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AN INTELLIGENT ALZHEIMER'S DISEASE PREDICTION USING CONVOLUTIONAL NEURAL NETWORK (CNN)

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ABSTRACT

Deep Learning is a subset of machine learning, designed to continually analyze data with logic similar to human. It uses a layered structure of an algorithm called Artificial Neural Network (ANN). They are mainly used in medical diagnosis for making critical decisions like disease prediction, robotic surgery, and radiation treatments. Disease prediction includes identifying and classifying Alzheimer's disease. It is the most common cause of dementia which affects around 46 million people in the world. The disease has several stages and it is classified into Mild and Severe. The symptoms include reduced ability to remember the information, impaired speaking and writing. Many machine learning algorithm techniques like Decision tree classifier, Independent Component Analysis, Linear Discriminant Analysis (LDA) were used to predict the disease based on their stages, but the precision in identifying stages of the signals is not much good. In this work, a Deep Learning based technique is proposed which improves the accuracy of classification by using the Convolutional Neural Network (CNN). This work analyzes the Electroencephalogram (EEG) signal, *extracts the features using Fast Fourier Transform(FFT) and classifies the disease by CNN.*

Keywords - Alzheimer's Disease, Electroencephalogram , Convolutional Neural Network, Brain.

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1. INTRODUCTION

Alzheimer's disease (AD) is the neurodegenerative disease among older adults and affects around 46 million people in the world. The early symptom of the disease is forgetting recent events or conversations. As the disease progresses, it brings severe impairment in memory and loss the ability to take over every day's task. The beginning of the damage takes place in the region of the brain which is responsible in controlling the memory, but the process starts years before the first symptom. The loss of the neuron spreads to other regions and later the brain has shrunk significantly. The disease has the following stages: Mild, Moderate and Severe. The mild stage is the early stage and it includes the problems coming up with the right word or name and losing or misplacing the valuable object. The moderate stage is the middle and longest stage which includes forgetfulness about one's own personal

History and confusion about where they are and what day it is. The severe stage is the late stage and includes experience changes in physical abilities and has difficulty in communicating. More than 4 million people are suffering from Alzheimer's and other forms of dementia in India, which gives the third highest caseload in the world, after China and the United States. India's dementia and Alzheimer's burden is forecast to reach almost 7.5 million at the end of 2030. Predicting the disease priory brings down the risk of death rate. To do so, various methods are used to implement the classification of the disease.

The Alzheimer's disease prediction at the early stage brings down the rate of death. It uses the neuroimaging or brain scanning to image the function, structure or pharmacology of the brain directly or indirectly. The brain scanning is done by the following ways: Magnetic Resonance Imaging (MRI), Electroencephalogram (EEG), Positron Emission Tomography (PET). EEG is a method that measures the brain neural electric activity from the scalp of the head. An EEG estimates the electrical driving forces in your mind by utilizing few terminals that are appended to the scalp. A terminal is a channel through which an electric flow enters or leaves. The terminals move data from your cerebrum to a machine that measures and records the information. Using EEG as a cognitive biomarker to detect and predict MCI and AD in individuals is a new effort which is considered to be economical. EEG is normally partitioned in various regular recurrence groups, for example, delta (δ, 1-4 Hz), theta (θ, 4-8 Hz), alpha (α, 8-13Hz), beta (β, 13-30 Hz), and gamma (γ, 30-40 Hz) [3].AD appears to influence the sign power in those various groups. The significant impact is known as the EEG "slowing", that implies a power increment in low-frequency bands such as delta and theta and a power decline in higher frequency bands such as alpha and beta [2]. EEG gives a neurophysiological biomarker that is inexpensive and available at community clinics.

2. RELATED WORK

The supervised method in machine learning is to classify the patients affected by AD from the one who is affected by Mild Cognitive Impairment (MCI) and Healthy Control (HC) samples. Giulia Fiscon , Emanuel Weitschek et.al [1] proposes this method by recording the EEG signals and apply Fast Fourier Transform(FFT) and Discrete Wavelet Transform(DWT) to extract the features. The features are arranged with matrix of 109 rows and 913 columns. Decision Tree Classifiers allow handling noisy datasets and over-fitting. C4.5 algorithm is an algorithm for the generation of decision trees used for classification. The outcome provides proper classification on the stage of the disease for different datasets.

The Relative Power (RP) in Deep Neural Network metric quantifies the abnormal EEG pattern "slowing" is used to distinguish HC and MCI. Donghyeon Kim and Kiseon Kim [2] proposes the deep Neural Network based classifier using Relative power of theta, alpha and beta is calculated and normalized for discriminating the features. In the step of classification, the number of hidden layers are changed according to the classifier. Leave-one-out(LOO) cross validation is used to investigate the proposed system. The Correct classification rate(CCR) is examined in which is the ratio between the number of correct classification and total 59 trails per subject.

EEG recordings are analyzed with five EEG rhythms(δ,θ,α,β,γ). Katerina D.Tzimmoutaa ,Theodora Afrantoub et.al [3] proposes this approach by calculating 38 linear and non-linear features. In order to examine the severity of 38 extracted features and its MMSE score, Multi-regression Linear Analysis is conducted. Regression Models are created for each channel and for cluster of channels according to the electrode placement. All the assumptions are examined and ANOVA analysis is performed. Carmina Reyes-Coronel, Markus Waser et.al [4] made the study to check whether an AD patient will be suffering from RCD by using neuropsychological test scores and quantitative EEG (QEEG) markers . Each feature was tested individually and Support Vector Machine (SVM) was used to classify between RCD and non-RCD patient. It yeilds 72.1% and 77.9% accuracy which is based on leave-one-out validation technique. The neuropsychological test scores improves the classifier into accuracy, sensitivity and specificity by 80.9%, 80% and 81.1% respectively.

Xin Hong , Rongjie Lin et.al [5] proposes a predictive model that uses Long Short Term Memory(LSTM) which is a Recurrent Neural Network(RNN) that predicts the Mild Cognitive Impairment from Alzheimer's Disease. In this work, the data are taken in the form of image and the pre-processing is handled by skull strip, normalization, registration, smoothing and segmentation. After pre-processing the training is taken by feeding s sequential data with time steps to the model and the state of the next six months is predicted by the model. During model testing, when the 18th and 24th month's feature data is given, it predicts 30th month's state of the subject. Similarly Maryamossadat Aghili, Solale Tabarestani et.al [6] proposes a method that deals with Recurrent Neural Network(RNN) to analyze the longitudinal data for discriminating the Alzheimer's disease person from healthy individuals. The data is pre-processed and the feature is normalized. After pre-processing the data, it is fed into LSTM and GRU. In LSTM and GRU model, each subject's time point data is fed to the corresponding cell along with its final diagnosis label to learn the pattern of change in the data. The result models for all arrangements of the data are compared with the results of non-recurrent networks, i.e., Multi-Layer Perceptron (MLP). The data is fed into the MLP once for each patient. The LSTM models have a large number of trainable parameters, which is necessary to be trained greatly for sequential data and , they are still prone to overfitting to the training data.

Escudero J, Ifeachor E et.al [7] proposes a machine learning approach is used for cost-effective diagnosis of AD. By utilizing ADNI information, we arranged AD versus controls and MCI patients who advanced to AD inside a year, against the individuals who didn't. It utilizes locally weighted learning for training a classifier model to the patients and figures the grouping of biomarkers most practical to analyze the patient's stage. Consequently, it enables us to tailor the classifier to every patient by designating the most significance in preparing to the cases most like the patient. In deep learning model, Siqi Liu , Sidong Liu et.al [8] proposes a technique consisting of stacked sparse auto-encoders and a softmax regression layer. It has the capacity to analyze multiple classes. The auto encoders obtain deep representations of the original input. The dimensionality reduction is performed to alter the neurons. The softmax layers classifies instances by selecting the highest predicted probabilities of each label. All the MRI images are nonlinearly registered and further segmented into 83 functional regions. The grey matter volumes are extracted and the features are further selected with Elastic Net before each classification task. The features are normalized to zero mean and between 0 and 1. Random search in a log-domain was applied to choose the hyper-parameters that could be sensitive to the results and this method is then compared with single-kernel SVM, multi-kernel SVM. The structure is evaluated using 10-fold cross validation on the softmax layer. About 90% subjects is used for training (including the pre-training of the deep neural nets) and the rest subjects were used for testing in each fold of cross validation. The distinction between various Region of Interest (RoI) is clearly visualised by the dark regions. It posses darker regions to be more sensitive to the progression of AD and MCI than the lighter ROIs.

The intention of the unsupervised feature learning is to pinpoint the Alzheimer's disease using the concept of unsupervised feature learning. Firouzeh Razavi , Mohammad Jafar Tarokh et.al [9] proposes the method that uses Sparse filtering that learn the expressive features of brain images. The SoftMax regression is trained to categorize the conditions. There are three stages in the first step: Sparse Filtering is trained and its weight matrix of W is estimated. The learned sparsed filtering is used to obtain the local features from each sample. These local features are averaged to obtain the features learned from each sample. Padilla P, Lopez M et.al [10] presents a novel PC helped conclusion (CAD) strategy for the early determination of the Alzheimer's ailment (AD) in view of nonnegative lattice factorization (NMF) and bolster vector machines (SVM) with limits of certainty. The SPECT and PET databases are investigated by applying the Fisher discriminant proportion (FDR) and nonnegative grid factorization (NMF) for highlight choice and extraction of the most pertinent highlights.

Hongming Li, Yong Fan et.al [11] proposes this paper to distinguish when and where the Mild Cognitive Impaired person will convert to Alzheimer's patient. The pattern classifiers build on longitudinal data works well than cross-sectional data. The deep learning model RNN is used to obtain informative representation about cognitive measures of individual and combine them with hippocampal baseline to build prognostic model for AD progression. The LSTM encoder is taken to learn informative representation about cognitive measures to predict the conversion of MCI to AD patients. The result shows the promising prognostic performance in distinguishing the MCI individual to AD patient Similarly Tong Tong, Qinquan Gao et.al [12] proposes a novel grading biomarker for the prediction of MCI to AD conversion. MRI brain images is pre-processed by ADNI pipeline. After pre-processing the feature are selected by sparse regression technique..In this work, Elastic net is used for an input of millions of features. This work uses AD and NC subjects for feature selection. A grading value is calculated for each MCI subjects and used as biomarker for classification. The MCI subject and the training population relation are modelled by using a weighting function. Sparse Representation is done using Elastic Net technique. For training classifier, with single type of features, SVM with a linear kernel was used in SVM. The SVM implementation is performed using liblinear. Global grading biomarker is evaluated using different levels of regularisation:

1. Hippocampus is segmented.
2. Segmented hippocampus was transformed to the temporal space.
3. The clinical labels are propagated from NC and AD subjects to MCI subjects at voxel level using patches.
4. Average grading value within hippocampus is calculated for MCI subjects.

Charlotte Cecere, Christen Corrado et.al [13] made an analysis based on the comparison of different machine learning techniques is done using EEG features to determine diagnostic utility of the EEG. Various techniques like SVM, naïve Bayes, MLP, CART trees, k-nearest neighbour (kNN), and AdaBoost on various sets of features extracted from event related potentials (ERP) of the EEG are compared. For comparison, a nested dual cross-validation scheme is used. Each 5-fold is used to obtain feature sets and classifier parameters. The feature set has DWT coefficients. These coefficients are of different combination of 11 electrodes, two stimulus tones and the aforementioned 4 frequency bands, which results in 88 possible feature sets.After analysing the accuracy for different techniques are obtained. The classification algorithms which has high accuracy are kNN, CART, AdaBoost, and naïve Bayes that stands at 85.7% classification accuracy. Then SVM has its accuracy as 78.5%. On the other hand, the MLP has 82.1% accuracy.The CART classification shows its best since it uses 5 maximum divisions per node.The AdaBoost is also best since it utilizes just 5 classifiers. The result describes that there is useful information in the ERP of the EEG for early diagnosis of AD.

3. PROPOSED WORK

The proposed work uses EEG signal to classify the stages of the disease. A deep CNN network design is proposed that is trained to classify multi-channel human EEG signal data into different stages, and that improves upon the classification performance. This work contains the following modules:

- Pre-processing
- Feature Extraction and
- Classification

3.1. PRE-PROCESSING

The EEG signal is collected from physionet and the signal used is in European Data Format(EDF). If the signal contains any noise or artifacts, preprocess it using Low Pass Filter. The noise of the signal includes eyeball moments, muscle contraction etc. The Low Pass filter is set to high cutoff frequency as threshold to allow the low frequency signal and to remove such noises.

3.2. FEATURE EXTRACTION

The features are extracted from the preprocessed data using FFT. It is the process of selecting the subset of features that is to be used in constructing the model. FFT converts a function of time domain into frequency domain. The Discrete Fourier Transform can be described as:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-i\pi 2kn/N} \qquad (1)$$

where k denotes the frequency domain, n denotes time domain, N is the length of the sequence. The FFT reduces the computation time than the Discrete Fourier Transform from the problem size $O(N^2)$ to $O(NlogN)$. By utilizing the FFT, different relative band power like delta(0-4Hz), theta(4-8Hz),alpha(8-12Hz) and beta(12-30Hz) are generated. Then the features like magnitude of the power spectrum, frequency vector, order of the signal, signal coefficients, average of the relative band power signal are extracted. The optimal features from the power spectrum, relative band power and its average are selected by the classifier. These features provide better classification on the dataset.

3.3. CLASSIFICATION

Classification is a process of identifying the category to which a new observation belongs, which is based on the training set of data that contains the observation. The classification is taken by using Convolutional Neural Network(CNN). CNN is a class of deep learning neural networks, which is commonly used to analyze the visual imagery and signals. It uses layered structure of an algorithm called Artificial Neural Network. In CNN, the network is fed by the individual features and it is trained automatically by various datasets. The network train itself to segregate the disease.

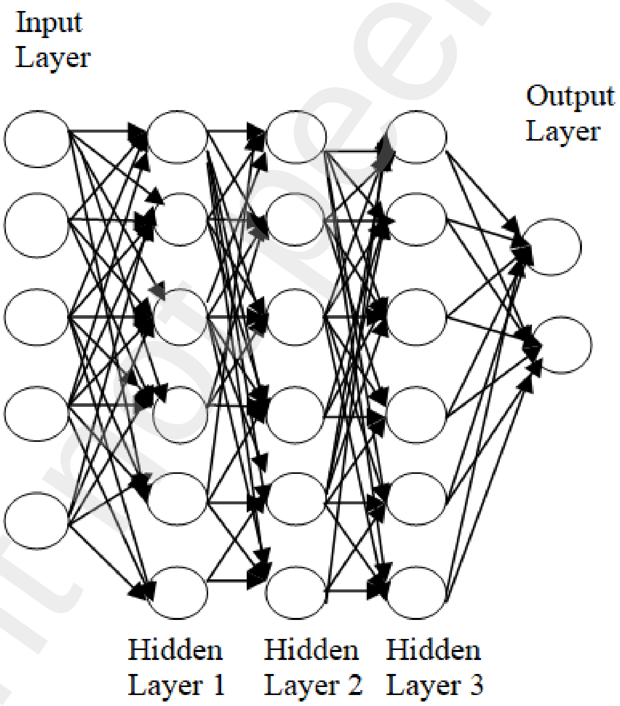

Figure 1 Representation of CNN in ANN

From the Figure 1, the input layer accepts the signal as input. The Hidden Layers carry out feature extraction by performing certain calculation and manipulation. There are multiple hidden layers like Convolution Layer, ReLU Layer, Pooling Layer etc that performs the feature extraction. In the Output Layer, the Fully Connected Layer identifies the category of the input belongs to.

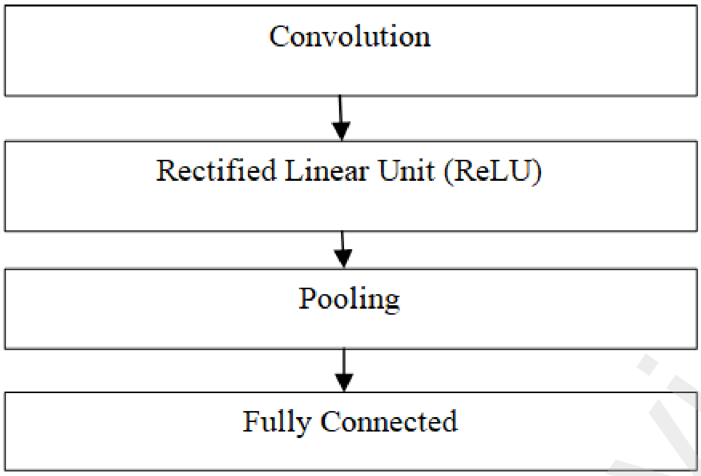

Figure 2 Common Building Block of CNN

Figure 2 describes the building block of proposed CNN.

The Convolution layer is the first layer, which uses a filter to perform convolution operation(2).

$$C_m = \sum_{n=0}^{N-1} f_n k_{m-n} \qquad (2)$$

where f,k,N,C denotes filter, signal, number of datapoints in k and output respectively.

The ReLU activation function is applied to the convolution layer to get the rectified feature map. The Pooling Layer reduces the amount of parameters and computation in the network. The Fully Connected Layer recognizes and classifies the signal(3).

$$x_i = \sum_j w_{ji} y_j + b_i \qquad (3)$$

Where w denotes the weights, b biase, y represents the output from the previous layer while x is the output of the current layer. The output from the last fullyconnected layer are fed into the softmax function that determines the category of the output.

The architecture of the proposed work takes input signals and train it to classify the disease.

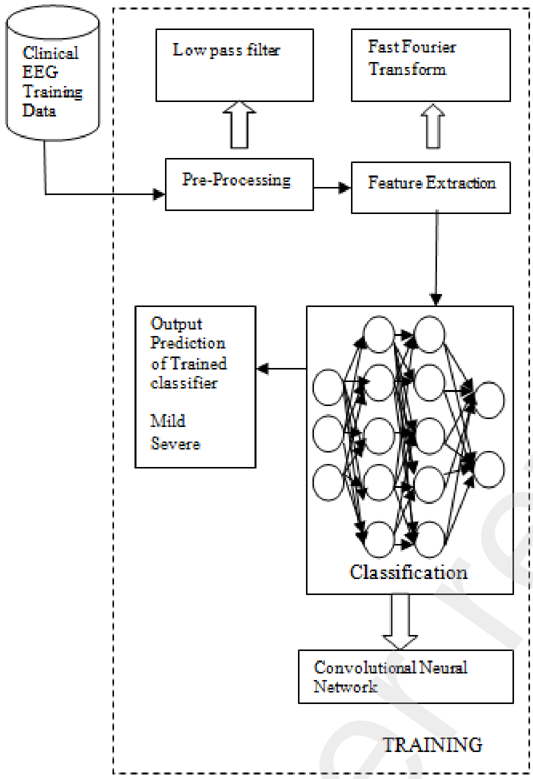

Figure 3 Architecture of Prediction System-Training phase

The architecture in Figure 3 describes the training phase of the prediction system. The clinical dataset is given as an input and it is pre-processed using Low Pass Filter, the feature is extracted using Fast Fourier Transform and the extracted features are given to CNN. It predicts the output based on the given features. The model is trained based on different values.

The architecture in Figure 4 describes the testing phase of the system. The trained classifier is trained by input samples and the testing data are pre-processed by the Low Pass Filter, features are extracted by the Fast Fourier Transform. Then the extracted features are fed to the trained classifier to predict the output (Stages of disease: Mild or Severe).

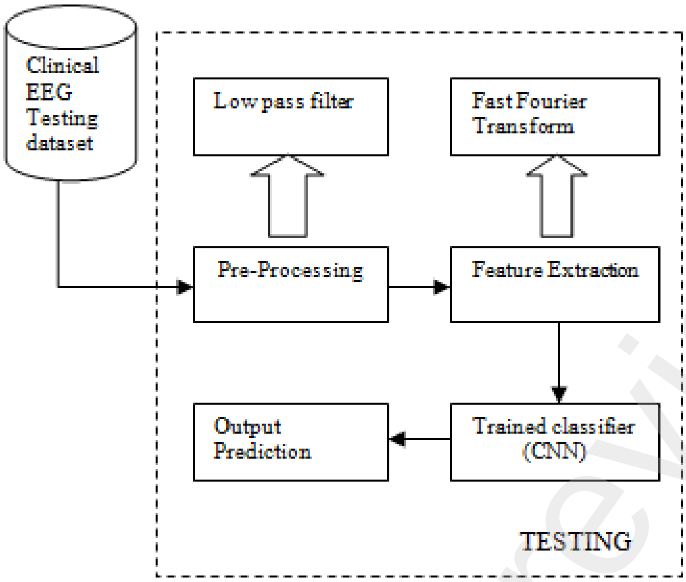

Figure 4 Architecture of Prediction System-Testing phase

4. RESULTS AND DISCUSSION

To evaluate the proposed method, the EEG signal in EDF format is given to the Matlab software. The original signal is predicted and pre-processed as shown in Figure 5.1. It is plotted as time versus amplitude.

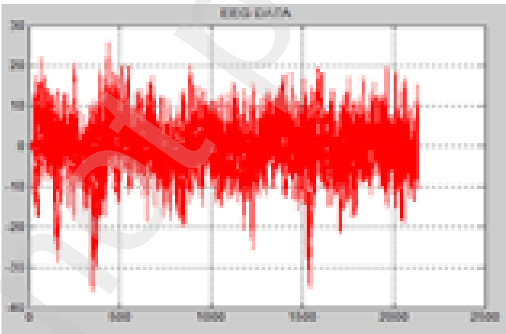

Figure 5.1 EEG signal for the input data

The pre-processed signal is then fed to Fast Fourier Transform and various features are extracted like magnitude of the power spectrum, frequency vector, order of the signal, signal coefficients, average of the relative band power signal are extracted. The power signal is obtained as shown in Figure 5.2 It is plotted as frequency versus amplitude.

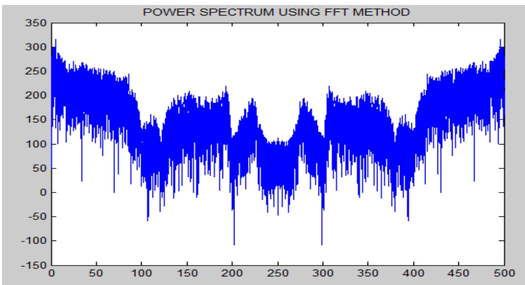

Figure 5.2 Power spectrum for the given input data

The Figure 5.3 describes different frequency relative band power signal.It is plotted by number of samples on the x-axis and amplitude on the y-axis. The signals have variation of increment on the lower frequency bands(delta,theta) on Figure 5.3 a, Figure 5.3 b and decrement on the higher frequency bands(alpha,beta)on Figure 5.3 c, Figure 5.3 d.

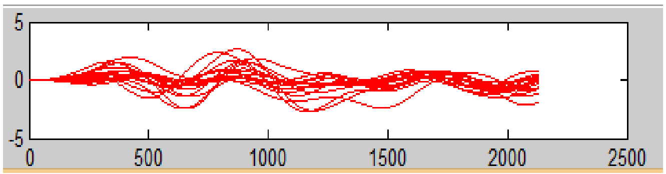

Figure 5.3 a

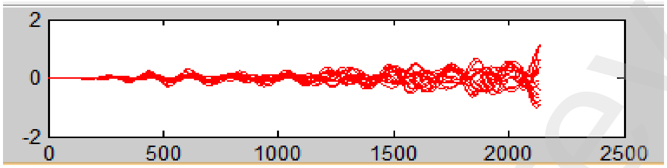

Figure 5.3 b

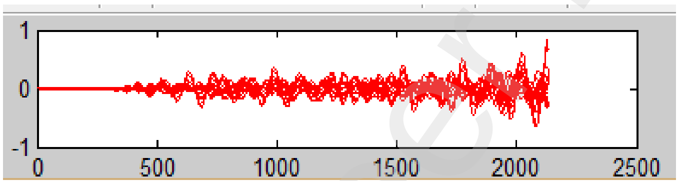

Figure 5.3 c

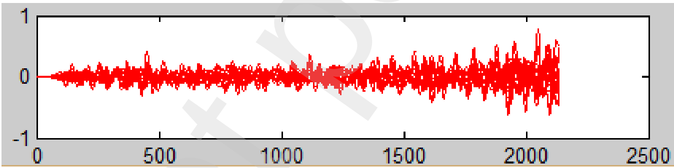

Figure 5.4 d

Figure 5.3 Different frequency relative band power

These signals and its average reltive band power are given to the Convoltional Neural Network for classifying the disease stages.

5. CONCLUSION

In this paper, the EEG Signal is used which is cost effective than MRI and other scans. The features from the pre-processed signals are extracted according to the signal by using Fast Fourier Transform. Then the extracted features are fed to the Convolutional Neural Network which classifies the disease as Mild or Severe. The CNN in deep learning suits best for the classification since the network can be designed more deeply and used for spatial data.

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