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Exploring The people Cases of Epileptic Patients and Healthy by the CNN Architecture

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Abstract

Using electroencephalography (EEG), a unique screening method has been developed to diagnose epileptic episodes. Deep learning is one of the disciplines of artificial intelligence (DL), which is a broad field. Before the emergence of deep learning, traditional machine learning methods that involved feature extraction were used. This restricted their performance to the skill of the people who crafted the features by hand. On the other hand, feature extraction and categorization in DL are fully automated. Significant progress has been made in many fields of medicine since the introduction of these procedures, including the diagnosis of epileptic seizures. Findings indicate that the proposed strategy outperforms cutting-edge techniques with a dataset showing 95.43% accuracy, 0.95% precision, 0.96% recall, and 0.96% F1 score.

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1. Introduction

D. Reymond (Du Bois Reymond) is credited first for starting the study of the chemical processes in the brain when he showed in 1849 that the brain had electrogenic qualities, just like nerves and muscles[1]. in whatever way it took the German physician Hans Berger 75 years to record the first electroencephalogram (EEG), in 1924[2] . Following its widespread usage in the medical community, this phrase gave rise to the new scientific discipline of neuroscience. The first event-related potential (ERP) in a conscious state was recorded in 1935–1936 by Pauline and Hallowell Davis.people, and their findings were released in 1939, a few years later[3]. This greatly raised the acceptance of EEG use in clinical settings. ERPs are time-bound variations in EEG activity voltage that are linked to certain motor, sensory and cognitive processes, EEG signals aid in the recognition of emotions[4].
The EEG influences assistive technology and rehabilitation by facilitating the control of external devices during motor imagery activities[5, 6]. EEG is used in neurofeedback therapy to control brain activity, which may be beneficial for disorders like anxiety[7]. EEG is used to determine cognitive stress and measure mental exertion during tasks that are essential to human-computer interaction [8]. EEG is essential for traumatic brain damage assessment, Because of this, ERP analysis is used to identify and measure specific electrical impulses associated with cognitive processes. These signals can then be utilized to operate external devices like computers or prosthetic limbs[9, 10]. EEG (electroencephalogram) signals are vital for many uses and are a useful tool for studying and working with the human brain[11]. Among the notable uses are sleep monitoring, which helps with the diagnosis of sleep disorders and the analysis of sleep patterns[12]. By associating distinct emotional states with patterns epilepsy diagnosis and monitoring, and brain function assessment[13]. These uses demonstrate how adaptable EEG signals are in a variety of situations involving the human brain. Furthermore, the EEG is one of the key components of brain-computer interfaces (BCI), which enable direct communication between the brain and external devices[14]. control, have distinct qualities that call for a thorough comprehension of the underlying physical processes.

For instance, a number of factors affect how well sleep is controlled, with frequency being one of the most important[15]. Rapid eye movement sleep, awareness, and four non-REM sleep phases are the six stages of sleep that humans go through. Every level has its own frequency[16, 17]. as seen in Figure 1.

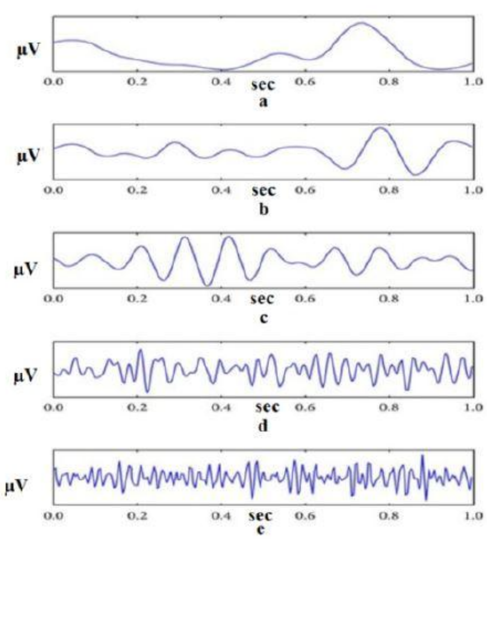

Fig. 1 shows an example of an EEG broken down into its frequency bands (theta, beta, gamma, alpha, and delta frequency bands are from top to bottom) [18].

Previous research has shown that EEG signals have non-linear features that make it difficult to mathematically describe them[19, 20]. Furthermore, the non-linear relationship between the item of interest and EEG data is hard for conventional methods to capture. Poisson's equation states that electrochemical synaptic activity, which is quantified as current density, and EEG data are linearly related [21, 22]. More attention to the underlying mental or cognitive processes than only the electrical activity of the brain is required for practical applications. For example, there is a nonlinear link between emotions and brain activity.Together with the linear mapping of brain activity to EEG data, this implies that emotions and EEG signals do not have a linear relationship.

CNNs' ability to handle non-linear dependencies and efficiently break them down into their characteristic frequency components has been demonstrated by recent advancements in the technology[23]. Because of this, a lot of established designs can function using just raw EEG data and don't require any more processing. However, because CNNs are "black boxes," using them has limitations[24, 25]. wherein an output is produced without the knowledge of how it happened. However, even though CNNs are widely used in many different disciplines, we continue to believe that understanding the data processing is essential to appreciating the architecture's significance[26].

1.1 Statement of the Research Problem

Authors of review papers on machine learning for EEG typically avoid using general themes like "review of EEG algorithms" in their work due to their wide nature. Instead, they usually focus on using machine learning to cure specific diseases[27]. However, in our opinion, this approach limits machine learning's potential and doesn't show how one machine learning algorithm may be changed to be used to different jobs requiring the extraction of features from EEG data. Thus, our main objective in this work is to demonstrate how CNN architectures may be tailored to specific requirements in response to task changes. To accomplish this, we want to provide readers with a thorough grasp of how a CNN processes information and look at every facet of the CNN tuning procedure about EEG signals. Since CNNs are one of the most promising applications of artificial intelligence, we have decided to concentrate on them[28, 29]. When working with signals that have non-stationary and non-linear features, real-time processing is crucial, and they are particularly well-suited for this. Instead of classifying CNNs based on the tasks involved in their applications, we have separated them into the following groups for analysis:

- The conventional use of CNNs
- Architectures based on RCNs;
- Architectures based on Decoders;
- Architectures in the form of Cascades.

It helps to have a foundational grasp of signal processing to properly comprehend particular CNN architectures. By doing this, we intend to arm readers with the background information they need to understand and value different CNN designs.

1.2 EEG Machine Learning CNN

The numerous categorisation schemes and terms now in use show how vastly diverse the topic of machine learning is, including a multitude of subfields[30]. EEG data is commonly classified using traditional machine learning techniques based on amplitude, frequency, and coherence, among other factors. Among these methods are support vector machines, random forests, and decision trees[31, 32]. These algorithms are popular and have shown to be successful in several EEG analysis-related applications.

CNNs are mostly employed for visual image processing and are a subclass of artificial neural networks (ANNs)[33]. They are multilayer perceptrons in a regularized form. Fully connected networks, in which each neuron in one layer is connected to every other layer's neuron, are referred to as multilayer perceptrons. Scholars like Albawi [34]. as well as Indolia[35]. have taken into consideration general knowledge regarding CNN structure and have attempted to provide an understanding of CNNs. More directly linked to our subject, CNNs have been used in the interpretation of medical images[36]. Advances in comprehending how 3D CNNs behave to diagnose Alzheimer's based on brain imaging[37]. In this situation, complicated non-linear correlations between EEG inputs and output classification labels can be analyzed by ANNs, including CNNs[38, 39]. Various cognitive states, such as wakefulness, sleep stages, or different kinds of epileptic seizures, are classified using this analysis of EEG signals[40, 41]. CNNs have the ability to scale big datasets, automatically extract features, gather temporal information, and adapt to a variety of EEG applications. At the same time, band-pass filters are frequently thought to be useful for a variety of data processing tasks that call for the identification and dominance of the frequency range in EEG signals. But while bandpass filters may only pick up basic frequency patterns, CNNs can automatically learn and extract complicated characteristics from raw input data.

A thorough evaluation of alternative architectures is provided by a number of review publications on the subject of machine learning for EEG. In a renowned journal, Lotte et al[15]. provided a thorough introduction to machine learning for EEG. Eleven years later, a new analysis was carried out, offering insights into the topic in a more contemporary setting[42]. The revised work included a variety of methods for processing EEG data, however it was too light on deep learning architectures and had less detail on feature extraction. As a result, the article described a number of designs that are not commonly used in practice, which would have confused readers. Furthermore, the significant developments in neural networks over the past five years are not sufficiently reflected in the text. Numerous studies have thoroughly examined the use of machine learning in EEG data processing for illness diagnosis and other objectives. For example, Maitin et al[43]. gave a perceptive overview of the application of machine learning to the diagnosis of Parkinson's disease, whereas Rodrigues et al[44]. gave a thorough discussion of the application of machine learning to the diagnosis of several illnesses, including alcoholism. Moreover, Rasheed and colleagues[45]. researched a number of machine-learning architectures for identifying epilepsy in EEG recordings, while Lucas et al. looked at the use of machine learning for the detection of pathologies in EEG signals. Concerning the recognition of feeling, Bazgir et al[46]. Xiao-Wei et al. [47], and Nedelcu et al. [48] performed in-depth analyses of many methods for applying machine learning to eliminate artefacts from EEG recordings. Aggarwal et al. [49], focused on the use of machine learning in signal processing, including feature extraction and real-time processing, as well as brain-computer interfaces.

Numerous evaluations on a lesser scale, such "Brain-Computer Interface and Emotions" [50], as well as several other review papers on the application of machine learning for illness diagnosis based on EEG signals [51-54]. Roman et al. [55] have also looked at the application of machine learning for signal processing in EEG analysis. and Shedeed et al. [56].

Reviews of previous architectures can be useful in choosing the right architecture for a given situation, but they might not give a thorough understanding of the building blocks of a convolutional neural network (CNN) or how to adapt the architecture to suit changing EEG measurement conditions. Although the topic of feature extraction from EEG data using machine learning has generated a large number of review publications, the material offered in these papers is usually inconsistent in terms of evaluation criteria and presentation. Therefore, our goal in this study is to offer a thorough manual on how to prepare, analyze, and construct CNN architectures for EEG signals. We also cover other crucial topics like tuning hyperparameters, estimating models, running in real-time, and other related tasks.

To make the process of monitoring EEG signals more pleasant, there has been a tendency in recent years toward the creation of novel kinds of brain-computer interfaces [57, 58]. Using ear-based sensors to measure EEG waves is one promising method [59]. Despite the improved convenience these devices provide, higher noise levels usually result in worse-quality communications. Dry electrodes, another option that has grown in favor recently, are also known to provide noisier signals. Thus, it becomes even more imperative to build better machine-learning techniques to extract meaningful features from EEG signals.

2. The Signal Processing

Both the potential of an electrode on the earlobe and the potential of electrodes placed on the surface of the skull are measured in microvolts, to identify EEG potentials. Although the reference electrode's potential ought to stay constant over time, potential readings may fluctuate due to the scalp's electrically active conduction system. Recalculating the drifts of the EEG signal about the total averaged reference is one of the simplest ways to deal with this problem[60] . However, because EEG is non-stationary and extremely susceptible to many forms of noise, especially electrical noise, it is extremely difficult to evaluate raw EEG data and derive useful information from it[61] . One of the greatest challenges to using EEG outside of a lab setting continues to be the noise issue [61].

An essential first step in getting the EEG ready for additional analysis is pre-processing it. This entails a variety of methods designed to eliminate artifacts and lower noise so that a clean signal is prepared for further processing. Eliminating noise from external electromagnetic fields is the first stage in this procedure [62]. Motion artifacts must then be handled because they may adversely affect the EEG signal. Principal Component Analysis (PCA) is one of the most widely used methods for eliminating noise and artifacts from non-linear EEG signals[63] . PCA effectively eliminates artefacts from the data and reduces dimensionality and duplication by combining the original variables in a way that maximises variance. Another popular technique for analysing EEG data is Independent Component Analysis (ICA). By separating the multi-component EEG signal into its separate components, ICA removes noise and interference from blinks, eye movements, heart contractions, and muscle activity in the case of multi-channel data. This technique has proven to be quite effective in eliminating artefacts from multi-channel EEG recordings. Canonical Correlation Analysis is another technique for enhancing the quality of EEG data (CCA). CCA looks for linear modifications to maximise the correlations between two datasets. It has been utilised to improve brain-computer interface (BCI) performance in a number of scenarios, such as code-modulated visual evoked potentials, steady-state visual evoked potentials, event-related potentials like P300, and error-related potentials.

2.1. Machine Learning and Signal Processing

Despite more than fifty years of research on EEG artifact removal techniques, no one can agree on an ideal solution for a given use case [70]. Nevertheless, EEG artifact removal techniques—which can be applied using online and offline techniques that are both automated and human—are essential for making the most of EEG data. The most widely used techniques for removing EEG artifacts are PCA [73,74] and support vector machines (SVM) [71, 72]. Even though these techniques are frequently employed, there are a ton of alternative approaches that can be employed, and a number of review publications attempt to investigate various strategies for artifact removal [75,76,77,78]. For scholars looking to assess the efficacy of various artifact removal techniques, these review papers are an invaluable resource. Even though the best algorithm is still up for debate, research on EEG artifact removal techniques is still being conducted to improve the quality of EEG data and the accuracy of analysis. SVM and PCA are two methods that can be used to efficiently reduce artifacts in EEG signals, allowing for the full use of EEG data in a variety of applications. In recent years, several researchers have explored the use of CNNs for EEG noise reduction, demonstrating promising results. In a 2020 study, Sun et al. [**79**] introduced CNN-1D-ResCNN, one of the first applications of CNN for EEG noise reduction. Similarly, Yang et al. [**80**] used weights in an objective function along with CNN and an auto-encoder to eliminate artifacts without sacrificing the integrity of the EEG field signal. These experiments show that CNNs have the ability to successfully minimize EEG signal noise.

Combining recurrent neural networks (RNNs) with convolutional neural networks (CNNs) is another intriguing method for EEG noise reduction. Zhang et al. [81] introduced EEGdenoiseNet, a design that eliminates dangling artifacts by combining CNNs and a recurrent neural network (LSTM). This architecture's use of RNNs allows the network to take into account the temporal relationships present in the EEG signal, which improves the efficiency of the noise reduction procedure. Moreover, Mashhadi and colleagues [82] effectively converted every EEG wave into an image for use as an input in a model intended for image segmentation applications. This model highlights the flexibility of CNNs in processing EEG data by allowing the selection of weights and filters that eliminated artifacts from the EEG signal. It is based on the convolutional neural network architecture known as U-NET [83]. In general, there is potential for reducing noise and artifacts in EEG signals through the use of CNNs, RNNs, and other deep learning approaches. These techniques should grow more and more successful in enhancing the quality of EEG data available for analysis as research develops.

Before machine learning techniques for EEG artifact removal are widely used, there are still several restrictions, even with the promising results. The non-linear character of artifacts is one of the main obstacles, making it more difficult to separate artifacts while keeping the important information in EEG signals. The high processing power needed for machine learning algorithms is another major barrier that makes them less useful and accessible for many researchers. As such, rather than using direct artifact removal, researchers frequently choose to use machine learning to extract features from EEG data. With this method, it is possible to create a hybrid model in which the later layers extract features and the earlier ones remove artifacts. However, the use of machine learning for EEG artifact removal is still being investigated, and future developments in computing power and machine learning algorithms should improve the efficiency and usability of these techniques. As such, it is expected that machine learning methods will play a bigger part in EEG artifact elimination in the future.

Apart from artifacts, extrinsic noise sources including electromagnetic interference [84], inadequate skin-electrode contact, or insufficient electrode quality [85] can potentially impact EEG readings. In order to overcome these problems, scientists have created denoising algorithms that try to remove undesirable noise while maintaining the non-linear properties of the EEG signal [86].

Typically, denoising techniques incorporate wavelet decomposition, averaging, and filtering as part of signal processing. To make sure that the denoising procedure does not alter the natural EEG signal or eliminate any important information, it is necessary to use these methods carefully. As such, researchers need to carefully evaluate the merits of several denoising algorithms and decide which one is best for their particular need. To sum up, denoising is an essential part of the EEG signal processing pipeline and is required to get accurate and consistent results from EEG investigations.

used the short-term FT of EEG signals in combination with two-dimensional CNN algorithms to investigate the critical elements required to separate preictal information from the interictal phase. To get high accuracy in any appliance, significant feature extraction is a crucial step in machine learning or pattern detection. Not every researcher uses the same handcrafted features. Deep learning techniques for programmed feature extraction on any raw data have therefore been developed in the field of pattern recognition. By seeing specific patterns in EEG data, medical experts can estimate the number of seizures. They automatically extracted features from their brains using prior knowledge they had acquired throughout medical school or practice. As a result, many researchers have automated the extraction of features from seizure data using DL approaches[64]. The investigation was carried out by using the VGG16 model and transfer learning for tomato ripeness detection and categorization[65].

In order to forecast epileptic seizures, this study aims to differentiate between epilepsy patients (who do not have seizures) and healthy controls. The algorithm predicts when seizures will start by analyzing EEG signals obtained from electrodes affixed to patients' heads. There was usage of an improved deep CNN network. Architecture: We were able to increase accuracy and forecast seizures.

3. Encouragement

The underlying motivations for research efforts in seizure prediction are examined in this section. Millions of people worldwide are impacted by this common neurological abnormality, which has a significant and frequently negative impact on their entire quality of life. By offering early warnings and interventions, seizure prediction has the potential to completely transform the treatment of epilepsy and improve patient safety and wellbeing. But there are many obstacles in the way of good seizure prediction, one of which is the requirement for precise, dependable, and instantaneous forecasting. Our research therefore aims to solve these issues and make a significant contribution to this important field by creating sophisticated deep learning and hybrid models that aim to improve the lives of people with epilepsy.

4. Methodology

Section 1: Importing the Data and Preparing It

First, the code clears all variables, closes all open figures, and clears the workspace. This guarantees that the surroundings are sanitized and prepared for the fresh dataset.The "DataSet.csv" CSV file is where the dataset is loaded from. The data is read into a matrix using the "readmatrix" function. The dataset is divided into labels and data characteristics. While the labels are kept in the variable labels, the data features are kept in the variable DataS. In this instance, the labels indicate the category to which each observation belongs, regardless of whether the observation is consistent with an epileptic seizure. The "mat2cell" function is used to turn the data features into a cell array. This is required for the CNN instruction.

Part 2: Dividing Data into Sets for Testing and Training

The "randperm" function is used to generate a random permutation of the data's indices. The data will be divided into training and testing sets using this. The training and testing indices are defined using the random indices. Thirty percent of the indices are utilized for testing, while the first seventy percent are used for training. Using the training and testing indices, the matching data and labels are extracted from the source dataset to form the training and testing sets. The variables Xtrain and LabelTrain contain the training set, whereas XTest and LabelTest include the testing set.

Section 3: Creating a Training Observation Image

The plot function is used to plot a single training observation. Plotting the time steps is done on the x-axis, while feature values are done on the y-axis. There is a legend used to identify the characteristics. The feature index appears after the term "Feature" in the legend. To guarantee that the complete observation is viewable, the axis boundaries are defined.

Section 4: Establishing and Educating the CNN Network

A layered sequence is utilized to define the architecture of the CNN network. Among the layers are "sequence Input Layer": An input sequence of data is received by this layer.

"convolution1dLayer": A 1D convolution operation is carried out by this layer. There are sixteen filters, with a filter size of five and a number of sixteen. Since'same' is the padding setting, the length of the output sequence and the input sequence are same. "reluLayer": The rectified linear unit (ReLU) activation function is applied in this layer. "layerNormalizationLayer": The activations of the preceding layer are normalized in this layer.

Convolutional Layer Repetition

There are two iterations of the convolutional layers, each with an increasing number of filters. As a result, the network can extract information at various scales.

Worldwide Max Pooling

A global max pooling layer is added after the convolutional layers. By calculating each feature's greatest value over the course of the whole time series, this layer lowers the dimensionality of the data.

Completely Networked Layer

Mapped features to output classes is achieved by adding a completely linked layer. The number of classes and the number of neurons in the completely linked layer are the same.

Layers of Activation and Classification

The softmax function, which normalizes the fully connected layer's outputs into probabilities for each class, is applied by adding an activation layer. In order to place every observation in the class with the highest probability, a classification layer is added at the end.

Choosing a Training Program

The training choices function is used to define the training choices. Among the choices are 'Adam': This designates the Adam optimizer as the optimizer to be used for training.

MiniBatchSize=10: This instructs the system to use a 10-batch size.
MaxEpochs=100: This specifies 100 as the maximum epoch count.
SequencePaddingDirection="right" indicates that the input sequences should have padding added to their right.
Plots="training-progress": Selecting this option makes the training progress visible.
Educating the Network
The train Network function is used to train the network. Several hours are needed for the training procedure, which varies based on the size of the dataset and the available computer power. Assessing the Network. The classify function is used to evaluate the network on the testing set. The network's accuracy.

5. CNN

CNN architecture is the foundation of deep learning neural networks and is widely used in signal processing and picture categorization. Deep learning models do these activities autonomously, negating the need for human feature extraction and preprocessing, in contrast to typical machine learning architectures. CNN Architectures facilitate learning by directly extracting features through the model, eliminating the need for specialized feature extraction abilities. The use of CNN architectures has skyrocketed in recent years due to this benefit. Convolution, activation, pooling, and fully linked layers are the four layers that make up CNNs.[66]. CNN structures usually have two pieces because they are layered. In the first, input, convolution, and pooling layers are combined to extract features. The categorization function is carried out by a fully linked layer in the second part. Because of the non-standard design of these layers, the layer sequences and parameter values of the network can be changed to create different models.

5.1 CNN Layered

The several layers and activation functions used in CNN architecture design are explained in this subsection..

5.2. Input Layer

CNN models use multidimensional array formats for data entry, whereas classical neural networks use one-dimensional arrays. The convolutional layer receives the raw picture data from the input layer in a matriline format. [67].

5.3. Convolutional layering

The convolutional layer uses filters with different sizes called kernels to extract features from the input image. These are the areas of the output where the features specified by each filter are located. through the convolution process[68].

5.4. The layer for pooling

By assigning each filter a predefined stepping value, the pooling layer moves certain filters around the image. This lowers the processing effort because the subsequent network levels have smaller input sizes. This layer is essential for reducing computational expenses and data size, as well as helping to lessen network overfitting.

5.5. Activation layer

Rectified Linear Unit (ReLU) and Softmax are popular activation functions in CNN topologies. However, additional functions like Sigmoid, Tanh, and Leaky ReLU are also employed [69]. ReLU: ReLU is frequently utilized in the intermediate layers of CNN and nonlinear systems, where it selectively stimulates neurons. It produces zero when the input value is negative, deactivating the neurons in that circumstance. Although it reduces synchronous neuron firing, it has the drawback of setting all negative values to zero [70].

$$f(x) = maks(0, x) \qquad (1)$$

Softmax: The binary classification-oriented sigmoid function is more helpful than Softmax, which is mostly utilised for multi-class classification tasks. The number of target classes in multi-class models is correlated with the number of neurones in the output layer [71].

$$\sigma(z)_j = e^{z_j} / \sum_{k=1}^{K} e^{z_k} \quad for\ j = 1, \ldots\ldots, K \qquad (2)$$

Sigmoid: This function converts input values into a range between 0 and 1, and is often utilized due to its consistent differentiability and dependable neuron output signals.

$$f(x) = 1/e\text{-}x \qquad (3)$$

$$f'(x) = 1\text{-sigmoid}(x) \qquad (4)$$

The particular job at hand determines which activation function should be used. For instance, sigmoid functions may produce superior outcomes in categorisation circumstances. However, because of the vanishing gradient problem, sigmoid and tanh are seldom used, particularly in buried layers.The approach states that the buried layers of the neural network design are where the ReLU activation function is most frequently utilized. This preference can be explained by the fact that learning in these layers is made easier by ReLU's one derivative[72].

5.6. The dropout layer

The dropout approach selectively deactivates nodes in the fully connected layer to prevent overfitting during training with huge datasets [73].

5.7. the surface of Level

The flatten layer converts matrix-sized data from the convolution and pooling layers into a one-dimensional array to speed up processing in the fully connected layer [74].

5.8. Fully linked and classifier layer

The CNN design places a completely connected layer on top of the classification layer. This layer converts multidimensional feature maps into a single dimension for classification. Based on the required number of classes, the fully connected layer's output is separated into classes [75].

This is the overall form(fig 2) of the structure of the CNN algorithm built by us. These layers are repeated in depth to extract information and improve performance.

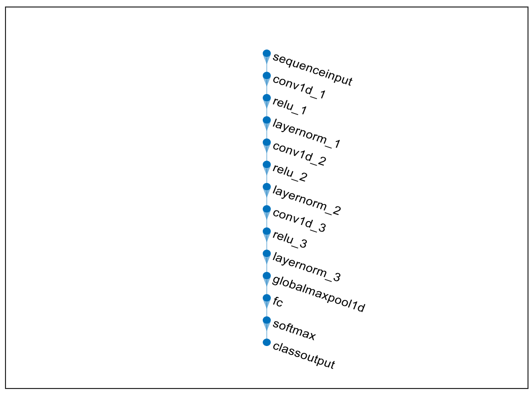

Fig.2. show of CNN architecture

6. Data Collections

One of the shortlisting criteria for datasets was the use of open-access datasets containing information from adult patients with epilepsy as well as those in excellent health. These UC Irvine ML Repository datasets were selected[76]. The quantity of features and samples in these datasets is displayed in Table 1.

Table 1 displays the distribution of samples for each class in UC Irvine dataset.

Title 1	Title 2	Title 3	Title 4	Title 5
UC Irvine	9200	2300 a	9200	11,500

6.1. UC Irvine ML Repository

With 100 signals per class, numbered 1 through 5, each class in this dataset has a duration of 23.6 seconds. Class 4 signals are those created with the eyes closed, while class 5 signals are those made with the eyes open. These classes deal with signals that were based on five healthy individuals. Five epileptic patients' signals are included in the last three classes (1, 2, and 3). Class 2 recordings were made in the patient's epileptogenic region, whereas class 3 recordings were made in the contralateral hemisphere of the patient's hippocampus pre-seizure area. None of the recordings were made during seizure episodes. Nonetheless, signals captured during epileptic episodes are included in class 1.

A 128-channel system with a sampling rate of 173.61 Hz and a 12-bit analog-to-digital converter was used to record all EEG data. Each of the dataset's 11,500 samples has 178 properties and is distributed regularly. Interestingly, those in classes 2, 3, 4, and 5 do not have a history of epileptic seizures; only those in class 1 do. As a result, the dataset analysis has a binary structure that separates instances of epileptic seizures from those that are not. The non-epileptic cases are reflected in Classes 2, 3, 4, and 5.

The dataset's sample distribution across several classes is shown in Table 1. Every class stands for a distinct mental health issue. Because it fairly reflects a wide range of brain states and situations, this balanced distribution enables accurate modelling and analysis for a number of applications in EEG data research and diagnostics[77]. A new column called "y" has been introduced to make the binary categorisation easier; cases with values of 0 indicate that they are not epileptic (classes 2, 3, 4, and 5); instances with values of 1 indicate that they are. Kaggle was the source of the dataset [77]. People in Classes 2, 3, 4, and 5 have never experienced epileptic seizures. Conversely, individuals who did not experience any seizures but had a history of epileptic seizures had their discharge records examined. Table Two shows the overall distribution of the samples throughout the five classes, with an equal number of samples assigned to each class. In particular, 2300 of the samples are epileptic instances, whereas the remaining 9200 are not.

Class	Description	patient status	sample count	type
١	Seizures are observed and documented from	Epilepsy in general	2300	samples of epileptic (2300)
٢	The tumor was seen in EP.	PE (absence of seizures)	2300	0.99
٣	An EEG signal was recorded in EP from a functional area of the brain.	PE (absence of seizures)	2300	0.99
٤	EEG signal obtained from healthy individuals with their eyes open specimens	Good health	٢٣٠٠	non-epileptic
٥	EEG signal obtained from healthy individuals with their eyes closed	Good health	٢٣٠٠	

Table 2 shows the distribution of samples for the UC Irvine dataset by class.

6.2. Measures of Performance

Four performance metrics were used to assess the classification results: F1 score, recall, precision, and classification accuracy. These indicators provide valuable information about the categorisation model's efficacy.The proportion of properly categorised samples to all samples in a test set is known as classification accuracy. It is an essential metric for evaluating the overall accuracy of the model's predictions. Equation (1) divides the number of properly categorised samples (NCCS) by the total number of samples (TNS) to determine the accuracy (ACC).

$$\textbf{Accuracy} = \frac{\textbf{TP + TN}}{\textbf{TP + TN + FP + FN}}\ \textbf{100\%} \ldots\ldots..(\textbf{1})$$

The F1 score and accuracy can be combined to provide a thorough analysis of categorisation. Precision and recall are combined to provide the F1 score, which balances false positives and false negatives. Precision, a measure of accuracy in detecting positive samples, is computed by dividing the total number of true positive and false positive forecasts by the number of true positive predictions. Equation (2) uses precision to evaluate the model's classification accuracy for positive occurrences. In a similar vein, recall shows how effectively the model can recognise each positive sample. The ratio of true positive forecasts to the total of true positive and false negative predictions is how it is calculated. Equation (3)'s recall assesses how well the model captures all pertinent positive[78, 79].

$$\textbf{Precision} = \frac{\textbf{TP}}{\textbf{TP + FP}}\textbf{100\%} \ldots\ldots..(\textbf{2})$$

$$\textbf{Recall} = \frac{\textbf{TP}}{\textbf{TP + FN}}\textbf{100\%} \ldots\ldots..(\textbf{3})$$

$$\textbf{F1 Score} = \frac{(\textbf{2 x (Recall x Precision)})}{(\textbf{Recall + Precision})}\textbf{100\%} \ldots\ldots..(\textbf{4})$$

Analyse our experiment's classification outcomes thoroughly using these empirically proven performance criteria to obtain a clear picture of the efficacy and dependability of our classification model[78, 80, 81].

7. Results

Our research entitled (A Convolutional Neural Networks Method for Classified of Epileptic Seizure Detection via EEG Diagnosis), compared two classify, the first (General Epilepsy) and the second included the rest of the categories As in the following Table 3. Regarding our ongoing study, we categorised the data set. Seizures from people with epilepsy (EP) (general epilepsy) are the first of three categories. The first instance involves seeing the tumour in EP (without seizures), the second involves capturing an EEG signal from a healthy brain area in EP, and the third involves combining the two cases. The first is an EEG signal of healthy patients (Healthy) with their eyes open, and the second is an EEG signal of healthy patients (Healthy) with their eyes closed.5.1. CNN algorithm

The results of the CNN algorithm classifier show its superiority over machine learning algorithms[32, 38]. Table 3 indicates that the CNN classifier that was more accurate,precision, recall and F1 score than the machine learning classifiers. We also noticed that when the dataset was split into different training/testing, the results showed different accuracy and the best result was at 96.17%. CNN algorithm.

Table 3: CNN classifier with the training set

Method used	Accuracy	Precision	Recall	F1 Score
50% training	95.67%	0.97	0.98	0.98
60% training	95.89%	0.98	0.98	0.98
70% training	96.17%	0.97	0.97	0.97
80% training	96.17%	0.97	0.99	0.98

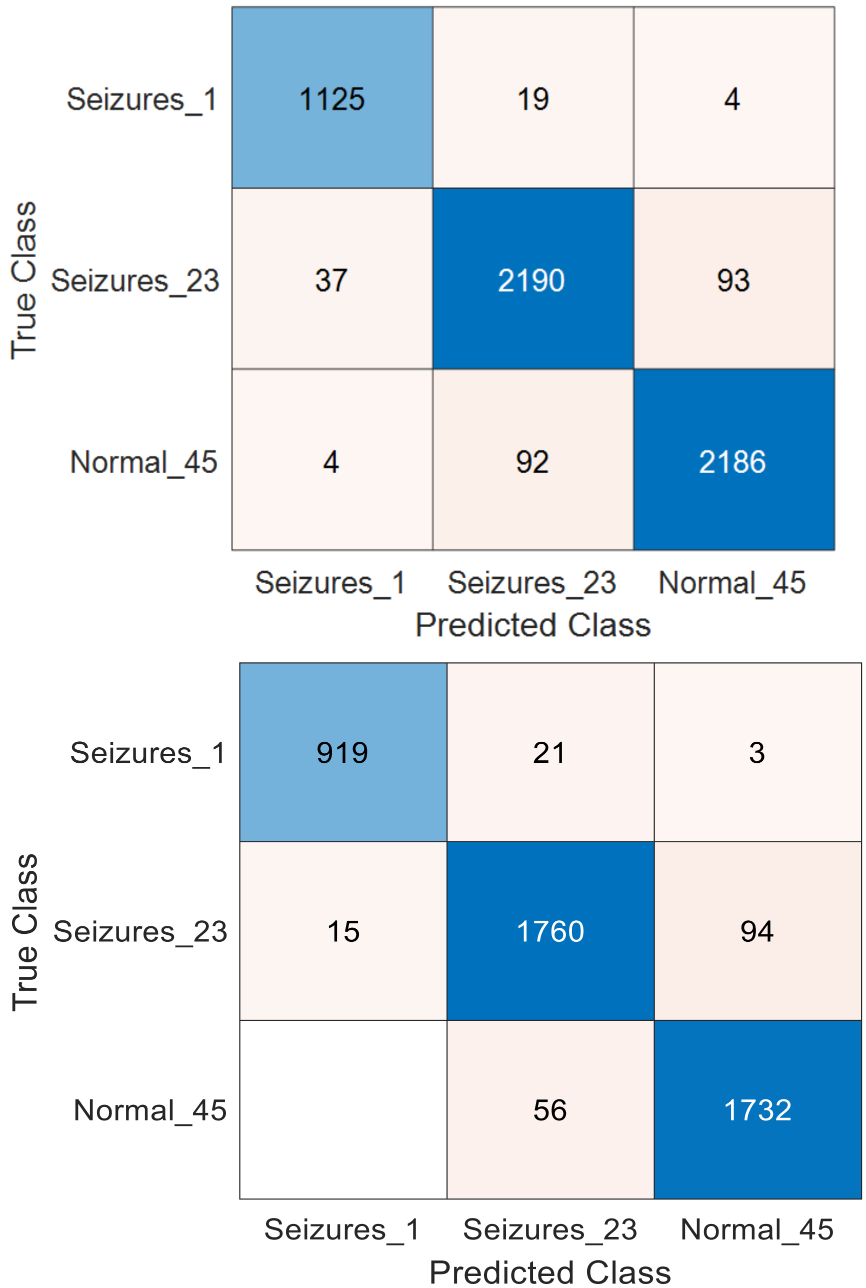

Fig. 4. CNN predicted class with the training 60 %

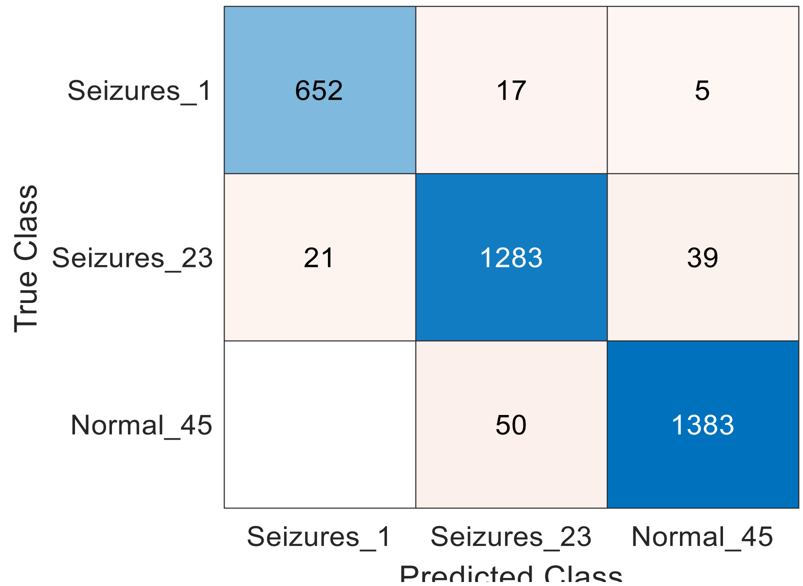

Fig.5. CNN predicted class with the training 70 %

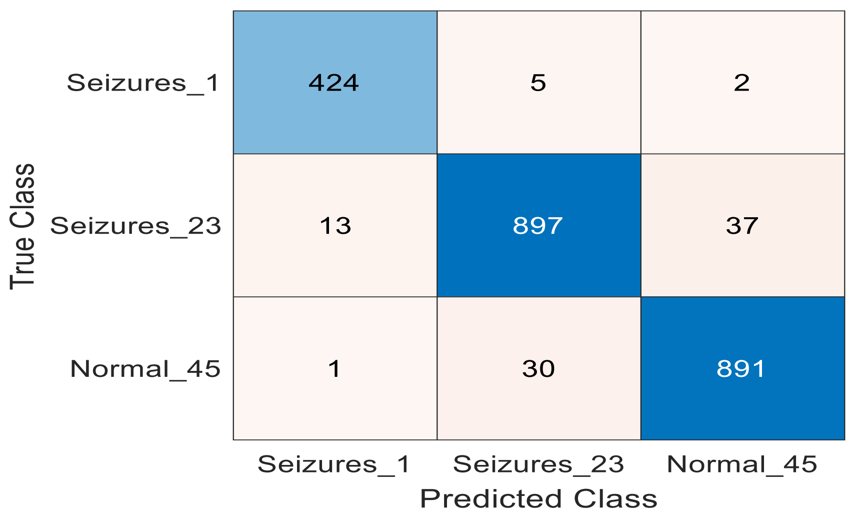

Fig.6. CNN predicted class with the training 80%.

6. Conclusions

Using the EEG dataset, the CNN algorithm found high-performing people who worked towards a diagnosis of epilepsy. The accuracy of the produced models varied from 0.95 to 0.96, while their F1 score ranged from 0.97 to 0.98. With the biggest dataset, the CNN algorithm did rather well, achieving 96.17 percent accuracy, 97-0.98 percent precision, 0.97-0.98 percent recall, and a 97-98 percent F1 score. The finest scientific findings regarding the use of EEG data for diagnosing epilepsy were obtained from this study. It demonstrates that high-performance diagnoses may be made by the CNN algorithm without the need for a medical expert's expertise. This study demonstrates how the CNN algorithm can analyse challenging EEG timeseries datasets and generate effective diagnosis solutions.

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