International Journal On Engineering Technology and Sciences – IJETS
ISSN (P):2349-3968, ISSN (O): 2349-3976 Volume XI - Issue V, May – 2024

EEG Signal classification using convolutional neural network for epileptic seizure detection

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ABSTRACT

Electroencephalography (EEG) is a technique used to capture an electro gram of the brain's spontaneous electrical signals. It is commonly used to identify epileptic seizures and provide vital information about brain electrical activities. In previous studies, various neural network approaches have been used to classify brain seizures. However, these methods have limitations in accurately identifying parameters such as output accuracy and sensitivity in epileptic seizure detection. To address these issues, three different classification techniques - K-Nearest Neighbors, Support Vector Machine, and Convolutional Neural Network (CNN) are proposed for detecting epileptic seizure detection. This method consists of four stages: input image, preprocessing, feature extraction, and three separate classifications. The input for this system is a dataset of EEG signal analysis, specifically the CHB-MIT dataset. The input data is preprocessed using a Bandpass Filter to remove noise from the electrical wave. Feature extraction is then used to identify the complex characteristics of the wave and eliminate unnecessary information. This process selects a more accurate subset of features, reducing the training time of the model. The features are assessed for their overall significance to determine if they are redundant or irrelevant. Finally, the classification is performed using the three different methods. K-Nearest Neighbors is used to categorize a data point according to the classification of its neighbors. Support Vector Machine divides the input area that has the largest margin. Convolutional Neural Network is used to identify the extracted wave of the electrical impulses and provide accurate results using the MATLAB tool. The proposed output has a classification result of 92.51% for KNN, 94.65% for SVM, and 97.65% for CNN from the CHB-MIT dataset, which is an improvement over existing methods

Keyword: Electroencephalogram (EEG), K-Nearest Neighbors, Support Vector Machine, Bandpass Filter, Feature extraction, Feature selection, Convolutional Neural Network (CNN).

INTRODUCTION

EEG recordings are a non-invasive method of measuring electrical brain activity. Electrodes are placed on the head, typically in the form of a cap, to capture these impulses. Cup-shaped electrodes are positioned at specific locations on the scalp, ensuring that the skin does not come into direct contact with the electrode material. The main concerns for detecting epileptic seizures are the prediction rate and classification performance, as the amount of data continues to grow. One potential solution is to use optimization techniques to improve classification performance. The electrodes also provide space for an electrolyte to be stored while recording the electrical signals.

The interface between the electrode and skin is affected by factors such as the temperature of the electrolyte, the surface area of the electrode, and the interface layer. During medical diagnosis, a neurologist can analyze the EEG signals to determine the presence or absence of seizures and make an accurate diagnosis. Given these considerations, it is crucial to develop an automated system for detecting epileptic seizures to expedite diagnosis and manage the increasing amount of EEG data. The primary objective of this research is to create an effective model for classifying epileptic seizures by selecting specific characteristics from the input EEG data to maximize system performance.

Brain electrical activity are recorded using Electroencephalography (EEG), a non-invasive method of neuro monitoring. Recently, there has been an increasing trend in the use of high density and long-term EEG signal monitoring systems. However, the current EEG clinical devices use a head cap that is attached to a computer and power supply, making it uncomfortable for extended periods of time and impractical for everyday use in a patient's natural setting. In situations where every EEG signal needs to be continuously read out, local pre-processing can be used as a lossless data compression technique. However, EEG signals are typically limited, and local pre-processing would be more beneficial if the system could identify relevant EEG events and transmit data only during those occurrences. It is important to note that this method can only reduce the system's average transmit power, not its peak transmit power.

In the brain, when a neuron receives stimulation from a nearby neuron, it produces an action potential. This is caused by changes in the permeability of the cell membrane, which allows sodium ions to pass through from the outside of the cell to the inside. This influx of positively charged ions results in depolarization, which continues along the axon towards the dendrites of the subsequent neuron, ultimately conveying an impulse down the nerve fiber. An examination of the signal collecting, de-noising, and feature engineering stages of the EEG signal processing process. The EEG signal is completely described, together with the time-frequency, high-order spectral, and nonlinear dynamic analytic evaluation criteria. Combining conventional and deep learning approaches to classify EEG signals. In addition, a review of the most often used datasets for EEG signal processing.

Objective

The goal is to develop an effective technique for detecting epileptic seizures. This technique will take gain of the waveform signal patterns that indicate the occurrence of a seizure. Pre-processing will involve using a band pass filter to reduce noise that can obscure brain activity. The pre-processing step will use a band pass filter to reduce noise, while feature extraction will uncover patterns for the supervised system. Feature extraction will be used to discover patterns for a supervised seizure detection system and will use EEG inputs and a KNN classification technique to determine seizure status. The waveform signal patterns will be specific and descriptive, allowing for accurate detection of seizures, EEG inputs and a SVM classification technique to determine the presence of a seizure. EEG inputs are electrical signals from the brain that will be used in the seizure detection system. Finally, the CNN classification technique will use the extracted information to accurately determine the seizure status.

EXISTING METHOD

In the existing method, Electroencephalography (EEG) is used for neonatal sleep staging and detection, using various classification algorithms. This study proposes the use of Automated Machine Learning (autoML) techniques for accurate and reliable multi-channel EEG-based neonatal sleep-wake classification. The aim of the study is to investigate the feasibility of autoML without the need for extensive manual selection of features or hyper parameter tuning. The data used in the study was acquired from newborns at a post-menstrual age of 37 ± 5 weeks. A total of 3525 30-second EEG segments from 19 babies were used to train and evaluate the suggested models. From each channel, twelve temporal and frequency domain characteristics were extracted. The input vector for each model consisted of 108 dimensions, containing the common characteristics of nine channels. The performance of each model was assessed using a range of evaluation measures. The AutoML-based Random Forest estimator achieved a maximum mean accuracy of 84.78% and a kappa of 69.63%, which is the highest accuracy reported for EEG-based sleep-wake classification to date. The AutoML-based AdaBoost Random Forest model achieved an accuracy of 84.59% and a kappa of 69.24%.

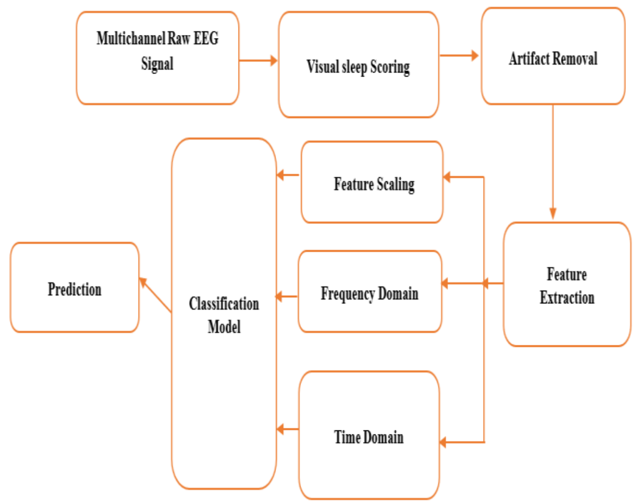

Figure 1 Existing Block diagram

EXISTING DRAWBACK

In the Feature Scaling, time domain, and classification of EEG signals to detect epileptic seizures, a high level of background noise and limited spatial detail require multiple electrodes due to the non-stationary nature of the signal. For example, when analyzing the EEG signal for epileptic seizures, it is important to consider the fluctuations in brain activity over time.

PROPOSED METHOD

In recent research analysis, there has been a growing interest in using EEG data for the identification and classification of Epileptic Seizure Detection. Medical professionals often rely on EEG signals, among others, for evaluation. Figure 1 above illustrates the use of three different methods for EEG classification. This method aims to improve the classification output and identify the most effective way to use EEG electrical waves, using the CHB-MIT dataset. Pre-processing is performed using the Bandpass Filter technique to reduce noise in the input image. Feature Extraction is then carried out to identify complex signals and minimize error waves. Feature selection further enhances classification performance by increasing accuracy and reducing misleading data. To extract the most crucial information from the data and identify its class, frequency band decomposition is used to convert the EEG signal into a feature vector. When applied, the Support Vector Machine determines that the continuous driving time is the critical factor in differentiating between serious and mild exhaustion. The K-Nearest Neighbors method determines the similarity between the sample and the training sample set, while the CNN classification method, using a minimum of two electrodes, has shown improved accuracy on the CHB-MIT dataset

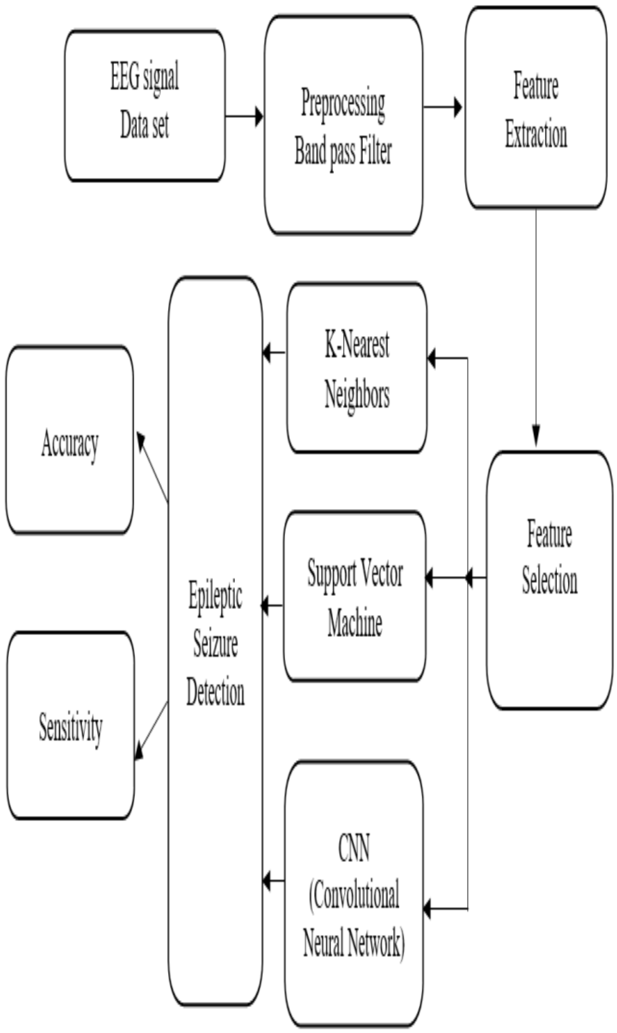

Figure 2 Proposed Block for ECG classify method

BLOCK DIAGRAM EXPLANATION

ELECTROENCEPHALOGRAPHY (EEG) AND CHB-MIT DATASET

An EEG is a diagnostic test used to detect abnormalities in the electrical activity of the brain, known as brain waves. During the procedure, small metal discs called electrodes are placed on the scalp to measure the electrical charges produced by brain cells. These charges are then amplified and displayed as a recording, either on paper or on a computer screen. The outcome are then interpreted by a healthcare provider. The CHB-MIT dataset is a collection of EEG recordings from different patients with uncontrollable seizures. These patients were observed for several days after discontinuing anti-seizure medication in order to assess their eligibility for surgery and to characterize their seizures. The dataset includes patients, each with two recordings, resulting in a total of hours of scalp EEG recordings and seizures. The Figure 4.2 shows input dataset contains three types of seizures: tonic, atonic, and colonic.

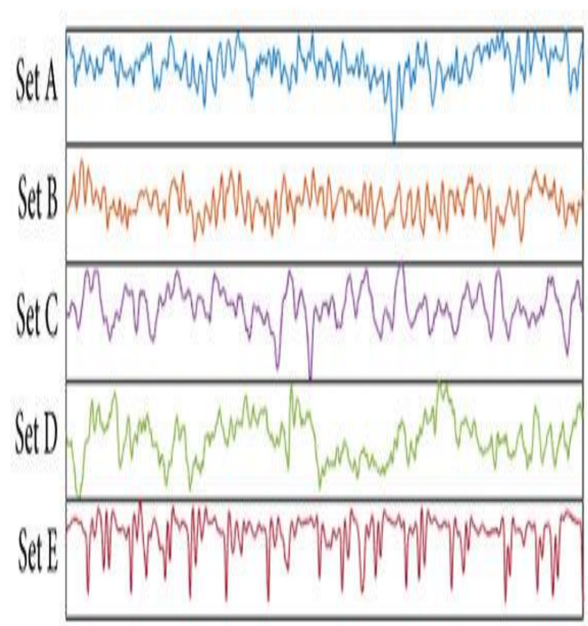

Figure 3 EEG wave form of CHB-MIT dataset

Electroencephalography (EEG) is a noninvasive tool for extracting information about the electrical functioning of the brain, indicating a large number of neuronal potentials on the membrane that will be measured by placing electrodes on the scalp, which is critical in epilepsy diagnosis. Visual identification of epileptic seizures using an EEG record is a tedious procedure that takes up a lot of time for the neurologist. On the other hand, the EEG signal provides a powerful biomarker for detecting many aberrant brain states, such as sadness and seizures for reaching specific treatment targets, it is crucial to automate epilepsy detection by identifying aberrant EEG conditions using machine learning algorithms.

The kind of EEG also influences how EEG datasets are used. While scalp EEG is noninvasive, it is less sensitive in identifying electrical synchronized and may contain noise and dropouts when compared to intracranial EEG datasets 1; nevertheless, the latter process is intrusive, costly, and more prone to problems. Long-term continuous data, such as EEG recordings with seizure start and finish timings, enables algorithms to evaluate circadian rhythms and employ time series models. Research suggests that seizures are unique to each patient, as opposed to the therapeutic method of classifying individuals.

Electroencephalography (EEG) is a non-invasive tool used to extract information about the electrical activity of the brain. This is done by placing electrodes on the scalp to measure the abundance of neuronal potentials on the membrane. EEG is critical in diagnosing epilepsy, but the visual identification of epileptic attacks through EEG records is a time-consuming and tedious process for neurologists. However, the EEG signal contains a powerful biomarker that can detect various brain disorders, such as depression and seizures. To achieve targeted treatment goals, it is crucial to automate epilepsy detection by using machine learning algorithms to identify abnormal EEG conditions. Epilepsy is a diverse category of neurological illnesses and syndromes characterized by repeated, uncontrollable, paroxysmal seizure activity.

This is usually accompanied by a clinic electrical correlate on the electroencephalogram. A diagnosis of epilepsy can be made after two or more spontaneous seizures. However, without a reliable witness account, diagnosing the disease in its early stages can be challenging, leading to delays in treatment. In cases of clinical doubt, paraclinical EEG findings can aid in earlier diagnosis and therapy. However, EEG collection and interpretation are time-consuming and expensive, as interpretation is limited to trained professionals.

This has sparked an interest in automated seizure recognition and While seizure semiology can provide clinical clues about the type and origin of a seizure, determining whether it originated in the left or right hemisphere can be difficult, especially in cases of temporal and occipital lobe epilepsies. This can also be challenging when attempting to apply seizure detection across multiple individuals. Current research in automated seizure identification using EEG recordings has focused on patient-specific predictions, where a classifier is trained and evaluated on the same person.

Epileptic seizures are classed into two types: focal seizures, which occur in a single area of the brain, and generalized seizures, which affect the whole brain. Epilepsy's a etiology is not usually understood, however it can be caused by a range of reasons including head injuries, brain infections, brain tumors, genetics, and developmental abnormalities. Epilepsy is a chronic neurological condition marked by recurring seizures caused by aberrant electrical activity in the brain. It is one of the most prevalent neurological illnesses, affecting around one percent of the global population. Seizures can occur in a variety of ways, from mild convulsions to severe convulsions, and their frequency can range from once in a lifetime to multiple times every day.

PRE-PROCESSING USING BAND PASS FILTER

The EEG waveform must adhere to certain limitations in terms of signal values, as shown in Figure 4.3. During the pre-processing stage, each signal value is examined and validated to ensure it meets the minimal threshold. If it does, it is approved for further processing. However, if the electrical wave value falls below the permitted threshold of 10 beats per minute, it is returned for additional processing. This approach effectively removes any artefacts from the recording, resulting in a cleaner and more relevant signal and filtered signals are then passed on to the next level.

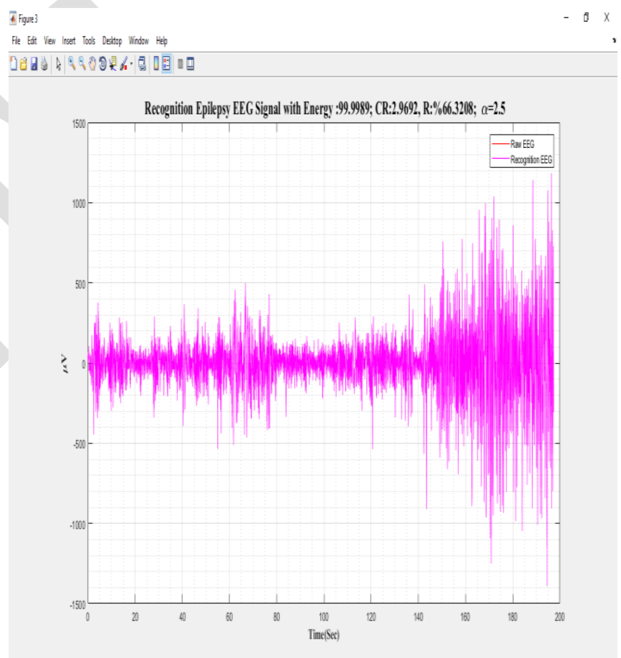

Figure 4 Preprocessing filter output of selected class of input data set

The Band Pass DE -noising technique operates on the assumption that a signal's coefficients contain random errors overall, while deterministic changes are encapsulated in a limited number of larger coefficients. A nonlinear thresholding function in the Band Pass domain will typically retain a small number of larger coefficients that reflect the underlying signal, while the noise coefficients will approach zero. In contrast, the wavelet de-noising technique applies the discrete wavelet to the original noisy data, then thresholds the detail coefficients before inversely transforming them to produce a de-noised time-domain signal.

In the preprocessing phase of EEG data, everyone tackled two issues: noise reduction and class imbalance. Individuals used Empirical Mode Decomposition (EMD) to eliminate noise from EEG recordings and enhance SNR. Another key issue in seizure prediction is the class imbalance problem. Only a few rectal state samples are collected during EEG data collecting, causing class imbalance and lower sensitivity and specificity. We propose rectal data production using Generative Adversarial Networks to decrease the class imbalance ratio between rectal and interracial state data.

FEATURE EXTRACTION

The initial feature vector is transformed using feature extraction techniques to lower its dimension from n to m, where m<n. Data is transformed by feature extraction techniques so that it may be projected onto a new, lower-dimensional feature space. Learning from the data and extracting knowledge to enable informed decision-making is the primary difficulty of feature extraction. In order to facilitate the next learning and optimization stages, feature extraction begins with an initial set of measured data and creates derived values (features) that are meant to be useful and non-redundant. Finding the collection of parameters that precisely and uniquely determine an object's form is known as feature extraction.

Seizures are detected through recordings, and these regions are further analyzed using EEG records. However, manual analysis of the EEG signal by physicians is not always accurate, making automated analysis essential for epilepsy investigations. Numerous methods have been developed to differentiate between focal and non-focal EEG signals, but an efficient and suitable system is needed for accurately detecting seizures in EEG signals. Additionally, various feature selection schemes have been developed to define and distinguish signals based on their characteristics. The optimal feature subset is selected by rejecting redundant and irrelevant features from the input signal. The output of this feature selection process determines which features are essential for describing the dataset signals.

The initial data preparation involved fundamental transformations, elimination of outliers, and normalization. The subsequent feature selection process was multi-stage. Initially, two methods were used for pre-selection, with each characteristic being analyzed independently using intra-distance. This resulted in the selection of 50 high-performing characteristics for each method. The authors then used forward feature selection methods on the pre-selected features, resulting in the identification of the most relevant features.

However, the model's approach of treating the first signals of each user's data as approved and the rest as unauthenticated is overly simplistic and does not account for real-world complexities. EEG data is known for its diversity and dynamic nature across multiple sessions and activities, therefore a more suitable method would be to consider it as a multi-class classification problem, with each user representing a distinct class. It would also be beneficial to test the model's performance on previously unknown data to evaluate its effectiveness in realistic scenarios

FEATURE SELECTION

One of the most important selections. Using feature selection methods can lead to faster training times, models that are easier to understand, less biased, and more accurate. There are many feature selection techniques, including filtering techniques, layering techniques, and machine learning techniques. Electroencephalography (EEG) is the recording of electrical impulses from the brain with a specific sensor or electrode. This approach is used for treating and diagnosing a variety of disorders. Researchers' demand for EEG has expanded significantly in recent years as neural network technology have advanced. Neural networks for training the model require data with low noise distortion. Signal filtering and other sign extraction methods are used to remove noise (artefacts) from EEG data. The current publication presents a complete overview of recent approaches for extracting the electrical signals of an EEG signal that have been employed in investigations during the previous decade.

This paradigm was created for them because the input method is more accurate than filtering and faster than the wrapping method. Standard regression models, which are measures that reduce correlation to zero and estimate predictions, are among the inclusion criteria. This adjustment was made at least for the first comparison. Transformation reduces the shape of the model by adding more dimensions to it. The electroencephalogram (EEG) is a tool used to examine the brain's electrical activity and evaluate the body's condition. It works by detecting potential differences between thin electrodes from collecting CHB-MIT dataset. Figure 4 illustrates the placement of the electrodes in relation to the global system 10/20. A total of twenty-one electrodes are typically placed on the top of the head. The EEG rhythms, also known as background rhythms, are typically divided into two different categories.

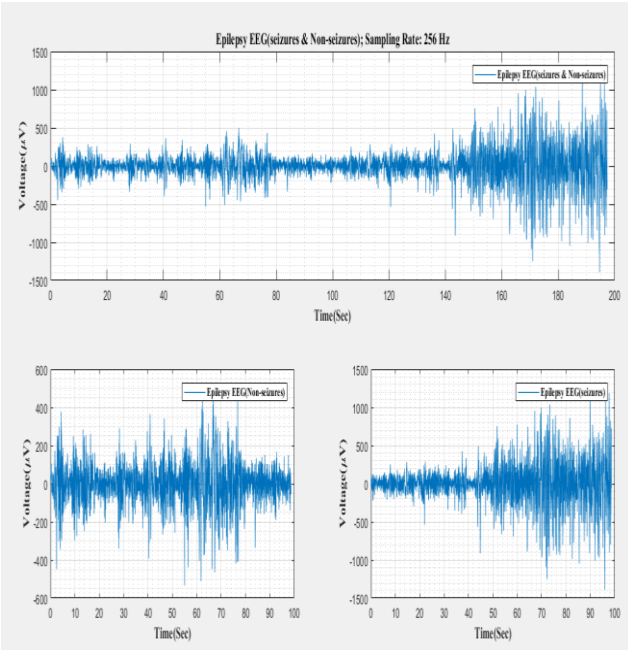

Figure 5Output extract signal in non-epileptic seizures and seizure electrical signals.

Filtering is necessary to reduce specific frequency components of a signal, which is especially crucial when dealing with EEG. Human EEG waves can be divided into four frequency ranges: Delta, Theta, Alpha, and Beta. Delta waves have a frequency of 3 Hz or less and are the slowest with the highest amplitude. They are typically prominent during the third and fourth stages of sleep and in children under one year old. Theta waves have a frequency range of 3.5 to 7.5 Hz and can be observed in individuals of various ages. Alpha waves have a frequency range of 7.5 to 13 Hz and are primarily generated in the posterior parts of the head. They are the dominant signal in a healthy adult when in a relaxed state. Beta waves have a higher frequency range.

K-Nearest Neighbors Classification

The K-NN approach initially selects a training sample set. Every sample category in the sample set is known. Determine the sample's resemblance to the training sample set in order to classify it. Choose the k samples with the highest similarity. The sample classification is based on the classes of k samples. K-NN is a type of instance-based or lazy learning that uses pre-defined classification and eigenvalues to process fresh samples. k-Nearest Nearby classifier is a non-parametric technique that classifies a given data point based on its closest neighbor and then classifies the data point into a specific class using the first step, Where

$$Distance\ (x, y) = \sqrt{\sum(x_i - y_i)^2} \qquad \ldots \qquad (1)$$

The KNN algorithm functions as a voting system, utilizing the majority class label to determine the class label of a new data point based on its k nearest neighbors in the feature space. To better understand this concept, imagine a small village with a population of a few hundred residents. In this village, you are faced with the decision of which political party to vote for. In order to make this decision, may turn to nearest neighbors and inquire about their political affiliations. If the majority of k nearest neighbors support party A, it is likely that would also vote for party A. This is analogous to the KNN algorithm, where the majority class label among the k nearest neighbors determines the class label of a new data point

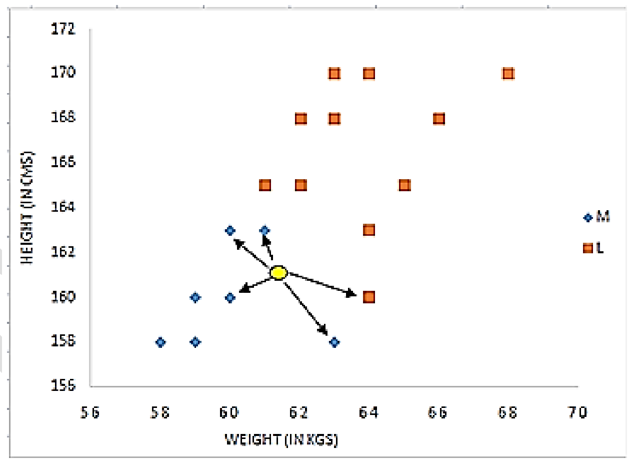

Figure 6 K-Nearest Neighbors classify output

Support Vector Machine

Support Vector Machine (SVM) is a popular supervised learning technique used for both classification and regression tasks in machine learning. However, it is primarily used for classification problems. The goal of the SVM algorithm is to find the optimal decision boundary, or hyperplane, that can divide an n-dimensional space into classes, making it easier to classify new data points in the future. This optimal decision boundary is determined by selecting extreme points, also known as support vectors. Therefore, the technique is called Support Vector Machine.

To perform the Fitness Calculation, first initialize the parameters and create a model of the support vector machine. Then, train the model using the training sample. Next, calculate the fitness function values for each particle using their respective fitness functions. Based on the particle's fitness value, adjust the position of the g_{best} parameter. Update the location and velocity of the particle according to the given formulas to obtain new values for the personal $p_{\ best}$ parameters. The iterative process should continue until either the error condition is met or the maximum number of iterations has been reached. If neither of these conditions is met, return to step 2 and repeat the computation. Figure 7 displays the classification output from the feature classification process.

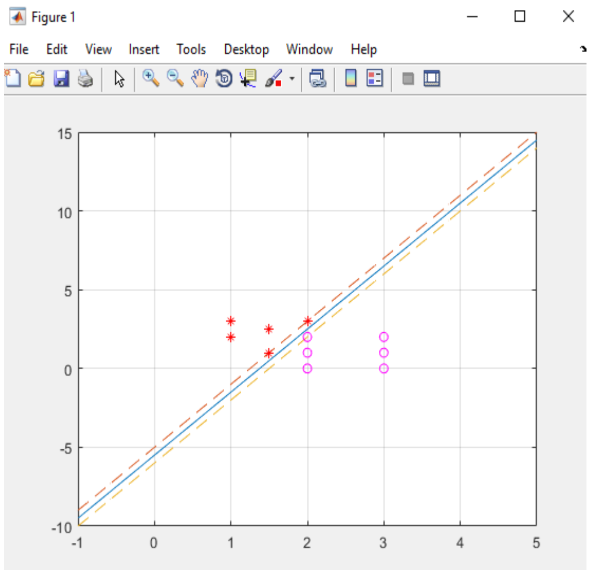

Figure 7 Classify Output of Support Vector Machine training Model

CNN Classification

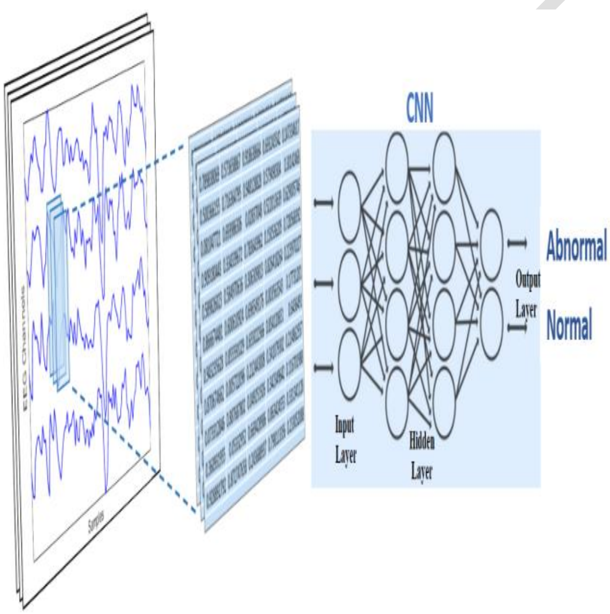

Figure 8 Architecture of CNN

Figure 8 displays the architecture of a CNN layer, which consists of an input layer, hidden layer, and output layer. The input layer plots recorded EEG data in microvolts for each EEG channel, providing a comprehensive set of solutions to aid in learning higher level nonlinear integration. The hidden layer plot shows changes in amplitude over time. The output layer filter saves time and helps to understand the abstract structure, while the plug-in filter removes material from the matrix.

Figure 9 shows the training model utilizes a convolutional neural network, consisting of an input layer connected to the data channel, followed by two hidden layers (60 and 40 neurons each) connected to each other. The final layer (output) generates a noise output, which is responsible for predicting outcomes in one of the tests. The neural network's performance was evaluated as follows: diagnoses present in the medical history database were assigned a code of "1", while the absence of a diagnosis was coded as "0". If the output signal of a neuron exceeded "0.5", a diagnosis was considered to be present; otherwise, a positive diagnosis was assumed to be absent.

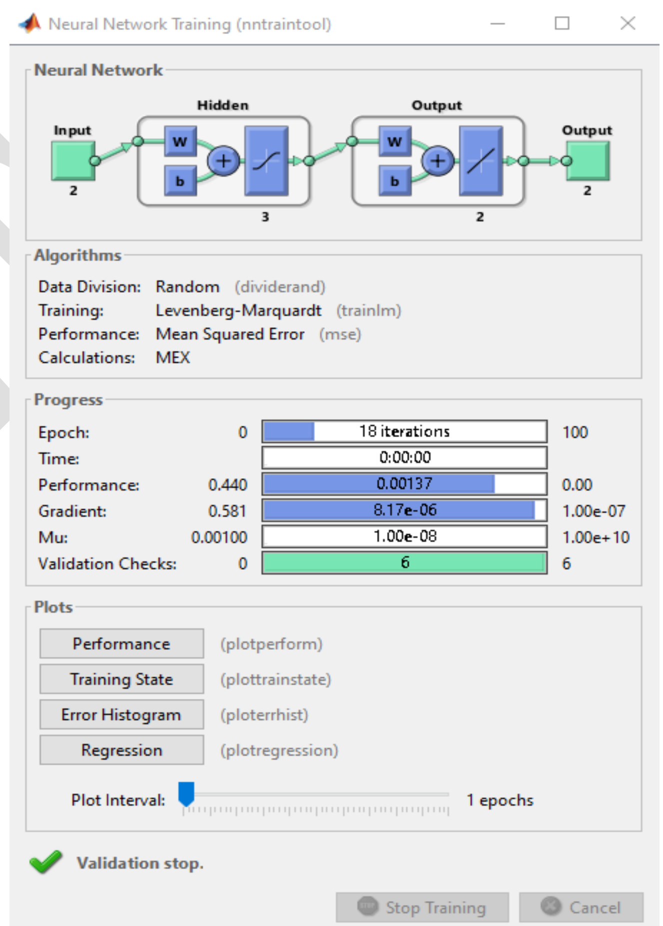

Figure 9 CNN Network training Model

RESULT AND DISCUSSION

The proposed three different classify technique based Epileptic Seizure Detection model was developed and evaluated using electric wave datasets from the CHB-MIT EEG database. This dataset contains single-channel

EEG signals, while the CHB-MIT dataset contains multi-channel EEG recordings. The main difference between the datasets is the type of electrode used, which directly affects the regions and quality of the recorded EEG signals. The majority of the CHB-MIT dataset consists of EEG signals recorded over multiple channels.

Epileptic Seizure Detection

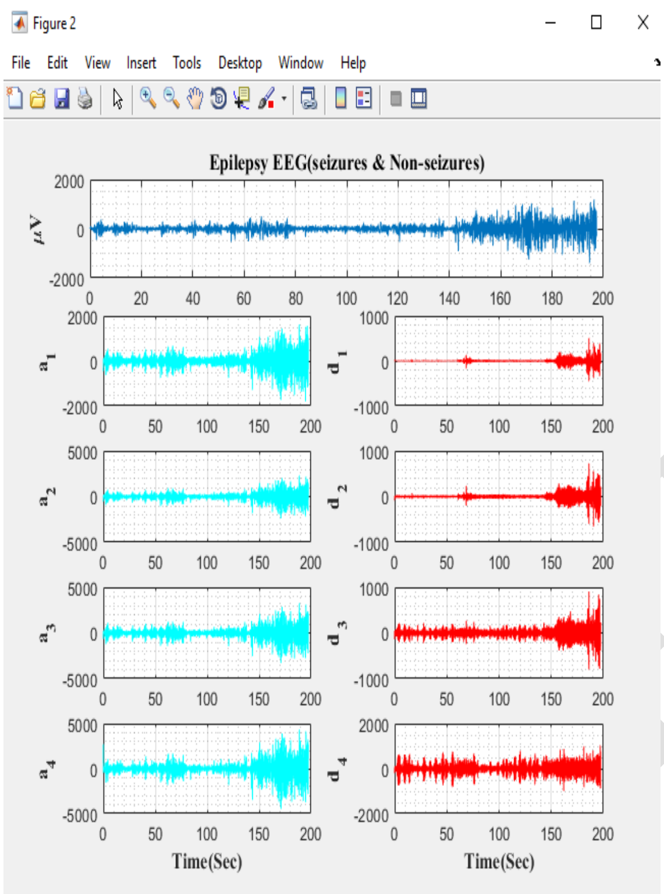

Figure 10 Output analysis for Epileptic Seizure Detection

The Figure 10 shows the extraction method that focuses on the performance of selected classes of a1, a2, a3, and a4 during seizure detection. In order to compare epileptic status, the electronic wave utilized the feature selection method. This involved creating a decision tree for each dataset and using a component-based approach to split the tree. It is estimated that between 15 and 30 out of every 100 individuals suffer from chronic acne. Interestingly, it has been found that approximately 50% of patients who are admitted to the hospital with suspected grand mal epilepsy actually experience non-epileptic seizure

Table 1. Classification accuracy calculation.

	Positive (CHD)	**Negative(Normal)**
Positive	True Positive =98	False Positive =02
Negative	False Negative =04	True Negative=96

Table 1 displays the values for true positives (tp), false positives (fp), true negatives (tn), and false negatives (fn) in that specific order. In medical electrical wave, a true positive refers to accurately diagnosing a medical condition.

Where,

Sensitivity

The following formula is used to determine precision, a measure that indicates the quality of all anticipated positives, including the total of true positives and false positives.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (2)$$

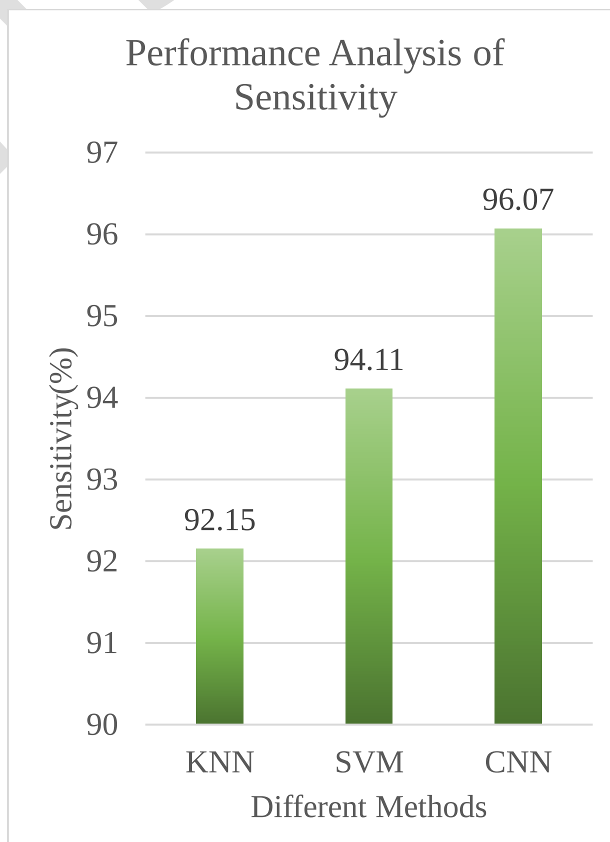

Figure 11. Performance analysis of sensitivity

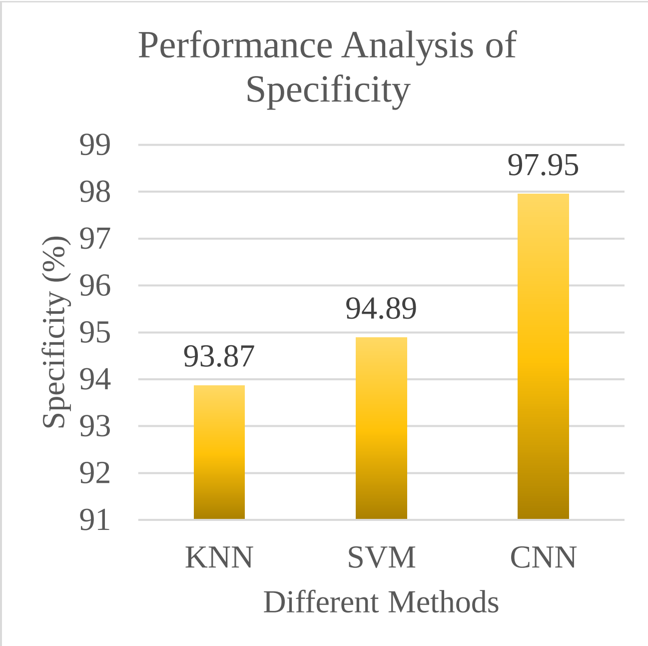

Figure 12. Performance Analysis of the specificity

Where,

$$\text{Specificity} = \frac{TN}{TN+FP} \qquad \ldots \qquad (3)$$

The randomly selected EEG data for training and testing were used to analyze the precision, recall of the proposed classify technique. The Figure 10 and 11 are shown the results were compared to the output of three different classification methods for epileptic seizure detection.

Table 2. Comparison of Accuracy output with existing method

Methods	Accuracy
Convolutional Neural Network (CNN)	97.65 %
K-Nearest Neighbors (KNN)	92.51 %
Support Vector Machine (SVM)	94.65 %
Random forest classifier neonatal sleep staging [11]	84.78%
k-nearest neighbors (KNN) [15]	87.83%

Table 2 shows a comparison of the existing K-Nearest Neighbors (KNN) with an accuracy of 94.86 %, Support Vector Machine with an accuracy of 94.86 % and the CNN (Convolutional Neural Network) method with an improved accuracy of 97.65%.'

CONCLUSION

The conclusion discusses the analysis of the Electroencephalogram (EEG) biomedical wave from the CHB-MIT dataset. The analysis includes pre-processing, feature extraction, and classification for Epileptic Seizure Detection. The data used in the analysis were collected from both healthy individuals and patients with Seizure, from multiple recordings with varying neuro cell durations. The proposed methods showed improved results compared to different methods, as shown in Table 2. The proposed methods achieved a classification result of 92.51% for KNN, 94.65% for SVM, and 97.65% for CNN. A confusion matrix, a mathematical function used for evaluating the effectiveness of a classifier, was used to display the expected target class and calculate parameters such as sensitivity, specificity, and accuracy

Future Scope.

In future work, the feature classification technique will be improved to categorize features into multiple categories. This study aims to demonstrate that the most accurate method for identifying a person's emotional state is by analyzing low classes of features. The ECG signal quality measure is effective in distinguishing between strong and weak data. However, there are some limitations to this image processing technology. In the future, the branding process will focus on both perfect and imperfect EEG signals.

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