DEEP LEARNING METHOD FOR ESTIMATING DEPRESSION USING EEG

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Abstract: In terms of prevalence worldwide, depression has surpassed all other mental illnesses throughout time. In the process of diagnosis, several factors that can impact the performance which becomes a challenging task. The best tool for diagnosing depression is EEG data, which show how the human brain is functioning. Deep learning algorithms are capable of recognizing pattern and feature extraction from the input raw data. In order to extract and categorize the EEG data of depressed and healthy people, this study suggests a Convolutional Neural Network (CNN). Combining CNN with Support Vector Machines (SVM) advances the task. CNN is used to extract the features, while SVM is used to classify them.

Keywords: - Deep Learning Algorithms, EEG Data, Convolutional Neural Network (CNN).

I Introduction

1.1 Depression:

Depression holds a substantial influence on people's quality of living and affects more than 264 million people worldwide. This mental illness encompasses a number of physical and mental disorders. Early depression identification is crucial for effective treatment since it can prevent symptoms including restless sleep, low self-esteem, discouragement, and food changes. Depression has an effect on the release of neurotransmitters. Given that the human brain affects the electrical activity of neurons, electroencephalographic recording (EEG) [1].

1.2 Electroencephalogram (EEG)

This signal, which records the complex physiological processes of the brain, can be decoded and understood using a variety of typical feature extraction approaches. EEG analysis can be used to diagnose many brain conditions. An electroencephalogram (EEG) is a check that appears for electrical activity in the brain through tiny metal discs (electrodes) attached to your scalp. The human brain cells are constantly sending and receiving electrical impulses even sleeping. On an EEG recording, waves can be visible during this action [2].

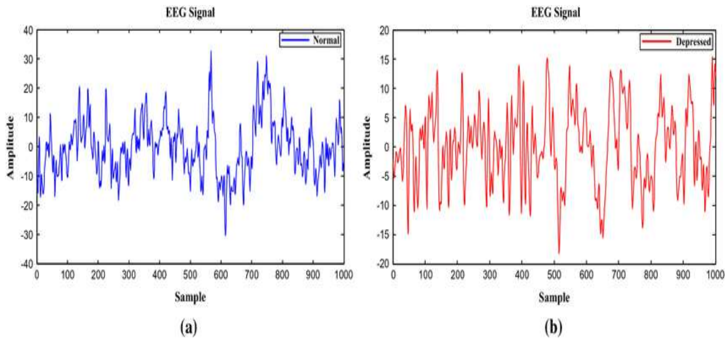


Fig.1 EEG signals from normal and depressed subjects

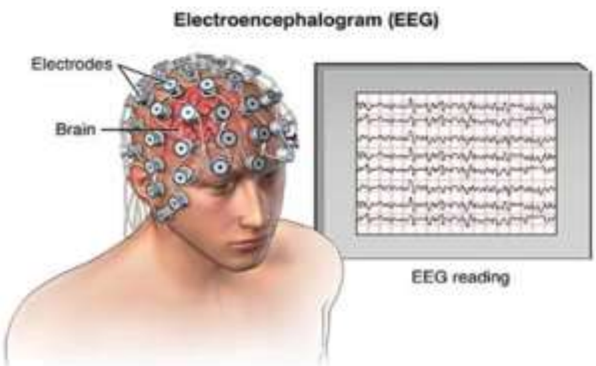


Fig2 . Figure showing the brain activity using EEG

A signal with poor spatial resolution and a low signal-to-noise ratio (SNR) is often produced by any elicited response that gets muddled up with continuing background activity. During signal recording, the information signal is masked by a variety of artifacts and interferences [6]. Muscle contractions, background activities, and eye blinking during the signal collecting procedure are only a few examples of the different artifacts that could affect the signal. EEG signals are gathered using advanced equipment in secure, noise-free labs to prevent interference, artifacts, and other sorts of noise. Despite having poor spatial resolution, EEGs have great temporal resolution of less than a millisecond. The signal's hertz frequency range is quite little when it is analyzed. These signals can be categorized using the frequency bands. EEG signal measurements last between 30 and 40 minutes. The EEG signals display the brain activity, which provides information on general bodily activity. With the help of proper signal processing and pattern recognition analysis, it is feasible to identify neurobiological abnormalities and prevent errors in the diagnosis of depression using EEG signal data that is collected using a non-invasive manner.

II Literature survey

This section reviews the studies that were done on EEG signals and deep learning techniques to diagnose and predict depression in participants**.**

Yasin et al. [17] examined studies that identified the two forms of depression, major depressive disorder (MDD) and bipolar disorder (BD), using EEG signals, neural network and deep learning algorithms. It used a variety of source engines and a combination of different keywords to search through articles that had been published during the previous ten years, and then it took some pertinent information from those publications. One of this review's strong points was its ability to classify exploited datasets, methods for extracting or analyzing features, and algorithms in papers. Additionally, a variety of tables are created to display the collected data and perform various comparisons between them.

The review [19] concentrated on paper which investigated depression as one of several mental illnesses using deep learning methods. Clinical data detection, using genetic data to diagnose diseases, analyzing different datasets, and using social media data, this study's four major objectives were to calculate the likelihood of mental illness used a variety of datasets, only three articles used the electroencephalogram dataset type to study the detection or prediction of depression. Here, thorough representations of the studied datasets were provided. Additionally, it went into a great detail on the opportunities and challenges, those using each dataset will definitely bring. Nevertheless, in the light of the fact that EEG concentrated on encompassing a range of mental disorder scenarios. It covers a number of articles on applying deep learning for EEG signal-based depression diagnosis and prediction.

Khosla et al. [20] reviewed the literature and examined how EEG signals and different classifiers could be used to track problems like emotion recognition and spot neurological conditions like depression. The information was gathered from a variety of publications, conferences, books, and thesis, with a focus on those that were published between 1999 and 2019 (only four papers were from earlier years). Only a handful of papers—roughly 10 that dealt with the diagnosis of depression were taken into account. Artifact removal, feature extraction, types of extracted features, feature selection, dimensionality reduction, and classifier methods were among the areas separated into which the approaches and data were thoroughly evaluated. According to paper various approved datasets were compiled and presented as local and public acquired classifications. It also contained information on functional neuroimaging techniques. It was unable to adequately address each topic, because it encompassed so many diverse areas of research on mental health problems.

III Implementation Study

The electroencephalogram (EEG) is a representation of the electrical action taking place at the brain's surface. This activity shows as waveforms of varied frequency and amplitude measured in voltage on the EEG machine's screen (specifically micro voltages).

EEG waveforms are often categorized based on the areas on the scalp where they are recorded as well as their frequency, amplitude and shape. EEG waveform frequency is used for the most popular classification (e.g.: alpha, beta, theta and delta). The age of the patient, level of alertness or depression and position on the scalp are combined with information regarding waveform frequency and shape to evaluate importance.

The frequency, amplitude and position of normal EEG waveforms like many other waveform types serve as their definition and descriptors.

• Frequency (Hertz, Hz) is a crucial factor used to categorize EEG rhythms as normal or aberrant.

• The majority of 8 Hz and higher frequency waves are common in an awake adult's EEG. Despite the fact that waves with a frequency of 7 Hz or fewer are frequently categorized as abnormal in awake people, they are typically visible in kids or adults who are not depressed. In some circumstances, EEG waves with an age-relevant frequency.

3.1 Proposed Methodology

A. EEG Signal:

The raw EEG data obtained from the 23 participants is stored in the database as .edf files. This database also offers pre-processed data in .mat format as well as raw data. For the segmentation of each EEG signal into 6 segments that correspond to the 6 scenarios, it was provided a MATLAB script. EEG data from individuals with clinical depression and data from healthy control subjects are both included in the DASPS dataset.

A. Pre-processing

Pre-processing EEG data is important for a number of reasons. First of all, because the spatial information is lost, the signals detected on the scalp may not accurately reflect the signals coming from the brain. Second, there is often a lot of noise in EEG data, which might mask weaker EEG signals. Blinking or muscle movement artifacts can taint the data and skew the image. The goal of this step is to distinguish the important brain signals from the random neural activity that is detected during EEG recordings. Pre-processing is the process of converting unprocessed data into a form that is more suited for additional analysis and user-interpretable. When it comes to EEG data, preprocessing typically refers to removing noise from the data to approximate true neural signals.

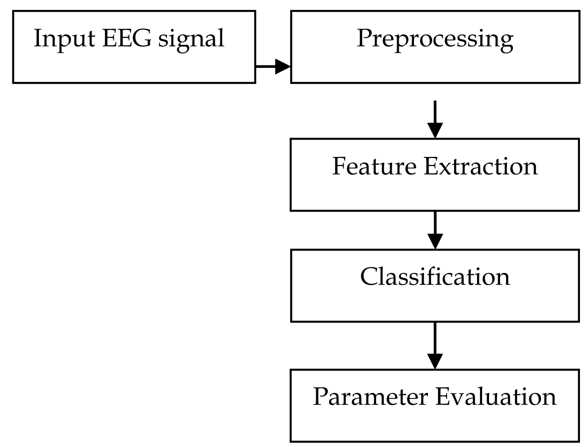


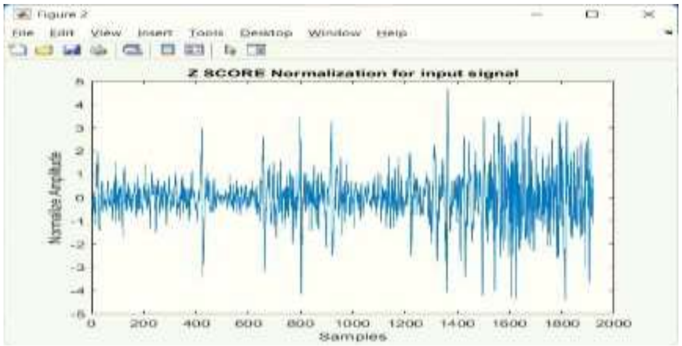
Fig 3: Block diagram of proposed system

C. **Feature Extraction using CNN Architecture**

Three different layer types make up a CNN: convolution, pooling, and fully connected. The CNN model used in the proposed system consists of 3 fully connected layers, 5 pooling layers and 5 convolutional layers. During training, the weighted vector filter is used to convolve the input and it is modified. The filter is set at 5 and 2 for the convolution and pooling processes respectively. The selection of filters 5 and 2 are made since they produce the most accurate results. Additionally, for the convolution and pooling processes to stride or how many sampling point windows are changed in each operation is fixed at 1 and 2 respectively.

D. Classification

Support vector machine classifiers are employed in the proposed system for classification. The



Support Vector Machine (SVM) technique was created for pattern classification but has lately been modified for additional applications like estimating distributions and discovering regression. The issue is to locate a hyper-plane that divides the data points by a maximum margin. The data points are classified as positive or negative.

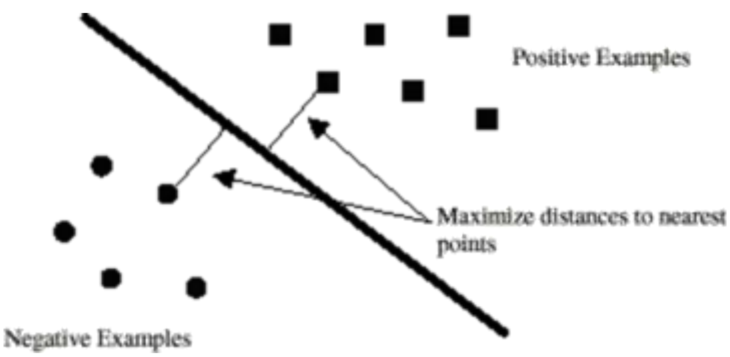


Fig 4: Data Classification

IV Results

The MATLAB software application is used to assess the database. It displays the input EEG signal that has been provided. The signal features are retrieved and categorized after processing. The final outcomes are displayed below

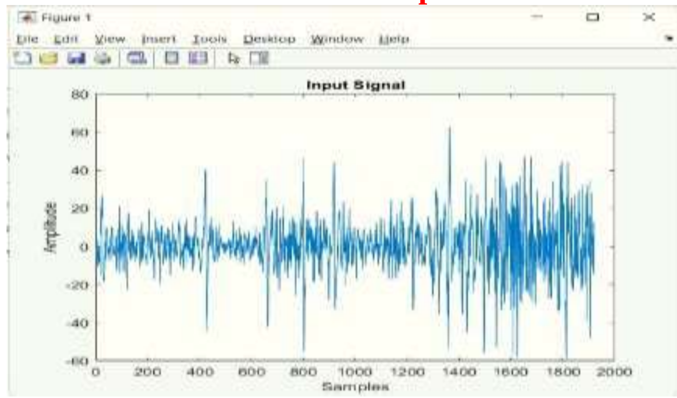


Fig 5: Input Signal

Fig 6: Normalization signal

4.1 Parameters

The performance of the suggested system is assessed using the metrics listed below: In the table 1, TP stands for correctly predicted depressed cases, FP for normal or depressed cases that the proposed system incorrectly classified as depression, TN for normal or depressed cases that are correctly classified, and FN for depressed cases that were incorrectly classified as normal or depressed cases.

Sensitivity:

Sensitivity is a measurement of the percentage of true positives that are correctly identified. (also known as the true positive rate, recall or likelihood of detection in various disciplines) (e.g., the percentage of disease that is correctly identified)

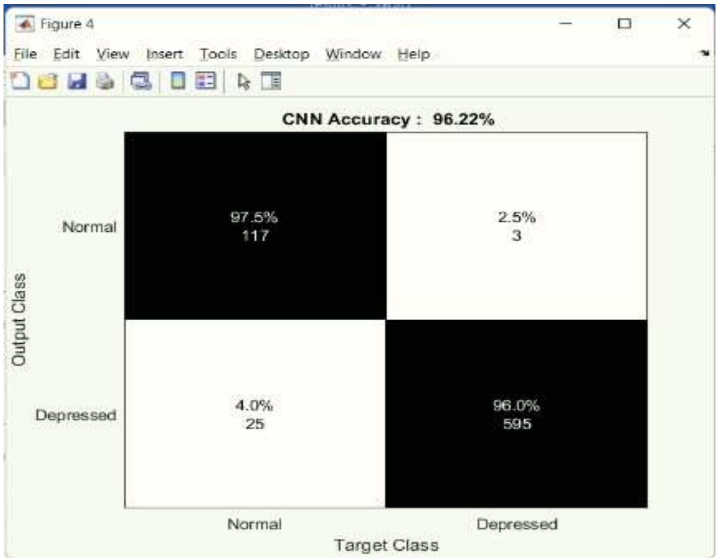


Fig 7: Confusion matrix for CNN

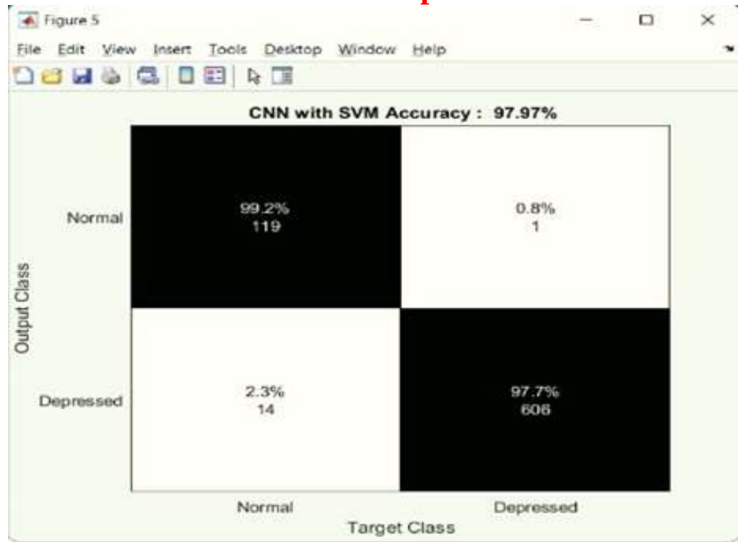


Fig 8: CNN-SVM confusion matrix

Table 1: accuracy table of CNN and CNN-SVM model

S. No	Parameter	CNN Model	CNN-SVM (proposed)
1	**Accuracy (%)**	96.21	97.9
2	**Sensitivity (%)**	99.49	99.83
3	**Specificity (%)**	82.3	89.4

A confusion matrix is produced to provide a summary of the findings on a classification problem and to provide a visual representation of the model's findings. It lists the forecasts that were accurate and inaccurate and split down by class. It demonstrates how the classification model becomes confused when it makes predictions and provides information on both the size and the nature of the errors that are created. True Positive: The observation and the prediction are both true positives. False Negative: Although the observation is negative, the outcome is optimistic. False Positive: The observation is good, but the forecast is bad. True Negative: Both the observation and the prediction are unfavorable.

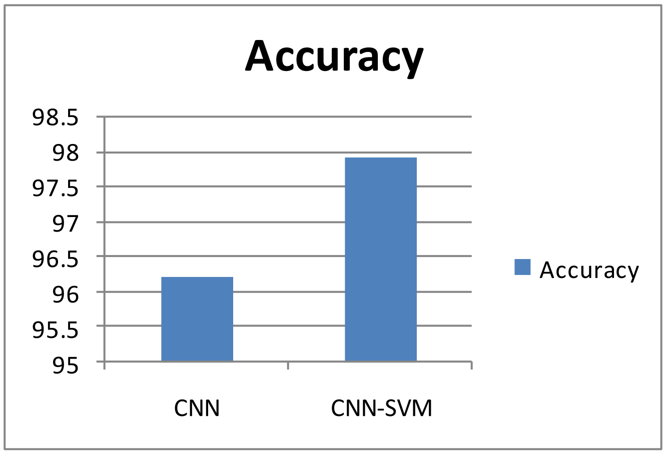


Fig.9: Accuracy between CNN and CNN-SVM

From Fig.9 accuracy has increased to 97.9% when the combination of CNN and SVM are used while When CNN alone is used accuracy remained 96.21%

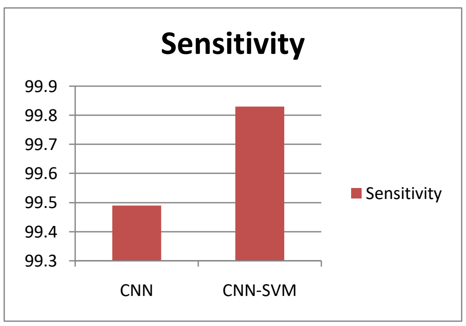


Fig.10: Sensitivity between CNN and CNN-SVM

From Fig.10 sensitivity of CNN is 99.49% and CNN-SVM is 99.83%.In comparison sensitivity has increased 0.34%

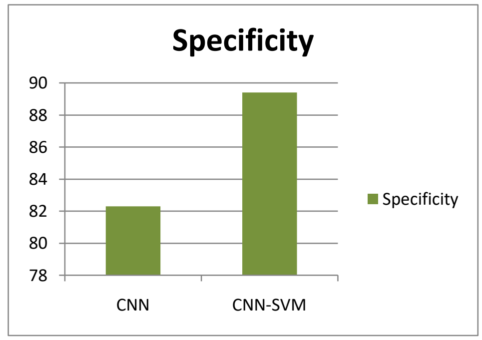


Fig.11: Specificity between CNN and CNN-SVM

From fig.11 specificity of CNN is 82.3% and CNN-SVM is 89.4%.Specificity has increased.

V Conclusion

The project demonstrated the first use of CNN, the deep neural network idea for depression diagnosis. The semi-manual feature extraction and selection for classification in the proposed CNN model is not necessary. Instead, during the algorithm's training, the model self-learn and take up distinct features. Using EEG inputs, the CNN-SVM system in the proposed system achieved a high accuracy of 97.9%. The CNN-SVM model can be utilised for computer-assisted diagnosis of depression quite accurately and according to the findings, utilising the suggested model with a small sample of EEG data. Moreover, this suggested algorithm can be used as a second opinion to support a clinician's diagnosis. Nevertheless, a bigger set of EEG data from the left or right hemisphere can enhance the analytical performance of the suggested model. The proposed algorithm can also be used to diagnose various neurological illnesses as well as depression in a variety of stages and degrees of severity. The gathering of the required data to train the model would be essential for its successful deployment in the clinical context.

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