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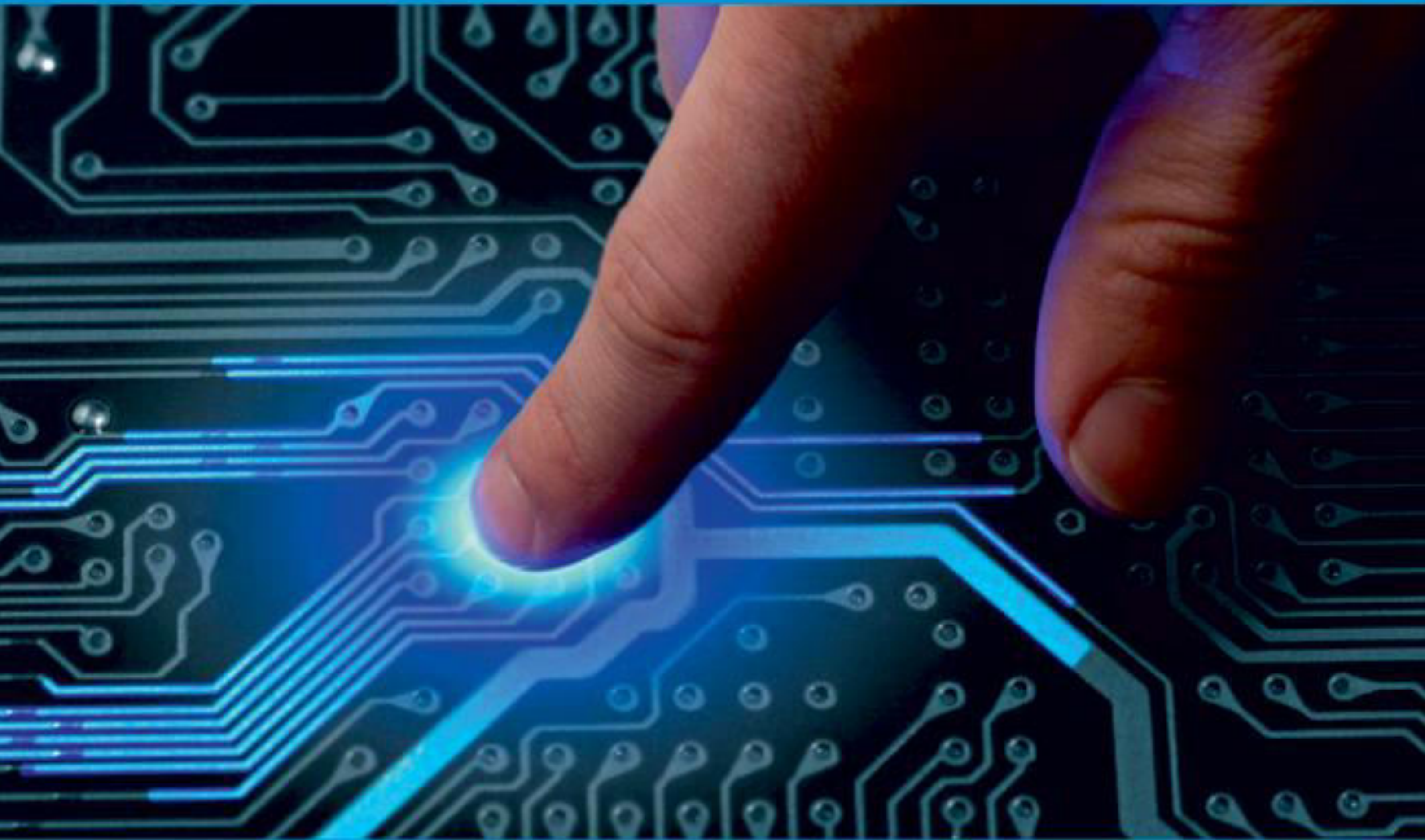

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Diagnosis of Alzheimer Disease Using EEG Signals

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ABSTRACT: Convulsion occurs due to neurological order in the human brain which affects the patient's health severely. Early prediction of Alzheimer is pretty useful for the neurological professionals to restrict the disease by means of medication. Manual detection of convulsion leads to higher time consuming and wearisome work for the neurophysiologists. It's vital to outline a manner to take a look at and prognosis correctly for the convulsion patients. Electroencephalogram (EEG) performs a full-size role most of the medical practitioners which facilitates to prognosis neurological issues with an inexpensive cost. The conventional technique makes use of system monitoring and statistical methods for predicting epileptic Alzheimers based on EEG indicators. The existing method based on EEG alerts uses preprocessing method for noise elimination and function extraction technique to classify epileptic Alzheimers. During this paper, a new approach is brought with the aid of the use of raw EEG alerts with none preprocessing method. The type of alzheimer is allotted employing a deep gaining knowledge of method sited on Deep Convolution Neural Network (DCNN) and additionally BWT to reform the accuracy. This mixed new technique can enhance a memory efficiency and additionally lessen computational complexity. Our non-linear, supervised and clustering technique demonstrates a prominent result to categorize alzheimer and non- alzheimer alerts with high accuracy the usage of cross-validation assessment metrics whilst examine with nation of the BWT.

KEYWORDS: Convulsion, EEG, CNN, BWT , Cross-validation

I. INTRODUCTION

Alzheimer is a neurological disorder in which brain activity becomes abnormal, causing Alzheimers or periods of unusual behaviour, sensations and sometimes loss of awareness. Approximately sixty five million people suffer from alzheimer worldwide according to the World Health Organization (WHO) [1]. It is estimated that 2.4 million people are diagnosed with alzheimer annually [1]. Alzheimer is a common brain condition that causes recurrent, unprovoked Alzheimers was defined by the Centers for Disease Control and Prevention (CDC). Till date, this disease is recovered by practicing medications and surgery; no complete cure exists and [[[[treatments with antiepileptic drug are not entirely beneficial for various types of epileptic Alzheimers [3] and [4].

Electroencephalography (EEG) plays a significant role to detect alzheimer, as it calculates the variations in voltage changes between electrodes along the subject's scalp by sense ionic currents flowing within brain neurons and provides secular and location information about the brain [5] and [6]. Epileptic Alzheimer detection with brain electrical signals requires an awaked classification by neurophysiologists as well as it leads to time-consuming and more effort. In addition, the neurophysiologists experience various levels at the time of diagnosis sometimes the diagnostic report may give contrary opinions [7] and [8]. Therefore, the development of an automated, computer- aided method for the genuine diagnosis of alzheimer and gauging of neurological disorders is urgently needed [9] and [10]. The diagrammatic representation of alzheimer is illustrated in Fig.1.

In the last decade, several brain electrical signal processing techniques have been developed to detect the epileptic Alzheimer automatically based on various machine learning techniques. The feature extraction and classification is the essential technique to classify the EEG signals in to Alzheimer and non-Alzheimer. The feature extraction techniques plays an important role while classifying epileptic Alzheimer in the existing methods, whereas this study aims to develop a innovative technique using raw EEG signals without implementing any feature extraction method.

In the existing literature, there are various methods proposed to classify alzheimer where trying to achieve higher

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classification accuracy with early prediction. Since EEG signal varies for each patient because variations in location and type of Alzheimer[11], therefore in most of the proposed method patient –specific concept was used to predict epileptic Alzheimer. In most of the methods, Alzheimer and non-Alzheimer classification are done using supervised techniques based on feature extraction and classification methods. In [12], the author uses supervised technique based on the Support Vector method (SVM) classifier for alzheimer classification. Most of the existing methods use SVM classifier like [13]-[15], to classify the epileptic Alzheimers. This classifier achieved outstanding performance compare to other classifiers in terms of specificity and sensitivity [16].

In the previous studies, the extracted features are classified based on domains like time domain, frequency domain, time-frequency and non-linear features [17],[18]. The classification technique implemented after the feature extraction process to predict varies EEG signals using different types of classifiers [20]. In [21], author uses Discrete Wavelet Transform (DWT) to extract features and with radial basis function it was trained by the SVM using gray wolf optimizer to detect alzheimer. In [21], author established a hybrid method using optimized parameters generated by SVM technique with the genetic algorithm and swarm pBWTicle optimization, which used as an efficient tool to classify the epileptic EEG signals. Moreover, these methods require manual feature selection to achieve higher accuracy [24]. These methods use feature extraction as significant tool in determining Alzheimer and non-Alzheimer classification, to show more accuracy. For the past few years, a new deep learning (DL) technique was introduced in which the task is carried using raw dataset without any feature extraction, which is used as a new avenue to over this issue.

In the past few years, DL has entered as a main idea in the vision of computer and also for machine learning in the last few years, which exhibits like super human brain for an image detection, speech recognition and many more [23]. Furthermore, in recent existing studies, feature extraction was not executed and the DL technique uses raw EEG signals for classification.

The main challenging task of the existing method is to determine the essential features of the signal also to improve accuracy, reduce computational complexity and also efficient memory. It was not an easy task during the real-time applications. Based on these challenges, we introduce a new innovative technique which encloses feature extraction and classification into mono framework BWT semi-supervised technique. The main contributions of the proposed work were summarized as follows:

- Developing mono automatic framework that enclose each characteristic extraction and class technique without the use of any preprocessing method.
- Introducing a supervised technique which could accurately classify Alzheimer and non-Alzheimer signals by extracting the important features from the EEG indicators by way of utilizing the DC-BWT.
- The two fully connected layers cluster the statistics by way of using the match map field functions based totally at the BWT work approach.
- All of the clustered records are transformed as categorized data at remaining it turned into directed to the basic feed forward Multilayer Perceptron (MLP) to reap better accuracy.
- The rest of this paper is organized as follows. The hassle system and the datasets are explained in section II. The methodology is introduced in segment III. Our experimental outcomes and comparisons with the country of the BWTwork are tested in phase IV. Eventually, the conclusion of our paintings is supplied in segment V.

II. PROBLEM FORMULATION AND DATASETS

On this work, we formulate the epileptic Alzheimer category problem consistent with the proposed approach. As an instance, within the semi-supervised based method, it is a classification problem. The goal is to categories the enter EEG recording into Alzheimer or non-Alzheimer group by giving a label to the predicted cluster elegance. Consequently, it's far a clustering trouble wherein the enter EEG recording is assigned to certainly one of two clusters this is based totally on the structure located within the information. In this have a look at, we used renowned EEG datasets to evaluate our approach.

Bonn Dataset

The EEG dataset used in this examine has been received from the Epileptology DepBWTment of Bonn University (Bonn) [24]. There are 5 sets of EEG recordings in this dataset distinct as A to E. Each set consists of records from 5 topics. Set A represents healthy subjects with open eyes. Set B is recorded from healthy subjects with closed eyes. Set C is recorded from non-epileptogenic sector of the epileptic patients' brain, whilst Set D is recorded from epileptogenic

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region. Eventually, Set E corresponds to epileptic patients for the duration of ictal duration. Each set incorporates a total of a hundred EEG segments. The period of each segment is 23.6 s and the sampling price is completed at 173.61 Hz. The iEEG signals were filtered the usage of fourth-order Butterworth band-skip clear out with cutoff frequency at zero.5 and 85 Hz. On this look at, we focus on set C, set D and set E as they constitute the Alzheimer and non-Alzheimer EEG indicators respectively. An instance of an EEG section from Set C and Set D is shown in Fig. 1(a) , Fig. 1(b) and Fig. 1 (c) respectively.

III. METHODOLOGY

In this proposed method, we implement a new innovative technique with an aim to classify Alzheimer and non-Alzheimer EEG signals accurately. Raw EEG data is used without delay as input to our models,i.e. without function engineering.The simplest preprocessing performed on the information is normalization. The large functions are extracted automatically to reduce the overhead and accelerate the type technique. Every segment in every dataset is used as a training batch for our models. In this work, we introduce a semi-supervised learning method based on Deep Convolutional Adaptive Resonanace Theory (DC-BWTMAP). DC-BWTMAP can extract the significant features to stumble on the epileptic Alzheimer the use feed forward propagation technique[25]-[28]. After training the DC-BWTMAP in an unsupervised manner, the pre-trained cluster dataset is pursued by a multi-layer perceptron (MLP) which matches because the EEG classifier that could differentiate among Alzheimer and non- Alzheimer indicators. The classifier is skilled the usage of labels and consequently the method is semi-supervised based. The technique is generalized over a benchmark datasets, its performance is evaluated by validation metrics. The diagrammatic representation of the proposed semi-supervised method is illustrated in Fig.3

A. Data Preprocessing

The raw EEG signals are preprocessed using the simple normalization method. The dataset are normalized by converting them to pursue standard normal distribution by zero and unit variance. This method is crucial to get the records on the same scale which allows in improving the performance. The standard rating corresponding to every records point is given where z is the standard score corresponding to the data point x in the EEG time series, μ is the data mean, σ is the data standard deviation.

B. Deep Convolutional Neural Network

The use of CNNs for massive-scale imaging and video identification has been very successful [29],[30] due to the established order of huge public photo repositories, such as ImageNet [31], and high-overall performance computing structures, inclusive big-scale dispensed clusters [32],[33]. Currently, some studies have begun making use of CNNs to EEG signals [34], and research interest in the use of CNNs for convulsion prediction has improved, in all likelihood because these techniques had been used notably and are thus higher set up and more familiar within the research network.

A CNN consists of an input and an output layer, in addition to more than one hidden layers. The hidden layers of a CNN typically encompass convolutional layers, pooling layers and completely linked layers. Convolutional layers apply a convolution operation to the input, moving the result to the subsequent layer. The convolution emulates the response of a person neuron to visual stimuli. Convolutional networks may include local or international pooling layers that combine the outputs of neuron clusters in one layer right into a single neuron within the next layer. Mean pooling uses the average edge from every cluster of neurons within the previous layer. Fully connected layers connect each neuron in one layer to every neuron in another layer. The CNN is in principle the same as the conventional multi-layer perceptron neural network.

As compared with conventional classifiers, CNNs have apparent blessings for studying excessive-dimensional records. CNNs hire a parameter sharing scheme, that's utilized in convolutional layers to manipulate and decrease the wide variety of parameters. A pooling layer is designed to step by step lessen the spatial length of the representation and the number of parameters and computation in the network, and in the end manipulate overfitting.

C. BWT

BWT is a biologically-spurious principle of how a mind learns to consciously attend, analyze and apprehend styles in continuously converting surroundings [24] – [27] . The idea states that resonance regulates learning in neural networks with feedback (recurrence). consequently, it is more than a neural network architecture, or maybe a own family of architectures. It’s a family of neural network architecture that have interesting attributes for applications in science and engineering technology[28]. This neural network is fast and stable which relevantly requires small memory and also it

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was a straight forward algorithm. The BWT neural network composed of two fully connected layers as feature representation layer and category representation field. Additionally it has a system that regulates both the search and the learning mechanism by allowing or inhibiting categories to resonate. The feature representation acts as a input layer, it simply works as a comparator and it satisfies the category layer, which is also called as comparison layer. The feed forward mode functions in the second layer named as recognition or competitive layer. The basic BWT uses two fully connected layers for the implementation of the comparison and competitive layer. In proposed method, DC-BWTMAP a semi-supervised technique where the convolutional layers are embedded with the fully connected layers of the BWTMAP. The architecture of the BWT is illustrated in Fig.().

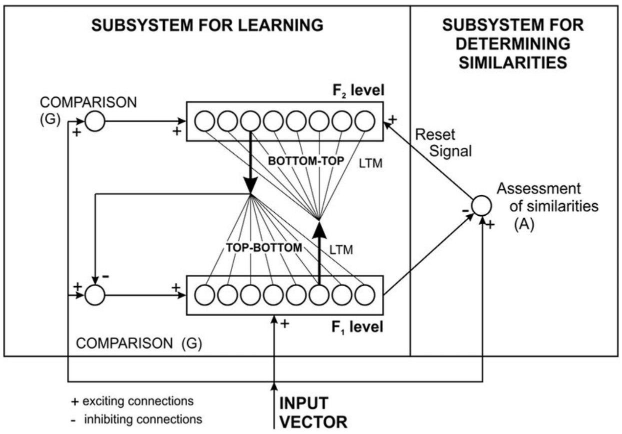

Fig. The architecture of the BWT Theory

D. Deep Convolutional Adaptive Resonance Theory

BWT is a type neural network that studies the data depiction through the unsupervised manner [30]. The main aim of the BWT is to address the stability-plasticity perplexity by introducing the flexibility to find out absolute input patterns in an exceedingly quick and stable self-organizing fashion while not tormented by harmful forgetting. DC-BWTMAP architecture of proposed method, works as follows the normalized data is entered as input to the first convulsion layer, then max pooling layer. The output of the Convolutional layer forwarded to the BWTMAP which is a supervised learning applications, which is used for pattern classification or classification tasks. In general, it consists of two fully connected layers as BWT units (BWT_a and BWT_b) it was interconnected using an associative learning network.

Typically BWT_a clusters the EEG signals while BWT_b clusters class labels as Alzheimer and non-Alzheimer in parallel. Therefore, during the time that BWT just maps samples to category, whereas an BWTMAP goes a step ahead maps categories to class labels. At the time of training , BWT_a has a agreement regarding the activities of BWT_b , latter it encodes the target labels. The second one is the vigilance test , it was performed by using the BWT_b's supervisory signal(i.e., response) which allows to learn whether the prediction is correct or incorrect otherwise it can say as to trigger mismatch prediction.

Moreover, if the prediction of BWT_a's disproven by BWT_b 's , then the map field provokes a match tracking mechanism in which the resonating category of BWT_a is inhibited, so that in basic vigilance is changed temporarily and again the stBWTs the searching process inorder to select another category by BWT_a. Furthermore, the map field is responsible to assess quality of mapping between the two fully connected BWT modules and also it is responsible if there is any necessary to add new node using the supervised signal. In general, BWTMAP reduces the training error by specificity.

Frequently, BWT_b is excluded and the labels of N_b-dimensional vector is used in that place (Because vigilance parameter of BWT_b is set to 0, which relates to number of categories equals to number of classes). Also, BWT_a's baseline vigilance parameter, which limits the quality of the space , generally the values minimum which correlates with improve the potentiality and network complexity (i.e., a higher level of compression). The diagrammatic of the DC-BWTMAP is illustrated in Fig.[].

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The training process of the DC_BWTMAP is performed using the labeled EEG segments in each dataset. The activation function[31] is defined by (ReLu) Rectified Linear Unit is used for the entire convolution and deconvolutional layers to introduce non-linearity and to assure robustness that the data is noise.

where $f(x)$ is the ReLU activation function and x is the sum of the weighted input data.

Batch Normalization[32] is used to improve the stability of the network , which increase the training speed and reduce overfitting given by equation .

$$BN_{\gamma,\beta}(x_i) = \gamma \frac{x_i - \mu_B}{\sqrt{\sigma^2_B + \epsilon}} + \beta$$

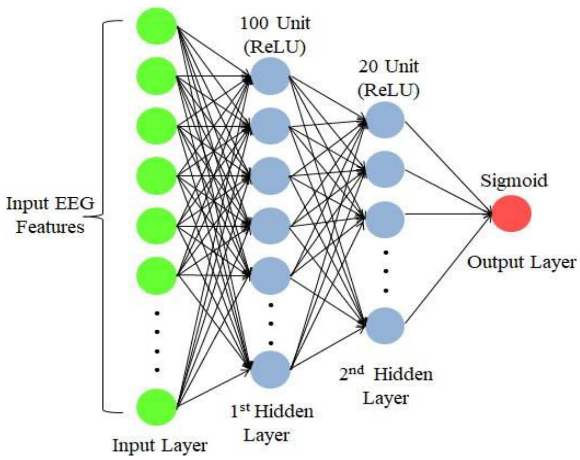
where x_i is the input vector being normalized in a mini-batch $B = \{x_1, x_2, \ldots x_m\}$. μ_B and σ^2 are the mean and variance of the mini-batch, respectively. ϵ is a constant added for numerical stability. γ and β are parameters being learned[27].

Adam optimizer is used for DC-BWTMAP, the loss function being optimized in which updates the exponential moving averages of the gradient(m_t) and the squared gradient(v_t) which estimates the first and second moment given by().
Equation---()
Where x_i is the input signal and m_t is the exponential moving average of the gradient , squared gradient (v_t) and theta are the network parameters being learned.

After training the DC-BWTMAP, the reconstructed parameters learned are stored in Long Term Memory(LTM) to be utilized in the whole classifier model as illustrated in Fig. (3). In the next stage, a feed forward neural network is trained to carry out the classification task in a supervised manner.

E. Multilayer Perceptron (MLP)
In MLP architecture, complex non-linear features are extracted to achieve more accurate classifications at the constant of parameter size. In our proposed method is used as backend classifiers to predict the label of the input EEG segment. The MLP architecture consists of two hidden layers as given in Fig.(). The training process is carried out using the backpropagation and the cost function is carried out using Adam optimizer. While training the MLP, we use categorical cross entropy as a cost function().

$$(y, \hat{y} = -[y \log(\hat{y} + (1 - y) \log(1 - \hat{y}] \qquad (5)$$
where $l(y, \hat{y}$ is the cost function, $\hat{y}$ and y are the true output and the predicted output respectively.
The ReLU activation function is used throughout the hidden layers and sigmoid activation function (6) is chosen for the output layer to predict the Alzheimer and non-Alzheimer EEG signals
where x_i is the summation of the weighted input data and p_i is the probability that the EEG signal is Alzheimer.



The architecture of Multilayer Perceptron Fig.

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F. Training and Testing Method

The testing strategy of our proposed methods is carried out by applying ten-fold cross-validation. This technique assures the robustness and validation when applying the proposed methods over different samples and subjects. In ten-fold cross- validation, the performance metrics are computed as an average over ten iterations. In each iteration, 10% of each epoch is used as unseen test set and the rest is split into 70% as training set and 30% as validation set on which the hyper- parameters are updated. The entire dataset of Bonn are used in our experiment. The Alzheimer and non-Alzheimer groups are balanced in both datasets.

In order to evaluate the performance of our first method, supervised model, some measures are calculated on the test set which is the 10% portion of the data unseen during the training. These measures include sensitivity (19), specificity (20), accuracy (21) and F1-score (26). Values of these metrics are extracted from the confusion matrix and averaged across all iterations. In this study, we consider the Alzheimer EEG segments as “positive” and the non-Alzheimer segments as “negative”.

With a purpose to evaluate the overall performance of our method approach, supervised manner, some measures are calculated at the test set which is the 10% portion of the statistics unseen at some point of the education. Those measures encompass sensitivity (19), specificity (20), accuracy (21) and F1-score (26). Values of these metrics are extracted from the confusion matrix and averaged throughout all iterations. In this study, we keep in mind the Alzheimer EEG segments as “postive” and the non-Alzheimer segments as “negative”.

$Sensitivity = TP + FN$

TN

$Specificity =$
$TN + FP$

$TP + TN$

$Accuracy =$
$TP + TN + FP + FN$

$cision * Recall$

$F1 - score = 2 *$
$Precision + Recall$

where TN, TP, FN and FP are the true negative, true positive, false negative and false positive respectively.

IV. RESULTS

Respectively, TN and TP are represented a total number of accurately detected events of a true negative and true positive. The FN and FP are representing a total number of inaccurately positive and negative events respectively. In many cases, the indices performance of Daubechies wavelet transforms were quietly similar to each other.

The statistical parameters are observed reaching the maximum number accuracy while using the Daubechies wavelet. The approximate EEG signals are more accurate with a comparison of results in Table1. The proposed method observed the accuracy of (99.52%) compared with the existing method for Alzheimer detection. The improved sensitivity is due to the features like testing and training set, Logistic Regression, feature extraction, and CNN.

	Alzheimer is Present	Alzheimer is Absent
Not Detected	False Negative (FN)	True Negative (TN)
Correctly Detected	True Positive (TP)	False Positive (TP)

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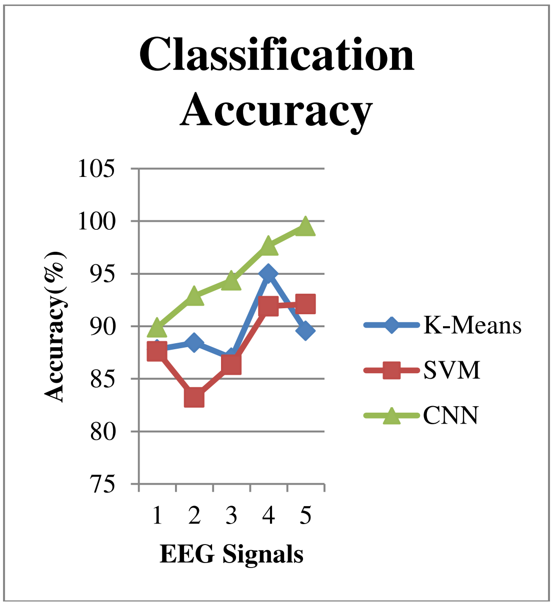

The accuracy of Alzheimer revealing in EEG classification is depending upon the feature classification and correctly segmented out of the signals. The performance level of CNN and the LR method is used to classify through the level of accuracy.

V. CONCLUSION

The trying out strategy of our proposed methods is executed with the aid of applying ten-fold cross-validation. This technique assures the robustness and validation when making use of the proposed techniques over extraordinary samples and subjects. In ten-fold cross- validation, the performance metrics are computed as a mean over ten iterations. In every generation, 10% of every epoch is used as unseen check set and the rest is cut up into 70% as training set and 30% as validation set on which the hyper- parameters are up to date. The entire dataset of Bonn are utilized in our experiment. The Alzheimer and non-Alzheimer organizations are balanced in the dataset.

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