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Automatic Detection of Epilepsy from Electroencephalography (EEG) Signals Using Artificial Intelligence (AI)

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Abstract

A central nervous system illness called epilepsy is brought on by aberrant brain activity and can produce convulsions or even unconsciousness in its victims. One way of diagnosing epilepsy is neurological. From a neurological point of view, the underlying cause of epilepsy cases is sometimes unclear. Therefore, the electroencephalography (EEG) technique is used by looking at human brain activity under various conditions. Experts will usually analyse visually the EEG signals to see the brain activity in people with epilepsy. However, with so much data, the visual analysis will take a lot of time and effort. In addition, sometimes there are errors in reading and deciding epilepsy results from EEG visualization results. The goal of the research is to use artificial intelligence (AI) to create an application that uses electroencephalography (EEG) data to identify epilepsy. Convolutional Neural Networks (CNNs) are the AI technique employed in this study. Pre-processing and identification are the two phases of this study approach, which involves categorizing data related to epilepsy (seizures) and no epilepsy (non-seizures). The pre-processing stage is carried out using a toolbox in Python software called EEGLAB, which will produce a feature in the form of the energy spectrum of the EEG signal. The Convolutional Neural Network (CNN) approach will then employ the feature extraction results as input for identification or classification. The Convolutional Neural Network (CNN) approach achieved 90% accuracy in the detection or categorization of epilepsy using EEG pictures.

Keywords: Artificial Intelligence; CNN; Epilepsy; EEG

1. Introduction

A condition of the central nervous system, epilepsy is brought on by aberrant brain activity and can produce convulsions or even unconsciousness in its victims. Epilepsy can occur repeatedly and will cause involuntary movements of certain body parts and even the whole body. Epilepsy can also affect life risks such as premature death. The disorder can occur in all age ranges and ethnicities and in both men and women. However, epilepsy usually appears in childhood and toddlerhood. According to the World Health Organization (WHO), people with epilepsy sometimes have many physical problems due to seizures, such as broken bones or bruises. In

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addition, the psychological problems of people with epilepsy are also quite high, such as anxiety and even depression (WHO, 2022). The death rate related to epilepsy disorders is three times higher than for other neurological disorders. Epilepsy can be caused by several factors, such as brain tumours, stroke, severe head injuries, and even genetic factors from parents who have a history of this disease.

Epilepsy is a neurological condition that affects around 50 million individuals worldwide, according to the WHO (WHO, 2022). With 80% of sufferers coming from countries with lower or middle income. About 1.5 million persons in Indonesia alone had epilepsy in 2016, accounting for 0.5% to 0.6% of the country's total population. There are approximately 700,000–1,400,000 cases of epilepsy in Indonesia, with an annual increase of 70,000 new cases; 40–50% of these cases are in children. (Rahmadani, Indriati, & Erwin, 2024).

There are various ways of diagnosing epilepsy, such as history taking in the form of observation, interviews, and even physical and neurological examinations (Weinstein, 2016)**;** Nowacki & Jirsch, 2017). Due to the high mortality rate, a technique is needed to diagnose epilepsy quickly, namely with EEG. From a neurological point of view, the underlying cause of epilepsy cases is sometimes unclear. Therefore, the electroencephalography (EEG) technique is used to look at human brain activity under various conditions and to distinguish neurological diseases, such as encephalopathy, brain death, coma, and epilepsy (Alkhachroum et al., 2022). Experts will usually analyse visually the EEG signals to see the brain activity of epileptics. However, with the large amount of incoming data, the visual analysis will take a lot of time and energy. In addition, sometimes there are errors in reading and deciding the results of epilepsy from the results of EEG visualization, and it can affect the next stage, such as the implementation of treatment (treatment) to the sufferer. Moreover, epilepsy also has various conditions that can determine whether a patient has epilepsy or not (Alkhachroum et al., 2022; Kim, Shin, Kim, Lee, & Cho, 2024). In addition, there is less clear evidence in distinguishing EEG results between epilepsy and other brain diseases such as meningitis, infarction, and others that allow patients to be treated with the wrong drugs.

To distinguish this, a handful of researchers in the fields of neuroscience, physics, biophysics, neurophysiology, biomedicine, or other fields try to help in identifying epilepsy more accurately by using other methods such as the use of computational techniques. Such as research conducted by Birjandtalab, Heydarzadeh, & Nourani (2017), They tried to classify EEG signals in epilepsy by using a machine learning algorithm, ‘random forest’ to find out the channels that produce epilepsy signals, as well as the K-Nearest Neighbours (KNN) algorithm for classification. They get an accuracy of about 87%. In addition, there is research conducted by Krishnaprasanna & Vijaya Baskar (2018), (Birjandtalab et al., 2017) that identifies epilepsy through the approach of classifying focal and non-focal EEG signals using the Support Vector Machine (SVM) algorithm method. Where they get an accuracy value of around 96.8%. Then there is research on epilepsy identification conducted by Shankar, Raminaidu, Raju, & Rajanikanth (2021). In this case, machine learning is used to process, detect, identify, classify, and even diagnose epilepsy from

EEG recordings. They try to detect epilepsy on EEG using the help of the ANN (artificial neural network) model algorithm, where they get the final result of accuracy around 97.55% (Shankar et al., 2021).

Some of the above studies show a fairly high level of accuracy when using machine learning. The research we have done is to identify the EEG signal of epilepsy in infants. The Neonatal Intensive Care Unit (NICU) at Helsinki University Hospital supplied the dataset that was used. EEG readings from new-borns with and without seizures are used in this investigation. Researchers and medical professionals can utilize the EEG signal's many pieces of information to determine whether a patient has epilepsy or seizures. The two phases of this study approach are the pre-processing stage and the identification step, which involves categorizing data that has undergone the pre-processing stage as either epileptic (seizure) or non-epileptic (non-seizure). The pre-processing stage is carried out using a toolbox in Python software called EEGLAB. The Butterworth band-pass filter will be used for the filtering step of the pre-processing process. The Fast Fourier Transform (FFT) and Power Spectral Density (PSD) will be used for the feature extraction stage, which will generate an energy spectrum feature from the EEG signal. The outcomes of feature extraction will then be sent into machine learning for classification or identification. Convolutional Neural Network (CNN) transfer learning is a machine learning algorithm utilized in this study to test the system throughout the classification phase.

2. Method

2.1 Materials

We made use of the CHB-MIT Scalp EEG Database, a renowned public data source (Faust, Acharya, Adeli, & Adeli, 2015). EEG recordings from 23 paediatric patients with uncontrollable seizures were gathered at Boston Children's Hospital and are included in this database. EEG signals were simultaneously captured on 21–28 channels at a rate of 256 samples per second with a resolution of 16 bits. Clinical professionals determined the start and finish times of seizure occurrences.

2.2 Classifying Epileptic Eeg Signals Using CNN

The suggested study uses a bidirectional recurrent neural network (BRNN) that combines CNN and LSTM to identify epileptic EEG signals in a novel way. Using a convolutional layer as the starting network to receive epileptic EEG data as input is the fundamental concept behind the CNN-LSTM combination. Figure 1 depicts the phases of research for epilepsy detection using EEG.

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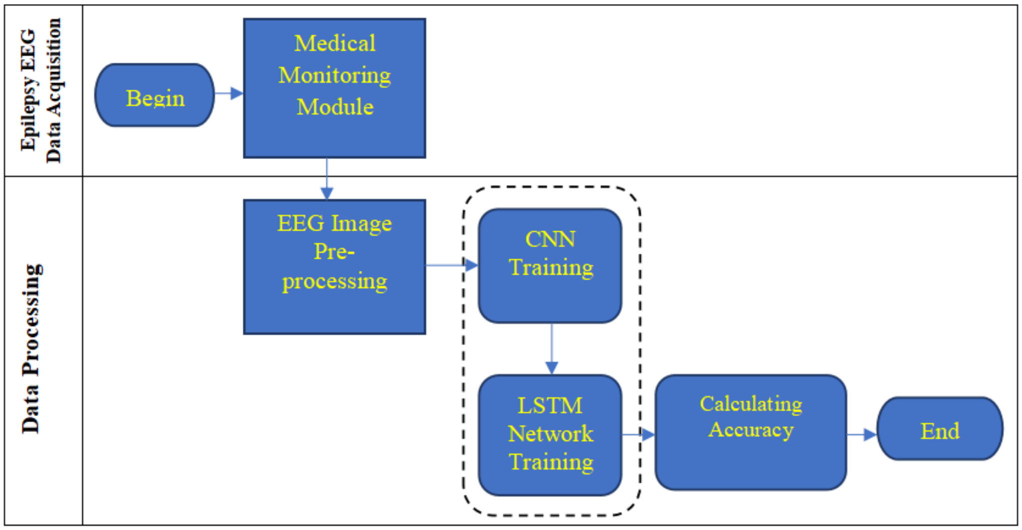

Figure 1. EEG Diagnosis of Epilepsy Based on CNN-LSTM Model

The method consists of four main modules. In detail, it can be explained as follows:

2.2.1. Data Acquisition

Digital EEG signal data can be obtained from the database available at the University of Bonn. This information was produced by Dr. Ralph Andrzejak of the University of Bonn's Epilepsy Centre in Germany and is accessible online (Übeyli, 2009). There are two kinds of EEG signal data from the University of Bonn: classes that contain data on epilepsy with seizures and classes that contain data on epilepsy without seizures. 100 single-channel EEG segments, each lasting 23.6 seconds, are included in each dataset. EEG recordings of both healthy and epileptic patients yielded the signals in sets A and B.

2.2.2. Pre-processing

The initial step was to obtain the unprocessed EEG data that were fed into the pre-processing module. A typical 10-20 system was used to record the raw EEG data, with a sampling frequency of 173.61 Hz. A frequency range of 0.5 to 50 Hz was obtained by applying band-pass filtering in order to achieve a practical frequency range. Additionally, 23.6 seconds were spent segmenting the EEG dataset. Prior to being included in the model, the data was normalized to have a unit standard deviation and a mean value of zero. The outcomes of the first generation of EEG pictures are displayed in Figures 2 and 3.

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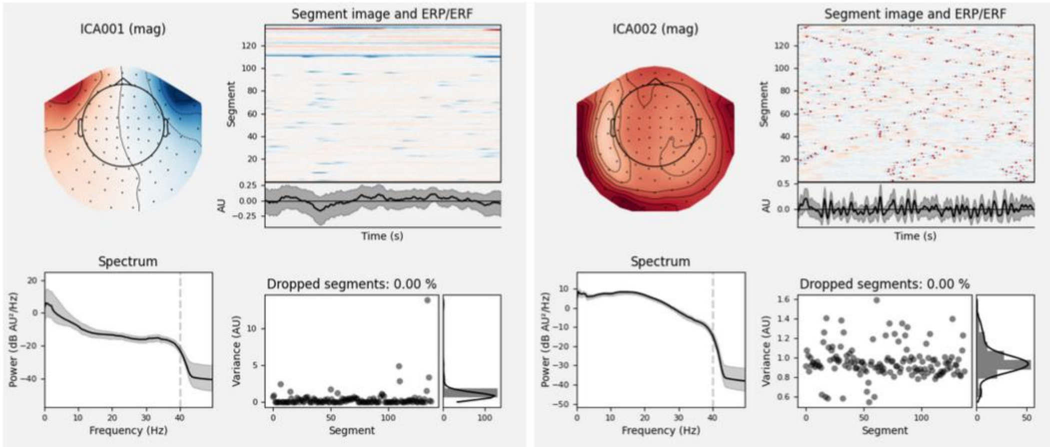

Figure 2. EEG Image Preprocessing Result

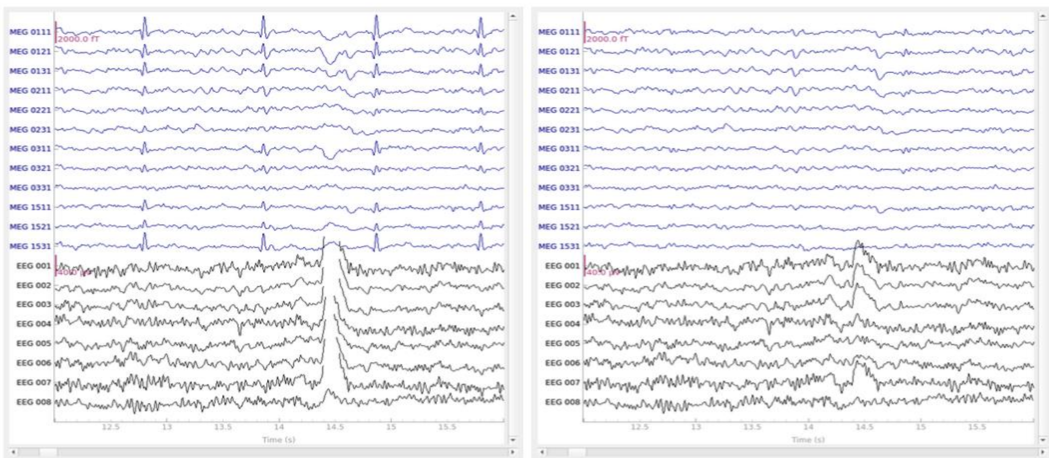

Figure 3. EEG Image Preprocessing Results on Duration 15 and Component 20

2.2.3. Epilepsy Detection from EEG Image Using CNN

GPU is employed for computation in this study. Installing Keras, a Python-based deep learning library, on the server and using TensorFlow, Google's deep learning framework, as the back end are necessary in order to implement the CNN model. Google's deep learning framework, TensorFlow, serves as the back end. The training data is then used to train the model. In order to maximize speed and attain more accuracy, specific parameters must be chosen based on model requirements and empirical experience, even though deep learning networks have powerful learning capabilities. A CNN network is then used to feed the signals into the automatic extraction and classification module. To extract spatial information, the convolution layer receives the pre-processed data. In order to extract time series information from the EEG data, the CNN is then directly connected to the pooling layer. Lastly, the classification process is finished using the dropout layer and the fully linked layer.

Feature learning and classification are the two phases of CNN architecture-based classification. A method called feature learning enables a system to automatically convert an image's representation into features—numbers that represent the image. At the classification step, the outcomes of feature learning will be applied to the classification procedure according to the identified subclasses.

1. Feature Learning

Using a technique called feature learning, a system may automatically convert an image's representation into feature numbers that represent the image.

a) Convolution Process

Convolution is the initial step in feature learning. Combining two sets of numbers to create a third set of numbers is known as convolution. The numbers in this convolution are represented as a matrix array if it is implemented. According to the input, the image's pixel size is 60x60x3, meaning that its height and width are 64 and that it has three channels—red, green, and blue, or RGB for short.

b) Pooling Process

Pooling is the process of employing a pooling technique to reduce the size of a matrix. Max-pooling is the technique employed in this pooling procedure. One of the frequently employed techniques by researchers in the field of deep learning is max-pooling. Dominik Scherer et al.'s study (Urbánek et al., 2010) demonstrated that the max pooling approach is better than the subsampling approach. This approach is among the most effective ways to pool resources.

2. Classification

The next stage is epilepsy detection from the EEG image. At the classification stage, there are two types of classification, namely Flatten and Fully Connected.

a) Flatten

Flatten or totally linked comes next. Currently, the MLP (Multi-Layer Perceptron) network only uses one hidden layer. Here, flatten creates a vector from the pooling layer output. The Dropout value is employed in this procedure prior to picture categorization, processing, or prediction. A strategy for regulating neural networks called dropout aims to randomly pick certain neurons that will not be used during training; in other words, the neurons are eliminated at random. Reducing overfitting during training is the aim of this procedure. The SoftMax activation function is used in the final step. Specifically, multiclass linear discriminant analysis and multinomial logistic regression classification techniques make use of this function.

b) Fully Connected Process

The Fully Connected Layer is the second step in the categorization process. The goal of this procedure is to change the dimensionality of the data so that linear classification is possible. The results of the classification are epilepsy patients and epilepsy patients with seizures.

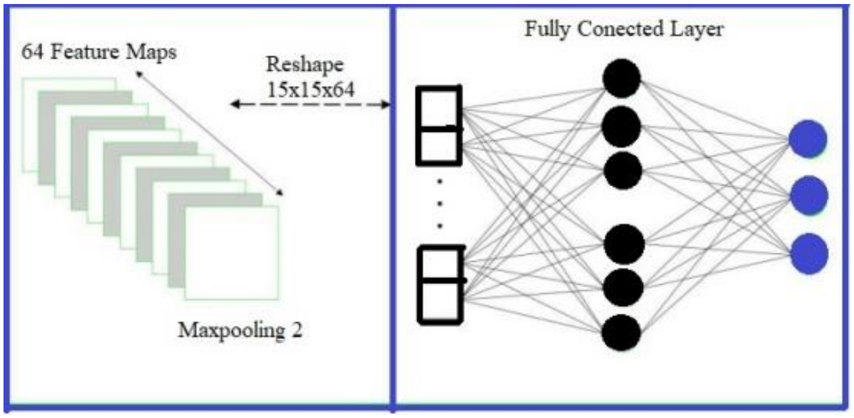

Figure 4. Fully Connected Layer Prosess

2.2.4. Calculating Accuracy, Sensitivity and Specificity

To test the accuracy of the proposed method using the Receiver of Characteristic (ROC) method. By comparing the classification results of the developed system with the detection results of experts (doctors).

3. Result

We divided the data into 80% training and 20% testing at random for testing. We present the average performance of the 5-fold cross-validation on the training data as well as the performance metrics of the test data as hold-out validation, which gauges the model's efficacy on fresh data. From the pre-processing procedure performed, we obtained four datasets as shown in Table 1. The data are patient-specific data consisting of three datasets, namely Chb01, Chb02, and Chb03. The other data is multiple patient data consisting of Chb01, Chb02, Chb03, Chb05, and Chb05.

Table 1. Summary of pre-processed EEG datasets

Patient Type	Sobject	EEG Hours	Number seizures	Total Epoch	Seizures Epoch
Patient Specific	Chb01	44	5	145610	505
	Chb02	35	3	126842	207
	Chb03	38	7	136464	465
Multiple Patient	Chb01, Chb02, Chb03, Chb05, Chb08	35	5	125685	430

Table 2. Classification performance of patient-specific classifiers on chb01 (44 hours)

Test Type	Accuracy Level	Data EEG			
		CHB01	CHB02	CHB03	CHB05
Cross Validation	Accuracy	0.9994	9.9993	0.9995	0.9984
	TPR	0,8577	0.5965	0.8750	0.6203
	FPR	0.0001	0.0001	0.0001	0.0003
Hold-on Validation	Accuracy	0.9996	0.9995	0.9998	0.9995
	TPR	0.8899	0.7273	0.9348	0.8684
	FPR	0.0000	0.0000	0.0000	0.0001

CNN detected more than 85% of the seizures for chb01 and chb03 with a false positive rate (FPR) of almost zero; however, the performance decayed to 59% for chb02. One reason for this significant drop in performance may be that chb02 has less than half of the seizure sample proportion than other subjects, making it more challenging for the algorithm to capture the minority class. The performance of our classifier is similar to existing patient-specific classifiers from the literature, which range from 70-90% TPR.

4. Discussion

Three metrics are used to evaluate model performance: accuracy, True Positive Rate (TPR), and False Positive Rate (FPR). Accuracy measures the overall percentage of correct classifications; TPR is the percent of true positives correctly classified, and FPR indicates the percent of samples incorrectly classified as positive. We chose these metrics with future application scenarios in mind. For portable seizure detectors, TPR is the most important because seizure detectors must correctly identify seizures to ensure rapid medical intervention. The second important reading is the non-convulsive FPR, as high false alarms can significantly worsen the user experience. In addition, the FPR can indicate how good the model is at correctly separating seizure signals from physiological and pathological EEG and various artifacts (Keijsers, 2010).

Conclusion

In conclusion, we built an accurate classifier for detecting epileptic seizures using multichannel EEG data, achieving 70-90% TPR and below 0.2% FPR. We observed that adjusting the class weight assignment can significantly improve the performance of minority class classification when the data is highly imbalanced. For future research, we recommend including a larger subject-specific dataset to better assess the performance of non-patient-specific classifiers.

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