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EEG Signal Classification using Deep Neural Network

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Abstract: - Electroencephalography (EEG) is a non-invasive technique used to measure and record the electrical activity of the brain. It plays a crucial role in various medical and research applications, including brain-computer interfaces, neurological disorder diagnosis, and cognitive state monitoring. In recent years, deep learning has emerged as a powerful tool for extracting meaningful patterns from EEG signals, leading to significant advancements in EEG signal classification tasks. This research focuses on the application of deep neural networks (DNNs) for EEG signal classification. The primary objective is to develop a robust and accurate classification model capable of identifying distinct brain states or patterns associated with specific mental activities or neurological conditions. To achieve this, we propose a multi-layered deep neural network architecture, leveraging convolutional layers to automatically learn spatial features and recurrent layers to capture temporal dependencies in the EEG data. Neural networks find utility in a several uses because the combination of classification being available in deep learning approaches. This study employs SVM to categorize EEG signals. recording of the brain's electrical impulses known as an electroencephalogram (EEG) can be used to diagnose many medical disorders. Parts of the brain are affected by partial epilepsy, and the EEG recorded from those areas is known as Focal-EEG, whereas the EEG recorded from another area is referred to along with Non-Focal EEG. When a patient has drug-resistant epilepsy, the Focal EEG identification helps the doctors locate the epileptogenic focus and, as a result, recommend surgical removal of those brain regions. In this, we have suggested a methodology for categorizing non-focal and focal EEG. Recent years have seen a growth in the utilization of a brain-computer interface has made it potential to investigate the brain's control mechanism using EEG signal. An effective focus based on a classification technique Recurrence plot CNN are suggested the address to issue of EEG signal categorization. To increase the signal intensity during the workout interval, EEG signals are first pre-processed. To build the feature mode of recurrence plot, Features in the time- and frequency-domains are extracted, respectively.

Keyword: EEG, Recurrence Plot, Support Vector Machine (SVM), Neural Network (NN).

I. INTRODUCTION

EEG signal which is used to detect brain related disease. A cheap instrument for analyzing the brain activity captured with some electrodes on the scalp is the EEG signal. Neurology specialists examine the signal visually to ascertain the beginning of epilepsy. Nonetheless, properly analyzing EEG signals is laborious, time - consuming, frequently results in incorrect alarms detection of epilepsy. To overcome the problem, epilepsy can be automatically detected using EEG signals considered. In cases of conditions, a person with epilepsy may experience sudden seizures that cause his muscles to twitch and even cause him to lose consciousness. EEG is a monitoring of "electrical" activity in the brain made from the scalp. The frequencies that were captured demonstrate the "electrical" behavior of the brain.

A person with epilepsy suffers from sudden seizures that cause convulsions in their muscles and, in some cases, even cause them to lose consciousness. 50 million individuals worldwide, or 1% of the population, suffer from epilepsy. A person with this disease is not well regarded in society, even to the point where marriages are forbidden. Although the sickness itself does not cause a harmful state, a loss of consciousness can be hazardous if the person is driving or swimming.

The electroencephalogram (EEG) is frequently used to examine different aspects of brain function. One such condition where EEG is used for clinical analysis is epilepsy. Some epileptics develop treatment resistance and require surgical excision of the brain regions responsible for the condition to regain health. The epileptogenic foci are those areas of the brain that result in epileptic seizures. The frequency of these operations has successfully eliminated or greatly decreased the incidence of epileptic seizures in the patients. The precise location of the area of the brain that is causing the epileptic seizures must therefore be determined.

Currently, the physician uses a clinical method that is subjective to manually locate the epileptogenic foci. This form of medication is used to manage partial epilepsy, often known as partial seizures. When only a small portion of the brain is afflicted by epilepsy whereas the rest of the nervous system is working normally, partial seizures take place. In this case, the term "focal EEG" refers to the EEG that is captured from the regions of the brain in which the initial "ictal EEG" abnormalities are identified. “Non-focal EEG”, on the other hand, is an EEG that is captured from brain regions that was not active when seizure first started. An EEG is primarily used to identify and research epilepsy, a disorder that results in recurrent seizures. An EEG will assist your doctor in determining what kind of epilepsy you have, any potential causes of your seizures, and the best course of treatment for you.

II. METHODOLOGY

A. Database

Five people with temporal lobe epilepsy were used to collect the EEG data. The acquisition is sampling at 512 Hz. 7500 focal and non-focal EEG signal pairings are included in the dataset. There are 10, 240 samples per signal. The first 50 pairings of data were used in this work to evaluate the algorithm. We merged that combinations of Focal and Non focal signals produce the 101 signals in both group—the “Focal and Non focal” groups. That signal combinations between the “focal and non-focal” sites serve as an illustration.

B. Data preparation and Pre-processing

Convert the data in row-by-row form and after that convert the data into image using recurrence plot.

C. Recurrence plot:

A sophisticated way for analyzing irregular data is the use of RP. It is a representation (or graphs) of a matrix form, where the matrix's components stand in for a dynamics program's states' recurrence intervals. Literally, the RP denotes all occurrences in which the “phase space trajectory of the dynamical system” passes over nearly the same region of the dimensional space.

We must employ the similarity distance measuring approach in order to gauge how similar the signal sequences are to one another. European distance, Manhattan distance, DTW, etc., are examples of common measurement techniques. These conventional similarity measurement techniques struggle to demonstrate the best identification performance when the SNR is low because of the significant noise interference and mismatched feature lengths.

To deal with the problem of reliable matches of complicated sequences with various length, an RP approach is put forth RP, a “nonlinear dynamic analysis method”, may reflect the characteristic architecture, matching criteria of time - series data. It can offer information and predictability based on past assumptions and disclose the internal structure of time series. Since the EEG signal is a time -series signal, better study may be done using recursive graphs. Using the function below, we transform to the recurrence plotting model for simple viewing of the EEG data analyzed:

$$R = \emptyset\left(\in - \left|\left|x(i_k) - x(i_m)\right|\right|\right) \quad i_k, i_m = 1,2 \ldots M$$

$$\emptyset(z) = \{1 \;\; z \geq 0$$

$$\{0 \;\; other$$

where M = number of states seen during feature training, ||.|| = Euclidean norm, $x(i_k)$ = “value of the feature sequence observed at the point of the i_k sequence and is the crucial gap.

$R(i_k, i_m) = 1$,if the value of an n-dimensional feature sequences is so very close to where the i_k and $i_m$patterns are spatially located; else, 0 is displayed. Black and white dots are used in the RP image to represent the graph's time series.

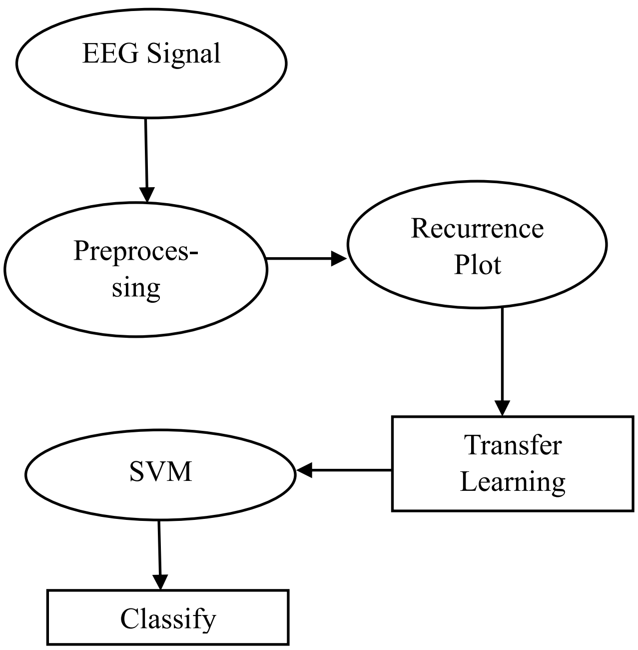
D. Convolutional neural network:

The convolutional layer, which makes up the majority of the computation in a CNN, is its core aspect. Inputs, a filter, and a set of points are among the things it requires. Make the assumption is the inputs consist of a color photo with 3-D pixels. It follows the inputs will have aspects- width, height, depth—which are comparable to RGB in a picture. The features detector is also called kernels or filters. Convolution describes this process.

A section of the image is represented by a 2-D array of weight acting as the features detector. Normally a 3x3 matrix, the input size also refers to the size of the receptive field but can differ in size. The dot product between it input features and the filter is calculated after the filter has been applied to a section of the image. This dot product is then supplied to the output vector. The filter shifts by a stride and repeats the process when the kernel has gone through the entire image. The last of the dot products from the input and filter is a feature map, activating map, or convolution layer feature.

E. RESNET-50: ResNet-50 is the designation of a CNN with 50 layers. A pre - trained model of the networks that have been trained on more than an ImageNet dataset is present in the ImageNet database. A number of animals, a mouse, a keyboard, and a pen are among the 1000 different object classes that the "pre - trained models" network can classify images into.

F. Classification: Algorithms for supervised classification include SVM. If there are more features, there may be an overfitting issue with the amount of input channels as well. This issue in supervised learning will be resolved by regularization in the feature selection process for the classification model.



Proposed Methodology Diagram

SVM Classification: SVM are used to data for regression and classification. It is a supervised learning technique that data into two groups. The right kernel function selection is essential for SVM classifier success. There are numerous traditional kernel techniques, including perceptron, linear, RBF, and polynomial. Low universal testing error is produced by the regulation, the kernel parameters (C, c), and their optimal combination (GTE). SVM performs better even when there are many elements and little training data. SVM can provide greater classification accuracy by using factors like output structure and spatial contiguity. For SVM, the boosting, AdaBoost, and Wang's boost algorithms perform well and enable better learning of the unbalanced data. SVM performance can be enhanced by employing O(n3) time complexity improvements. The grouping of observing places, however, are ignored. To create a better ensemble classifier, new drawbacks can be included by selecting a classifier with a sign basis and distance-based features. Multi-criteria inventory problem classification is aided by algorithms that have been increased and tweaked for SVM. For learning and analyzing imbalance data, SVM serves as a basis classifier. The classifier effectively uses kernel function. Two SVM variants, Wang boosted and modified boosted, are available to further enhance SVM performance.

G. Performance

The experiment is evaluated using a number of metrics including accuracy, confusion matrix, precision, recall, and f1 score.

Accuracy - The ratio of the number of accurate predictions to all the data set's inputs is known as accuracy. It is written as:

$$\text{Accuracy} = (TP + TN) / (TP + FP + FN + TN)$$

TP (True positive): A True Positive is the outcome where the model correctly predicts the positive class.

FP (False Positive): A False Positive is the outcome where the model incorrectly predicts the positive class.

FN (False Negative): And a false negative is an outcome where the model incorrectly predicts the negative class.

TN (True Negative): A true negative is an outcome where the model correctly predicts the negative class.

i. Precision: By dividing the genuine positives by any positive predictions, precision is determined.

$$\text{Precision} = \frac{\text{True Positive}}{(\text{True Positive} + \text{False Positive})}$$

ii. Recall: By dividing the real positives by anything else that should have been projected as positive, recall (also known as the True Positive Rate) is obtained.

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{Talse Negative}}$$

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iii. F1 score: The F1 score is the harmonic mean of Precision, Recall. One might consider the true benefits and drawbacks of this.

$$F_1 = 2 * \frac{Precision*Recall}{Precision+Recall}$$

iv. Confusion matrix: The prediction results of a classification task are summarized in such a confusion matrix. The confusion matrix shows how your classification method produces guesses even while it is confused. It provides you with information on the types of errors being produced, which is more essential than just the faults your classifier is making. This breakdown gets around the drawback of relying solely on classification accuracy.

III. Result

A. Plot EEG signal

i. Focal signal:

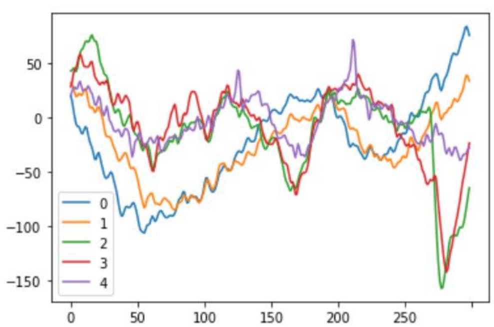


Fig. focal signal

I have plotted the focal seizure of 5 people.

ii. Non focal signal:

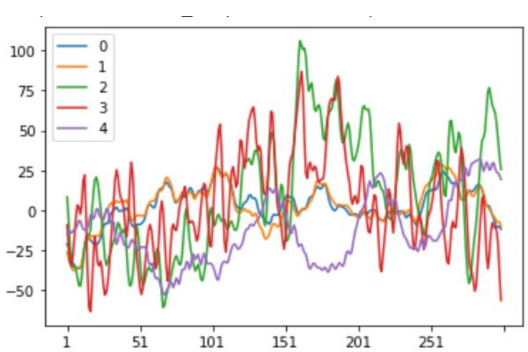


Fig. non-focal signal

I have plotted the non focal siezure signal of 5 people.

B. Image after Recurrence plot

i. Focal person image

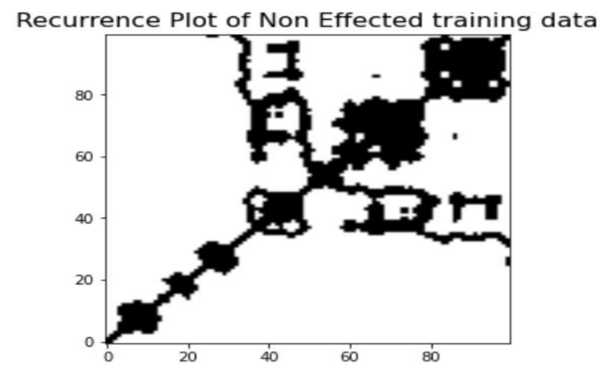


Fig. focal person 1 image

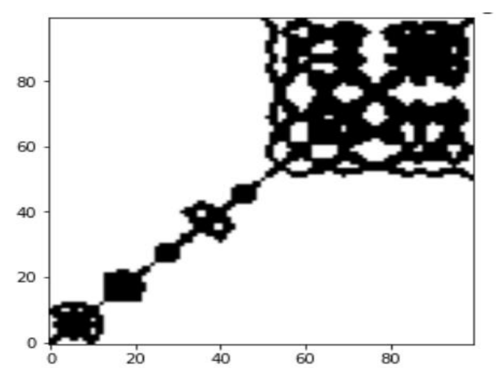


Fig. focal person 2 image

I have converted the focal person signal data into the image form.

ii. Non focal person image:

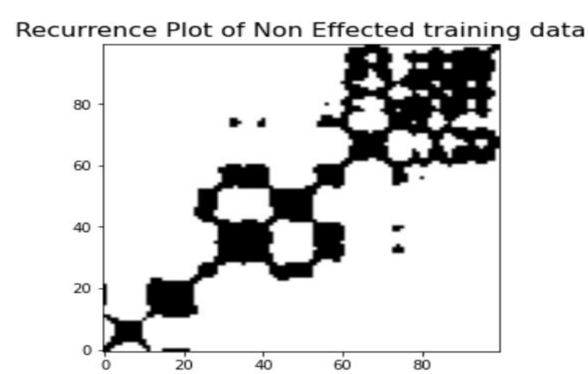


Fig. Non-focal person 1 image

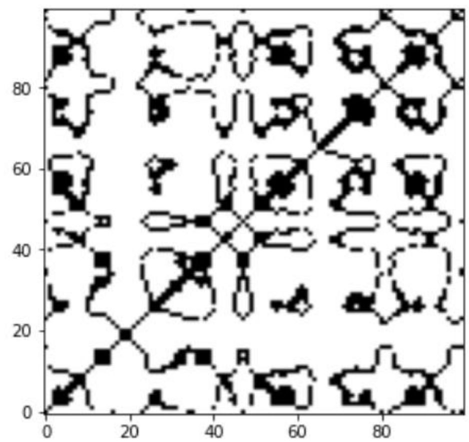
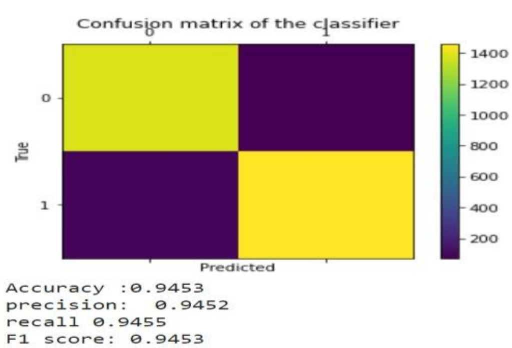


Fig. Non-focal person 2 image

I have converted the non-focal person signal data into the image form.

iii. Confusion Matrix:

A performance indicator for a deep learning classification task where the output could include two or more classes is the confusion matrix. There are four possible anticipated and actual value combinations in the table.



iv. Accuracy Report

SVM (Support Vector Machine): It is a supervised classifier that creates a high-dimensional hyperplane for dividing that can be used for classification. The hyperplane with the greatest distance to the closest data point for training any class achieves a decent separation.

```
              precision    recall  f1-score   support

           0       0.95      0.94      0.94      1473
           1       0.94      0.95      0.95      1527

    accuracy                           0.95      3000
   macro avg       0.95      0.95      0.95      3000
weighted avg       0.95      0.95      0.95      3000
```

In the above figure shown the result of Purposed Model.

Model	Precision	Recall	F1-Score	Accuracy
DT	71	70	71	71
KNN	60	61	61	61
GNB	56	62	59	61
RF	85	77	81	80
Proposed model	**95**	**94**	**94**	**95**

In the above table gives the accuracy achieved using different learning algorithms. It can be seen from the above table the proposed model outperforms and gives the highest accuracy among all the existing learning algorithms.

IV. CONCLUSION

In this study, we examined deep learning and machine learning techniques for classifying EEG signals. Python is used to implement traditional SVM and logistic regression methods in keras, coupled with a simple neural network, to evaluate performance. For higher performance of 95% percent accuracy in EEG classification, SVM and enhanced NN are recommended. The innovation that assists in obtaining superior the early layers of the upgraded NN use descent activation function with radial basis function, which improves precision, accuracy, recalls, and F1 score in contrast to conventional approaches. To evaluate the performance, simulations are run utilizing a range of optimization methods and activation algorithms.

To enhance classification accuracy of EEG signals, the CNN approach of Recurrence plot is presented. Feature extraction generates multi-feature fusing networks and a Recurrence plot assessment. The suggested procedure can reliably distinguish Moving left and right, according to experiments. It could therefore be used in "brain-computer interface" technology. For many years, we have been trying to start putting together pathological, clinical aspects of "EEG signal" information. Because it is now insufficient information to conduct research, additional investigations will be conducted using a combination of imaging and pathological and clinical characteristics.

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