig 2: Proposed Methodology

We used the kaggle dataset of EEG recorded signals. These data were pre-processed to remove the various noises and were taken from the processed data as features. Then with the help of keras we modelled and train the given dataset for classification. If such trends, parameters, and features are extracted effectively.

1. Import the Libraries
2. Load the Training Dataset
3. Use keras Train Your Model
4. Normalizing the Dataset.
5. Creating X_train and y_train Data Structures
6. Reshape the Data.
7. Building the Model by Importing the Crucial
8. Libraries and Adding Different Layers to CNN.
9. Fitting the Model.
10. Getting accuracy for training data.
11. Preparing the Input for the Model.
12. Predicting the Values for testing data.
13. Create the confusion matrix for training and testing data

This model was developed via Tensor flow's sequential technique, keras. The model is also trained, evaluated on a test, dataset, and then using Matplotlib, loss and accuracy curves are displayed for both datasets.

A. **Flowchart**



V. *PERFORMANCE METRICS*

Formulas:

Precision :It reveals the percentage of predictions in the positive class that were true positive predictions. The following formula should be used to determine precision:
Precision: TP/(TP+FP)

Recall: the number of relevant documents found by a search divided by the total number of existing relevant documents.
Recall = number of documents searched / total number of documents retrieved.

F1 score: Combination precision and recall is the harmonic mean of precision and recall.
$F1\ score = 2.\ Precision * Recall\ /\ Precision + Recall$

Accuracy: Accuracy is how close the value goes to the predicted output.
$Accuracy = No.\ of\ correct\ Predictions\ /\ Total\ no.\ of\ Prediction.$

Now the performance parameters for each model for all stress levels are calculated using above formulas.Based on the logarithmic values from the graph a matrix for each emotion is created, then above-mentioned formulas are implemented on that matrix in CNN to obtain the accuracy of each matrix to predict the stress level as output.

VI. *CONCLUSION*

In the present study, There are various ways in which stress state of human can be find our for example through the facial expressions or through voice recognition or through the texts of a person. So various studies shows that EEG can help to detect the stress level very accurately as this are the pulses directly generated from our brain so In this project, we have evaluated how feasible are the EEG signals for the classification of stress level states.

For that, we used the kaggle dataset of EEG recorded signals. These data were pre-processed to remove the various noises and were taken from the processed data as features. The data that we mostly focused on is the time series data that is fft data.Then with the help of keras we modelled and train the given dataset for classification. Using deep learning with CNN helped us to achieve a great accuracy rather than that of SVM or other classifiers which then gives output as high , medium , low stress.

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