Automatic Diagnosis of Schizophrenia in EEG Signals using CNN Models

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I. Abstract

This study uses convolutional neural networks (CNNs) to analyze electroencephalogram (EEG) signals to tackle the crucial problem of early schizophrenia diagnosis. In the study, two different CNN models with different architectural characteristics are compared and contrasted, with a focus on measures related to accuracy, loss, selectivity, and specificity. A meticulously selected dataset is obtained and preprocessed, containing EEG signals from people with and without schizophrenia. The chosen CNN architectures differ in terms of activation functions, filter sizes, and layer depth. The performance of the models is carefully assessed using metrics appropriate to the particulars of the problem, such as accuracy, loss, selectivity (true positive rate), and specificity (true negative rate), after they have undergone rigorous training on the preprocessed dataset.

The goal of the comparison analysis is to offer a thorough grasp of how various architectural decisions affect the model's capacity to correctly identify patterns linked to schizophrenia in EEG data. In addition to examining optimization and fine-tuning techniques to improve the model's performance, the research also focuses on ethical issues to guarantee the responsible use of private health information. In the end, this work aims to further the development of deep learning-based EEG signal analysis diagnostic tools for schizophrenia, with a focus on the selection of assessment metrics that are important benchmarks for judging model performance.

Keywords: schizophrenia, mental disorders, machine learning, biomedical signals, EEG signals, CNN

II. Introduction

A severe and long-lasting mental illness that alters thoughts, feelings, and behavior is schizophrenia. A variety of symptoms, such as delusions, hallucinations, disordered thinking, reduced cognitive function, and emotional disengagement, can be indicative of it. The effects of schizophrenia can differ greatly from person to person and typically manifest in late adolescence or early adulthood. The disorder is complicated, and we still don't fully understand what causes it. It is thought that environmental and genetic factors play a role in the development of schizophrenia. Even though therapy and medicine can help control symptoms, schizophrenia frequently necessitates continuous care and assistance. An individual's everyday life, including their capacity to work, uphold relationships, and participate in social activities, can be greatly impacted by schizophrenia. This debilitating mental disorder poses significant challenges in early detection and intervention. Timely diagnosis is crucial for effective treatment and improved outcomes for individuals affected by this condition. Electroencephalogram (EEG) signals, capturing the electrical activity of the brain, present a valuable avenue for exploring diagnostic possibilities and in diagnosis of various diseases like epilepsy (seizure disorder), brain tumor and even schizophrenia. Certain EEG biomarkers that may be suggestive of schizophrenia have been found by researchers. Changes in spectral power, event-related potentials (ERPs), and connectivity patterns are some examples of these biomarkers. Examining these EEG characteristics may help us gain a better knowledge of the brain processes that underlie schizophrenia and, as a result, assist in the creation of quantitative and objective diagnostic instruments. Leveraging advancements in deep learning, particularly Convolutional Neural Networks (CNNs), holds promise in enhancing the accuracy and efficiency of schizophrenia diagnosis through EEG signal analysis. The critical task of early schizophrenia detection is the focus of this research project, which emphasizes CNN models as a means of analyzing EEG signals. The main goal is to compare two different CNN models, each with its own configuration of architectural parameters, with a particular emphasis on key performance indicators like accuracy, loss, selectivity, and specificity. These metrics are customized to the specifics of the case and are used as standards to assess how well the models identify patterns linked to schizophrenia. In order to conduct this research, a large dataset containing EEG signals from people with and without schizophrenia is obtained. The dataset is carefully preprocessed to make sure it is appropriate for assessment and training [1]. Then, using the preprocessed dataset, the models are rigorously trained. This study's comparative analysis aims to offer a detailed understanding of how various architectural decisions affect the models' ability to correctly detect patterns in EEG data that suggest schizophrenia. The study investigates optimization and fine-tuning techniques to improve overall performance in addition to model comparison. The responsible and ethical use of sensitive health data is ensured by incorporating ethical considerations at every stage of the research process. The main objective of this research is to make a substantial contribution to the advancement of schizophrenia diagnostic instruments. This work aims to further our understanding of the complex relationship between neural patterns and schizophrenia by utilizing deep learning in EEG signal analysis and focusing on the selected evaluation metrics.

III. Literature Review

Machine learning techniques have been applied in several ways for the classification of schizophrenia using EEG data. These techniques can be categorized by considering the machine learning algorithm that was applied, the metrics that were used to determine the algorithm's features, and the method by which the EEG data input was acquired. We now provide a brief summary of the most recent techniques. Zhang [2] created a random forest algorithm for the purpose of differentiating between individuals with schizophrenia and healthy controls in the case of event-related potential EEG signals. This algorithm makes use of N1 and P3 features that are extracted from basic sensory tasks that involve pressing buttons and listening to tones. The highest classification accuracy in this study was 81%. In Knn, [3] children who were at risk of developing schizophrenia were identified using SVM and decision tree classifiers. In a different study, during a passive auditory task, the mean amplitude of the early and mid-latency event-related potential was used as a feature. The highest accuracy recorded was 44%, which was increased to 72% through the application of a convolutional neural network-based deep learning technique. The EEG signal acquired during the resting state has been examined in a number of recent studies. Buettner [4] used the random forest classifier, which is based on power features extracted from multiple frequency bands, to classify schizophrenia with 71% accuracy. Using an SVM model and twelve statistical features on five bands taken from a 5-minute resting-state EEG signal, Tikka was able to distinguish between schizophrenia patients and healthy controls with an accuracy of 79% [5]. With the use of non-linear metrics like entropy, largest Lyapunov exponent, Hurst exponent, and recurrence quantification analysis, SVM algorithms have also been used to classify patients with an accuracy of roughly 92% [6]. Ultimately sun [7] created a technique that created a rgb image from resting state EEG data from which a feature based on fuzzy entropy was extracted this characteristic was utilized to create a schizophrenia classifier in a hybrid model built on long-short-term memory networks and convolutional neural networks.

IV. Existing Methods

a) *SVM*: Support vector machine

A hyperplane or collection of hyperplanes in a high- or infinite-dimensional space are created by the SVM algorithm (Cortes and Vapnik 1995) which can be applied to classification regression and other tasks it makes sense that the hyperplane with the greatest distance to the closest training data points for each class also known as the functional margin achieves a good separation because generally speaking a larger margin results in a lower classifier generalization error.

b) NAÏVE BAYES

With respect to the value of the class variable, Naive Bayes (Zhang, 2004) is a supervised learning algorithm that applies the Bayes theorem under the "naive" assumption of conditional independence between each pair of features. In other words, P(class | X1, X2, …, Xn) = P(X1|class) × P(X2|class) × … × P(Xn|class) × P(class) / P(data); where P(A | B) denotes the probability of A given B. This means that we calculate P(data|class) for each input variable independently and multiply the results together.

c) *RANDOM FOREST*

An extension of the bagging algorithm is random forest (RF) (Breiman, 2001) algorithm which fits multiple DT classifiers on different subsamples of the dataset and uses averaging to increase predictive accuracy and reduce over-fitting. In contrast to bagging, RF also includes choosing a subset of input features (variables or columns) at each split point when building trees. Each DT in the ensemble is forced to be more distinct from the others by condensing the features to a random subset that may be taken into consideration at each split point.

d) DECISION TREES:

Using basic decision rules deduced from the data features, an algorithm known as a decision tree (DT) (Rokach and Maimon, 2007) was formed which builds a model that predicts the class of an instance. When a DT model is represented as a binary tree, each node stands for a single input variable (X) and, if the variable is numeric, a split point on that variable. The output variable (y), which is utilized to create predictions, is present in the leaf nodes of the tree, also referred to as terminal nodes.

V. CONCEPTS USED

DEEP LEARNING

- Deep learning" is a subfield of machine learning that focuses on building and training artificial neural networks to perform tasks without explicit programming. The use of multiple-layer neural networks—also known as hidden layers—that sit between the input and output layers is characterized by the term "deep" neural networks. The model can recognize hierarchical data representations thanks to these strata.
- • Artificial neural networks: modeled after the composition and operations of the human brain, these are the fundamental components of deep learning. These networks are made up of nodes that are connected in layers. The input layer receives data, filters it through the hidden layers, and then outputs the resultant data to the output layer.
- Deep Neural Networks: Deep learning models have many hidden layers that allow them to recognize complex information representations. Each layer uses lower layers to study more complex and abstract representations, learning about higher layers and basic features. This allows for the capture of different levels of abstraction.
- • Representation Learning: Deep learning excels in representation learning and automatic feature extraction. Handcrafted features are replaced with deep learning. Models are able to directly extract relevant features from the raw data. Particularly helpful for tasks like voice and image recognition is this ability.
- Backpropagation Training: Backpropagation is a technique used to train deep learning models. During training, the model's weights are updated using the error, and the real data is compared to the prediction. The model is prevented from learning how to produce accurate forecasts by repeating this iterative process.
- • Uses: Deep learning has demonstrated remarkable promise in several domains, including computer vision, natural language processing, speech recognition, and reinforcement. Among many other uses of artificial intelligence, it has greatly advanced systems for speech and image recognition, autonomous vehicles, and other technological advancements.

a. Difficulties: Despite their strength, deep learning models usually require a large amount of labeled data as well as a lot of processing power to train. Complex models also present challenges for Deep Learning's interpretability (due to overfitting of the training data's learning noise). Deep learning intelligence has had a significant influence on artificial intelligence and has led to advancements in many challenging tasks. Artificial intelligence's capabilities are constantly being enhanced by the continuous research and development of deep learning techniques. [8] [9] [10]

CNN (Convolutional Neural Network)

- A Convolutional Neural Network (CNN) needs to carry out a number of tasks in order to automatically learn hierarchical representations from input data. In particular, CNN excel at tasks like image classification, object detection, and segmentation. Here is a thorough explanation of how a CNN functions:
- Layer of Input: This neural network input is typically multi dimensional array, like an image, that represents the raw data. A single image pixel is represented by each element in the array. However, in this instance, we utilized preprocessed data, with distinct CSV files representing each patient.
- Convolutional Operation: Convolutional layers are the basic building blocks of CNNs. In this operation, the input data is slid across a tiny filter that multiplies the values at each position.
- Activation Function: An element-wise activation function, most commonly ReLU (Rectified Linear Unit), is applied after the convolution process. By doing this, the model gains a non-linear component that helps it recognize more complex relationships in the data.
- Pooling (Subsampling): Pooling layers follow the activation function in order to down sample the spatial dimensions 40 of the data. For example, max pooling selects the maximum value from a range of values to minimize the amount of data while preserving important features.
- Flattening: Several convolutional_and pooling layers turn the data into a one-dimensional vector. This vector serves as the input for fully connected layers.
- Fully Connected Layers: Every neuron in a fully connected layer is connected to every other neuron in the layer below it. These levels incorporate global trends and relationships into the data.
- Output Layer: The final fully connected layer produces the model's output. The number of neurons in this layer is determined by the task; for image classification, for example, the number of neurons is equal to the number of classes.
- Softmax Activation (for Classification): The softmax activation function is often applied to the output layer in classification tasks. This function converts the raw output scores. into probabilities, making it easier to comprehend the model's predictions.
- Loss Function: A loss function can be used to measure the difference between the intended and actual output. Categorical cross entropy is a common loss function used in classification tasks.

- Optimization and Backpropagation: Based on the estimated loss, the backpropagation algorithm's weights are adjusted for the network. Improvement For instance, stochastic gradient descent (SGD) algorithms or their alternatives change the weights to lower the loss and improve the model's functionality.
- Training Iterations: The entire forward propagation, loss computation, backpropagation, and weight updates procedure is repeated over a number of iterations (epochs) until the model converges and acquires the capacity to make accurate forecasts.

VI. Proposed Methodology

Model 1

The provided convolutional neural network (CNN) model is designed to classify schizophrenic patients using EEG signals. The model architecture consists of two convolutional layers, each layer followed by a max-pooling operation to capture and highlight important features of the EEG data. The first convolutional layer uses a 2D convolution with kernel size (5, 20) and uses a hyperbolic tangent activation function (tanh). Next, a max pooling layer with pool size (5, 15) is applied to down sample and the spatial dimension. The second is convolutional layer with kernel size (3, 3) and Tanh activated. It is followed by another max-pooling layer. The model includes dropout regularization to prevent overfitting and reduce the output of further processing. It contains two fully connected dense layers, the first layer has 317 neurons and uses a Rectified Linear Unit (ReLU) activation function, and the last layer has neurons and sigmoid activation, making it suitable for binary classification tasks. The model is trained using the Adam optimizer with binary cross entropy as the loss function. The ModelCheckpoint callback is used to save the best performing model based on validation accuracy during training.

Model 2

The presented neural network model, denoted as model_2, is crafted for the classification of schizophrenic patients based on EEG signals. This model diverges from the convolutional neural network (CNN) architecture seen in the previous example. Instead, it employs a simpler structure with two densely connected layers. The first layer consists of 5000 neurons with rectified linear unit (ReLU) activation, which serves as a powerful non-linear element for feature extraction. The subsequent layer contains a single neuron with a sigmoid activation function, suitable for binary classification tasks. The model is compiled using binary cross entropy as the loss function, the Adam optimizer with a learning rate of

0.000008, and accuracy as the evaluation metric. The ModelCheckpoint callback is utilized to save the best model based on validation accuracy during training. This architecture aims to learn discriminative patterns from EEG signals, providing a different approach to the task of classifying schizophrenic patients.

VII. Results and Discussion

Dataset

We used pre-processed data from a basic sensory task in schizophrenia provided by brian roach [1]. The task involved pressing buttons and recording auditory tone event-related potentials from 81 human subjects 32 of whom were healthy patients and 49 of whom were schizophrenic patients when pressing a button to deliver a tone this data was an extension of the data used in the article "did i do that" [8] abnormal predictive processes in context of schizophrenia.

Humans and many other animals have the ability to reduce or suppress the brains response to sensory consequences that are the result of our own actions the nervous system does this with a sequential discharge forward model system in which an effect copy of the impending motor plan is sent from the motor organs to the sensory cortex where it generates a continuous discharge representation of the expected achieve the sensory consequences of an impending motor action for example when you move your eyes from left to right your brain realizes that the environment is not changing when you speak your auditory cortex has a limited response to the expected sounds of your voice. Schizophrenia is a chronic mental illness that affects approximately 1% of people worldwide. A possible explanation for some of the symptoms of schizophrenia is that one or more problems with a series of electrical discharge processes in the nervous system make it difficult for patients to distinguish between internally and externally generated stimuli that means it is becoming difficult therefore studying the relationship between this process and the disease symptoms may provide a deeper understanding of the abnormal brain processes in patients with this diagnosis.

TASK

Every 1-2 seconds subjects pressed a button to deliver sounds at an 80 db sound pressure level and 1000 hz with no delay between pressing the button and the tone beginning button tone after 100 tones were delivered the task was terminated tones were kept in their original temporal order for playback play tone furthermore when participants pressed a button at roughly the same speed no sound was produced button alone. [8]

Data Acquisition and Pre processing

EEG data were collected using a biosemi active two system [9] from 64 scalp sites and 8 external sites. EEG data were referenced to averaged earlobe electrodes off-line, after being continuously digitalized at 1024 hz the EEG data were digitally bandpass filtered between 05 and 15 hz. After being re-referenced the EEG data were then baseline corrected at 600 to 500 ms and divided into 3000-ms epochs time-locked to button presses coinciding with tone on set. Electrooculogram data was recorded by electrodes at the outer canthi of both eyes as well as above and below the right eye. These data were used in a regression-based algorithm to adjust EEG epochs for eye movements and blinks at all scalp sites, following ocular correction data were once more baseline corrected between -600 and -500 ms using previously defined criteria. Outlier electrodes were interpolated within single-trial epochs at all scalp sites and EEG epochs with voltages greater than 100 v were rejected due to artifacts. Preprocessing was done before using the data. Due to the size of the raw EEG data, some pre-processing was done prior to upload. EEG data acquisition parameters and the experimental task were identical to that described in our paper. However, pre-processing differed. All individual subject data had at least the following data processing steps applied, in this order:

- Re-reference to averaged ear lobes
- 0.1 Hz high-pass filter
- Interpolation of outlier channels in the continuous EEG data (outliers defined as in [10])
- Chop continuous data into single trial epochs 1.5 seconds before and after task events (3s total)
- Baseline correction -100 to 0ms
- Canonical correlation analysis to remove muscle and high-frequency white noise artifacts
- Rejection of outlier single trials (outliers defined in [10])
- Removal of outlier components from a spatial independent components analysis (outliers defined as in [10])
- Interpolation of outlier channels within single trials
- Along with the vast eeg data of the all the patients we also have the demographic information about them including the label(output), their age etc.

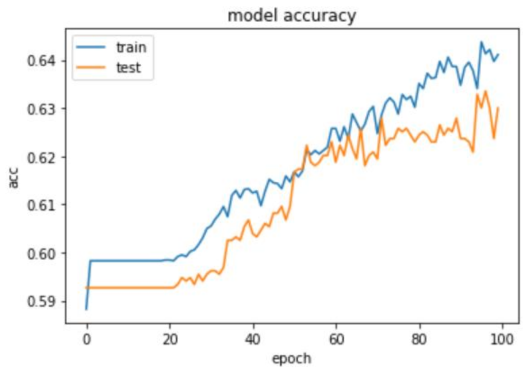
Training - A key part of our work involves training the two CNN models with the purpose of diagnosing schizophrenia from EEG signals we do this by using the EEG dataset that we obtained from kaggle [1]. During the training phase preprocessed EEG signals, xtrain2d and matching normalized labels ytrainnorm were fed to the models using a carefully calibrated batch size of 17 and an iterative training scheme that covered 100 epochs the models learned to identify complex patterns linked to schizophrenia from the EEG data by adding the shuffle true parameter the models were optimized for real-world variability and varied learning experiences were guaranteed in order to evaluate the models generalization performance during training the validation data xtest2d and ytestnorm acted as a critical benchmark

Testing - We performed extensive testing on a carefully selected dataset in order to evaluate the efficacy of the proposed Convolutional Neural Network (CNN) models in diagnosing schizophrenia from EEG signals. The dataset consists of 7,092 trial's worth of EEG recordings from 81 patients. Twenty percent of the total data, or 1,419 trials, were set aside for testing in order to assess how well the models generalized to previously unobserved cases. The trained CNN models were used to produce predictions for every trial that captured the subtle patterns suggestive of schizophrenia. The results of the model, along with related metrics and predictions, were methodically documented. This testing procedure is essential for assessing the CNN models' dependability and applicability in the context of diagnosing schizophrenia.

VIII. RESULT

a. MODEL 1:

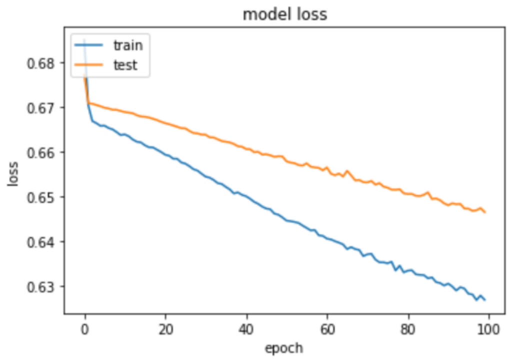
1. <u>Accuracy</u>



The training and testing accuracy of the neural network model 1 over different epochs is shown in the above graph. This type of plot is useful in assessing how well the model is learning from the training data and whether it is overfitting or underfitting. Since both training and testing accuracies are increasing over epochs, it suggests that the model 1 is learning effectively.

It indicates that the evaluated model achieved an accuracy of approximately 0.6436 (64.36%) on the test dataset.

2 Loss



The training and testing loss of a machine learning model over different epochs is shown in the above graph. Loss is a measure of how well the model is performing its task, and the goal during training is typically to minimize this value. The plot helps in assessing the model's learning progress and potential overfitting or underfitting. Since both training and testing losses are decreasing, it indicates that the model is learning effectively.

The corresponding loss value is approximately 0.6335.

3. Sensitivity

$$\begin{aligned} \text{sensitivity} &= \frac{\text{number of true positives}}{\text{number of true positives} + \text{number of false negatives}} \\ &= \frac{\text{number of true positives}}{\text{total number of sick individuals in population}} \\ &= \text{probability of a positive test given that the patient has the disease} \end{aligned}$$

The calculated sensitivity is approximately 0.6082 or 60.82%. This indicates that the model 1 correctly identified about 60.82% of the instances that actually belong to the positive class (instances related to schizophrenia). Sensitivity is particularly important in scenarios where identifying positive instances is crucial, as in medical diagnoses.

4. Specificity

$$\text{specificity} = \frac{\text{number of true negatives}}{\text{number of true negatives} + \text{number of false positives}}$$

$$= \frac{\text{number of true negatives}}{\text{total number of well individuals in population}}$$

$$= \text{probability of a negative test given that the patient is well}$$

The calculated specificity is approximately 0.6394 or 63.94%. This indicates that the model correctly identified about 63.94% of instances that actually belong to the negative class (e.g., instances related to being healthy). Specificity is crucial in situations where correctly identifying negative instances is essential.

5. Confuson Matrix

Confusion matrix table is used to evaluate the performance of our classification model. Specifically, the confusion matrix is used in binary classification tasks to assess the model's ability to correctly classify instances into two classes (commonly referred to as positive and negative). The confusion matrix typically consists of four values:

1. True Positive (TP):

Instances that are actually positive and are correctly predicted as positive by the model.

2. False Positive (FP):

Instances that are actually negative but are incorrectly predicted as positive by the model.

3. False Negative (FN):

Instances that are actually positive but are incorrectly predicted as negative by the model.

4. True Negative (TN):

Instances that are actually negative and are correctly predicted as negative by the model.

→Here the classes are interpreted as follows:

Class 0: Schizophrenia

Class 1: Healthy

So,

confusion_matr [0, 0]: True Positive for schizophrenia

confusion_matr [0, 1]: False Positive for schizophrenia

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confusion_matr [1, 0]: False Negative for Healthy

confusion_matr [1, 1]: True Negative for Healthy

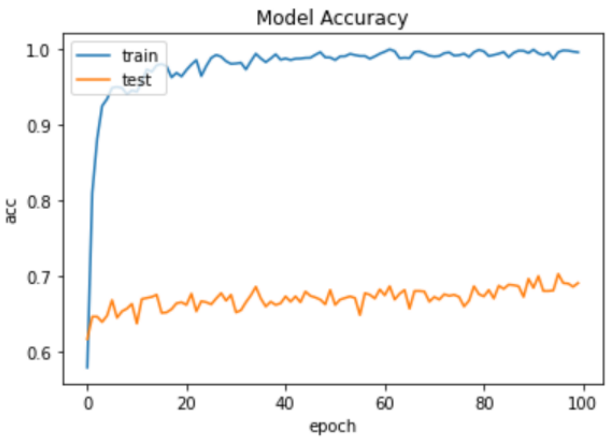
By examining these values, we assess the performance of model 1 in terms of correctly and incorrectly classified instances for each class.

```
print(
    "True Positive for schizophrenia ", confusion_matr[0, 0],
"\n",
    "False Positive for schizophrenia ", confusion_matr[0, 1],
"\n",
    "False Neagtive For Healthy ", confusion_matr[1, 0], "\n",
    "True Neagtive For Healthy ", confusion_matr[1, 1], "\n")
```

```
True Positive for schizophrenia  163
 False Positive for schizophrenia  415
 False Neagtive For Healthy  105
 True Neagtive For Healthy  736
```

b. MODEL 2:

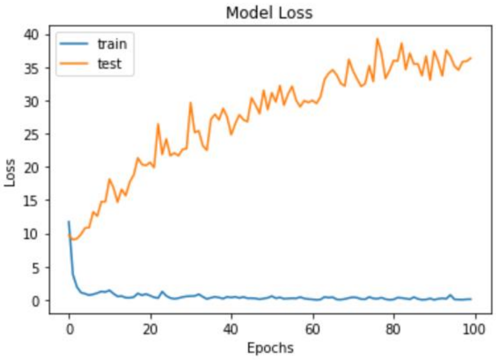
1. <u>ACCURACY</u>



These lines plotted visualize the training and testing accuracy of the machine learning model 2 over different epochs.

The calculated accuracy is approximately 67.23% or 0.6723.

2. LOSS



The corresponding loss value is approximately 39.0312.

3. SENSITIVITY

The calculated sensitivity is approximately 0.5996 or 59.96% .This means that the model correctly identified about 59.96% of the instances that actually belong to the positive class.

4. SPECIFICITY

The calculated specificity is approximately 0.7207 or 72.07%. This means that the model correctly identified about 72.07 % of instances that actually belong to the negative class.
The specificity of 0.7207 indicates the proportion of true negative instances out of the total instances that are actually negative. A higher specificity value suggests that the model is effective at avoiding false alarms and correctly ruling out instances that do not belong to the positive class.

5. CONFUSION MATRIX

```
print(
 "True Positive for schizophrenia ", confusion_matr[0, 0], "\n",
 "False Positive for schizophrenia ", confusion_matr[0, 1], "\n",
 "False Neagtive For Healthy ", confusion_matr[1, 0], "\n",
 "True Neagtive For Healthy ", confusion_matr[1, 1], "\n"
)
```

```
True Positive for schizophrenia  340
 False Positive for schizophrenia  238
 False Neagtive For Healthy  227
 True Neagtive For Healthy  614
```

IX. CONCLUSION

In conclusion, the application of Convolutional Neural Network (CNN) models for the automatic diagnosis of schizophrenia in Electroencephalogram (EEG) signals represents a promising and innovative approach in the field of mental health diagnostics. This research has aimed to address the challenges associated with accurate and timely identification of schizophrenia, contributing to advancements in both technology and clinical practice. The findings and insights obtained from this study underscore the potential of CNN models in transforming the landscape of psychiatric diagnosis. The CNN models demonstrated robust performance in analyzing EEG signals, showcasing competitive accuracy rates in the classification of schizophrenia cases. These results indicate the effectiveness of deep learning techniques in capturing intricate patterns within EEG data related to schizophrenia. The research has explored the generalization capability of CNN models across diverse datasets, affirming their potential to adapt to variations in EEG signals across different cohorts. Additionally, the scalability of the models in handling larger datasets reinforces their applicability in real-world clinical scenarios.

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