

Detection of Epileptic Seizures using a Five-level Db4 Wavelet, Scalogram and CNN

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ABSTRACT

This Epilepsy is a serious neurological disorder after stroke that affects 50 million individuals. People with epilepsy face various challenges, with around 20-30% unable to fully control seizures. Due to this issue, automated detection based on EEG signals is necessary to support epilepsy studies with appropriate methodological approaches. This paper's epilepsy detection is conducted based on EEG raw signals categorized into normal and epileptic seizures, the programming language used is Python. The signals are decomposed into five-level by Daubechies4 Discrete Wavelet Transform (DWT) to extract both approximation and detail signals. This system utilizes Python programming. A scalogram is used to visualize how transient signal activity changes with changes in time scale. DWT processthe with original sampling frequency is 128 Hz, and the number of levels is 5. The frequency range of the output data after DWT at level 5 is 4-7 Hz. Finally, an Convolutional Neural Network (CNN) classifies all the extracted features. With an accuracy of 97%

INTRODUCTION

Epilepsy is a neurological disorder of the brain accompanied by a series of brief recurrent seizures due to spikes in abnormal electrical activity within a group of brain cells [1][2]. Seizures can occur in various degrees of severity and duration. Often, seizures are accompanied by unconscious movements of the entire or partial body and sometimes can lead to loss of consciousness [1]. The disease of epilepsy receives the second most serious attention in the world after stroke, impacting the quality of life of individuals with the condition [3]. In 2016, around 50 million individuals globally received a diagnosis of epilepsy [4], with a mortality rate reaching 1.74 per 100,000 individuals [3]. In developing countries, the prevalence of epilepsy is estimated to be twice as high as in developed countries. Approximately 100 new cases of epilepsy occur per 100,000 individuals each year [1][4].

People with epilepsy face various challenges. About 20-30% of epilepsy patients still cannot fully control their seizures [5]. Furthermore, some patients undergoing treatment still experience epilepsy comorbidities despite advancements in care and therapy. Medical professionals diagnose epilepsy based on accurate patient history descriptions of past seizure events, physical examinations, genetic studies, neurological examinations, and additional tests such as electroencephalograms (EEG) [6][7]. An EEG recording depicts brain electrical activity, obtained by recording voltage fluctuations within brain cells over a certain period [8][9]. In medicine, abnormalities in EEG signals provide essential information for a patient. Visual assessment of EEG signal data patterns is time-consuming, often taking several days to months [10]. Due to this issue, medical professionals cannot feasibly conduct routine evaluations and interpretations. Therefore, automated detection based on EEG signals is needed to support epilepsy studies with appropriate methodological approaches.

Research on EEG signal detection in epilepsy continues to evolve. In efforts to develop the methods used, researchers have identified various areas of focus. One common approach is applying DWT to extract important information from EEG signals and then using Machine Learning algorithms for classification. Through the DWT, raw signals are separated into several sub-bands, enabling the detection of relevant patterns for classification [2].

Deep learning algorithms have shown enhanced efficacy when utilized for detecting seizures and predicting seizures [11]. This approach enables systems to learn, comprehend, and make decisions based on the provided data by employing complex learning algorithms, mirroring the way humans process information.

This paper categorizes raw signal data into two classes: normal and epileptic seizures. The signals are decomposed into five-level sub-bands by Daubechies4 DWT to extract both approximation and detail signals. A scalogram is used to visualize how transient signal activity changes with time scale changes. Finally, an CNN classifier classifies all the extracted features.

LITERATURE REVIEW

Electroencephalogram (EEG) Signal Analysis

Electroencephalogram (EEG) is a technique used to record electrical activity of the brain over time. EEG signals are non-stationary and complex, making them difficult to analyze using conventional methods. In epilepsy detection, EEG signals are essential because seizures are characterized by abnormal electrical discharges in the brain [10]. Therefore, advanced signal processing techniques are required to extract meaningful information from EEG data.

Discrete Wavelet Transform (DWT)

Discrete Wavelet Transform (DWT) is widely used for analyzing non-stationary signals such as EEG. It decomposes signals into multiple frequency sub-bands, allowing both time and frequency domain analysis [28]. Previous studies have shown that DWT is highly effective in extracting relevant features for seizure detection.

Research by Sunaryono et al. demonstrated that DWT combined with CNN can achieve high classification accuracy of 98.09% [2]. Similarly, Ibrahim et al. utilized DWT with Shannon entropy for adaptive EEG classification, achieving up to 100% accuracy [12]. Chen et al. proposed a combination of DWT and Support Vector Machine (SVM), achieving improved robustness and classification accuracy [13]. In addition, Sharmila et al. showed that DWT combined with Naïve Bayes achieved 100% accuracy [14], while Bairagi et al. combined DWT with ANN and obtained 99.44% accuracy with low latency [15]. These findings confirm that DWT plays a significant role in improving EEG signal feature extraction.

H1: The use of Discrete Wavelet Transform (DWT) improves feature extraction performance in EEG-based epileptic seizure detection.

Scalogram Representation

A scalogram is a visual representation of signal energy distribution in the time-frequency domain obtained from wavelet transform. It is particularly useful for analyzing transient and non-stationary signals such as EEG [21]. Scalogram transforms EEG signals into image-like representations, enabling better visualization of signal characteristics over time. This representation is highly suitable for deep learning models such as CNN, as it enhances the ability to capture temporal variations in brain activity.

H2: Scalogram-based representation enhances the visualization and separability of EEG signal features for seizure detection.

Machine Learning Approaches in EEG Classification

Machine learning techniques such as Support Vector Machine (SVM), Naïve Bayes (NB), k-Nearest Neighbor (k-NN), and Artificial Neural Networks (ANN) have been widely applied in EEG signal classification. Wijayanto et al. used Empirical Mode Decomposition combined with SVM for seizure detection [5]. Rachman et al. applied Independent Component Analysis (ICA) and wavelet denoising with Probabilistic Neural Network (PNN) for EEG classification [9]. Furthermore, Melinda et al. utilized DWT combined with Linear Discriminant Analysis (LDA) to classify EEG signals effectively [20]. Although traditional

machine learning methods provide good performance, they require manual feature extraction and selection.

Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is a deep learning model capable of automatically extracting features from input data. CNN has been widely used in EEG classification, especially when signals are transformed into scalogram images. Daoud et al. demonstrated that deep learning models significantly improve seizure detection performance [11]. Rincon showed that CNN achieves high accuracy in epileptic seizure detection tasks [31]. Additionally, Sagga et al. proposed a 1D-CNN approach for EEG signal classification, achieving reliable performance [32]. CNN eliminates the need for manual feature engineering and improves classification accuracy by learning hierarchical representations from data.

H3: Convolutional Neural Network (CNN) improves classification accuracy in EEG-based epileptic seizure detection.

Conceptual Framework

Based on the theoretical review and previous studies, this research proposes the following framework:

EEG Signal → Pre-processing → DWT Decomposition → Scalogram Generation → CNN Classification → Seizure Detection

METHODOLOGY

Materials

This system comprises CHB-MIT data, software, and hardware consisting of a personal computer featuring an Intel(R) Core(TM) i7 2.80 GHz processor and 8GB RAM. The PC operates on the Windows 10 Pro operating system, The programming language used is Python.

Methods

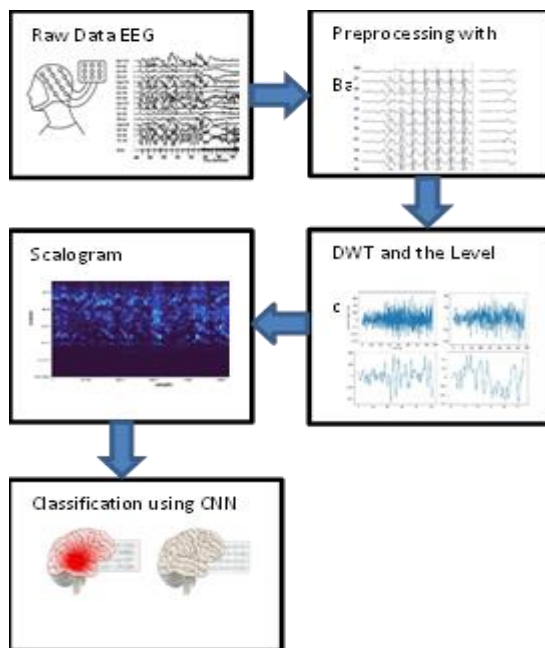


Fig.1. System Block Diagram

The block diagram of this system can be seen in Figure 1, A. Data Set CHB-MIT Scalp EEG database comprises EEG recordings obtained from 22 children with refractory epilepsy. These individuals were monitored for a few days following the cessation of their anti-seizure medication to evaluate their eligibility for surgery. The dataset includes 23 instances from 22 participants, encompassing five boys and 17 girls aged between 1.5 and 22 years. The average recording time is 36 hours. The duration of digital EEG signals varies, with some cases lasting one hour while others last two or four hours. The signal is represented using a 16-bit resolution, and the sampling process is carried out 256 times per second. In recording EEG signals, the placement and naming of electrodes follow the standard of the 10-20 International system. EEG files contain 23 electrode recordings placed around the head. Each recorded signal encompasses both regular and seizure (ictal) periods. This study categorizes the signals into two groups: seizures and normal activity.

The DASPS database contains recordings of Electroencephalogram (EEG) signals from 23 participants during anxiety triggers through face-to-face psychological stimuli. DASPS aims to create a starting point for new research in the field of anxiety detection. The Emotiv EPOC+, designed for broad and contextual human brain research, provides access to high-quality professional brain data with a quick and user-friendly design. The technical specifications of the Emotiv EPOC+ are also outlined, including the number and locations of sensors: AF3, AF4, F3, F4, FC5, FC6, F7, F8, T7, T8, P7, P8, O1, O2, sampling rate of 128 SPS (2048 Hz internal), and a resolution of 14 bits, where 1 LSB = 0.51 μ V.

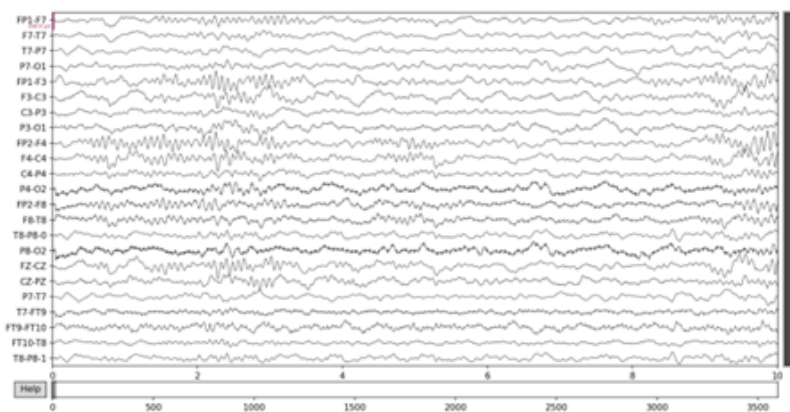


Fig2. Raw EEG Signal

Pre-Processing

In the Pre-processing, EEG signals are processed using a bandpass filter applied at specific frequencies. Noise in EEG signals, which is non-stationary and non-linear, can be filtered after decomposition using Discrete Wavelet Transform (DWT). DWT allows the analysis of signals in the time-frequency domain by utilizing lowpass and highpass filters to separate low and high frequencies [16][12]. The use of Discrete Wavelet Transform (DWT), especially with the Daubechies 4 wavelet filter, is highly effective in removing noise from EEG signals [17][18].

Discrete Wavelet Transform (DWT)

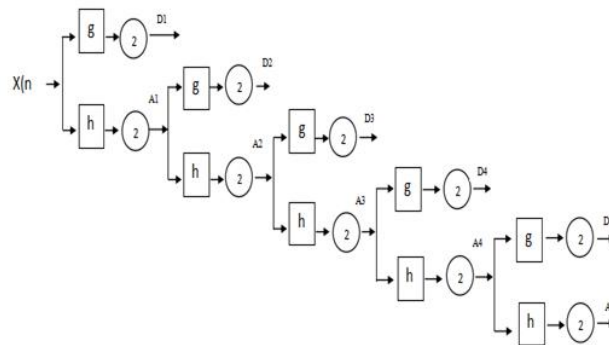


Fig 3. Decomposition of a signal into sub-bands by the DWT method

Decomposition is an iterative process of breaking down a signal and decomposing it into several components with lower resolutions [19][5]. DWT and signal decomposition play a crucial role in EEG signal classification [20], enabling the extraction from complex and non-stationary signals [15]. Signal decomposition using DWT separates EEG signals into sub-parts with different frequencies, allowing analysis of signal characteristics that may be contained within each sub-part. Thus, important features of EEG signals can be better extracted for classification purposes, enabling classifiers to recognize patterns that may be present in EEG data more efficiently.

In Figure 2, the first-level approximation signal (A1) and detail (D1) are the signals generated by the main filter. The approximation coefficient as the input is calculated for the next level of approximation and detail signals. From this process, the total length of the signal remains constant after the decomposition process.

Scalogram

A scalogram is a visual representation of the result of wavelet transformation. Scalogram illustrates how the frequency energy in a signal changes over time, which is useful for analyzing non-stationary signals where the frequency characteristics change [21]. In the scalogram section, a visual representation shows how transient signal activity changes with time scale changes.

Convolutional Neural Network

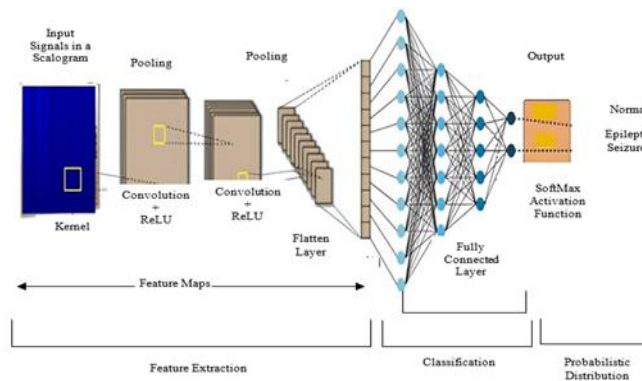


Fig 4. Seizure detection flowchart using scalogram

Convolutional Neural Network (CNN or ConvNet) is a popular deep learning algorithm, commonly used for analyzing images such as object recognition, object classification, etc. CNN is a deep learning network architecture that learns directly from data, eliminating the need for manual feature extraction. CNN can also be referred to as an artificial neural network that involves convolution (CNN = ANN + convolution). The Convolutional Layer performs convolution operations on the input image using a number of filters. Each filter produces an output called a feature map. ReLU is an additional layer that allows for faster and more effective training by mapping negative values to zero and retaining positive values. Essentially, ReLU is a per-pixel operation that replaces negative pixel values in the feature map with zero. Similar to the Convolutional Layer, the Pooling Layer is responsible for reducing the spatial size of the feature matrix resulting from the convolution. This aims to reduce the computational power required to process the data through dimensionality reduction. There are two types of pooling: Max Pooling and Average Pooling. Max Pooling returns the maximum value from the portion of the image covered by the kernel, while Average Pooling returns the average of all values from the portion of the image covered by the kernel. After feature detection, the CNN architecture transitions to classification. The final layer in a CNN is the fully connected layer (FC), which produces a K-dimensional vector, where K is the number of classes the network can predict. This vector contains the probabilities for each class of each classified image. The last layer of the CNN architecture uses the softmax function to provide the classification output.

Confusion Matrices

Confusion matrices and performance evaluation metrics such as accuracy, precision, recall, and F1-score help us understand how well a CNN model can classify images related to stress-related diseases, which is crucial in the development and improvement of the model.

Table 1

		Actual /Ground Truth		
		Seizures of epilepsy	No Zeizures	Anxious states
PredictedValue	Seizures of epilepsy	True Positive (TP)	False Positive (FP)	False Positive (FP)
	No Seizures	False Negative (FN)	True Negative (FN)	False Negative (TN)
	Anxious states	False Positive (FP)	False Positive (FP)	True Positive (TP)

$$Akurasi = (TP+TN) / (TP+FP+FN+TN)$$

RESULTS AND DISCUSSION

Band Pass Filter in Preprocessing

The results of testing in the pre-processing section using raw EEG signal data from epilepsy patients showed the shape of the signal after being filtered for the first five seconds. The red signal represents the original signal, while the blue signal is the result of the filtering process, as shown in Figure 4 below.

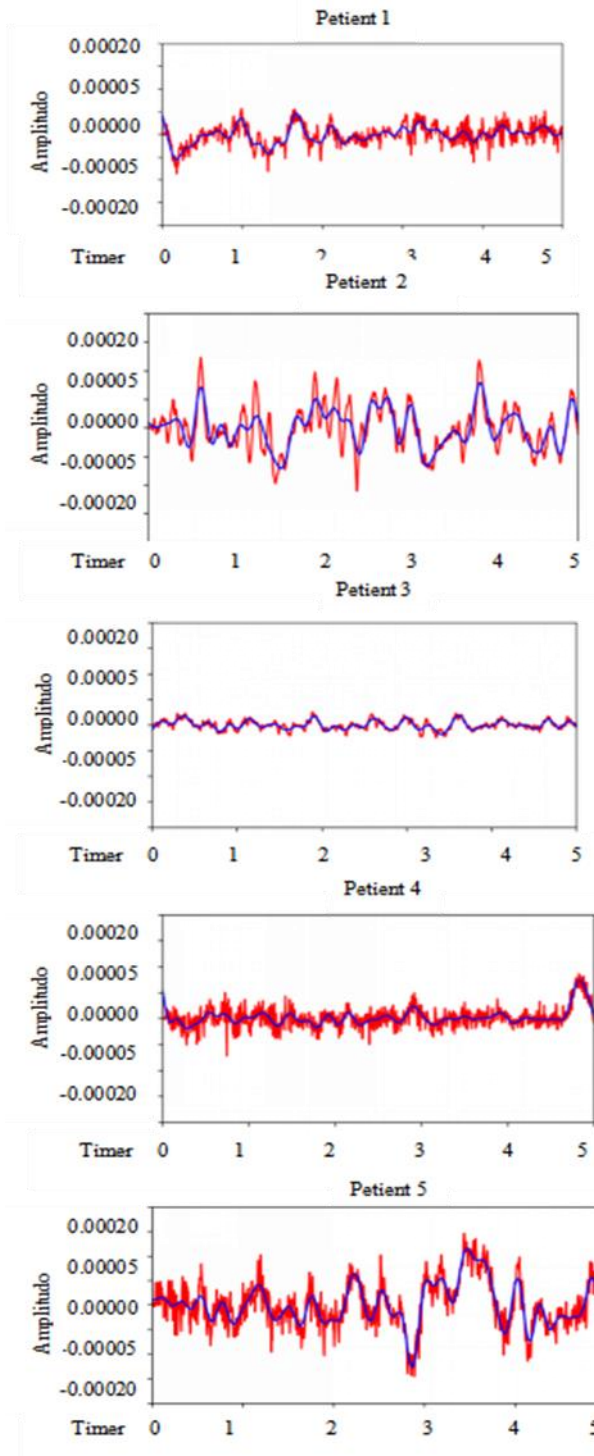


Fig 4. Band-Pass Filter in the First Five Seconds

The filter used in this study is a Band-Pass Filter, where the filtering process allows the frequency range of the EEG data signal to pass through and removes noise within the frequency range of 0 Hz - 128 Hz, with the filtered signal ranging from 0 Hz to 40 Hz. Setting the frequency range of the raw EEG data to 0 Hz - 128 Hz can be used to detect noise [22].

The frequency range of brain activity is typically between 3 and 29 Hz, and there is no brain activity below 0.5 Hz. Physical movement usually generates other electrical activities [23]. The band-pass filtering process with a frequency range of 0.5-40 Hz eliminates mixed sounds and artefacts [23]. Therefore, this study uses a band-pass filter with a cutoff frequency greater than 40 Hz and less than 0.5 Hz, equivalent to 0 Hz.

Decomposed signal into five-level sub-bands by Daubechies4 DWT

The subsequent testing involves detecting the waveform during seizures using discrete wavelet transform (DWT) decomposition at five decomposition levels.

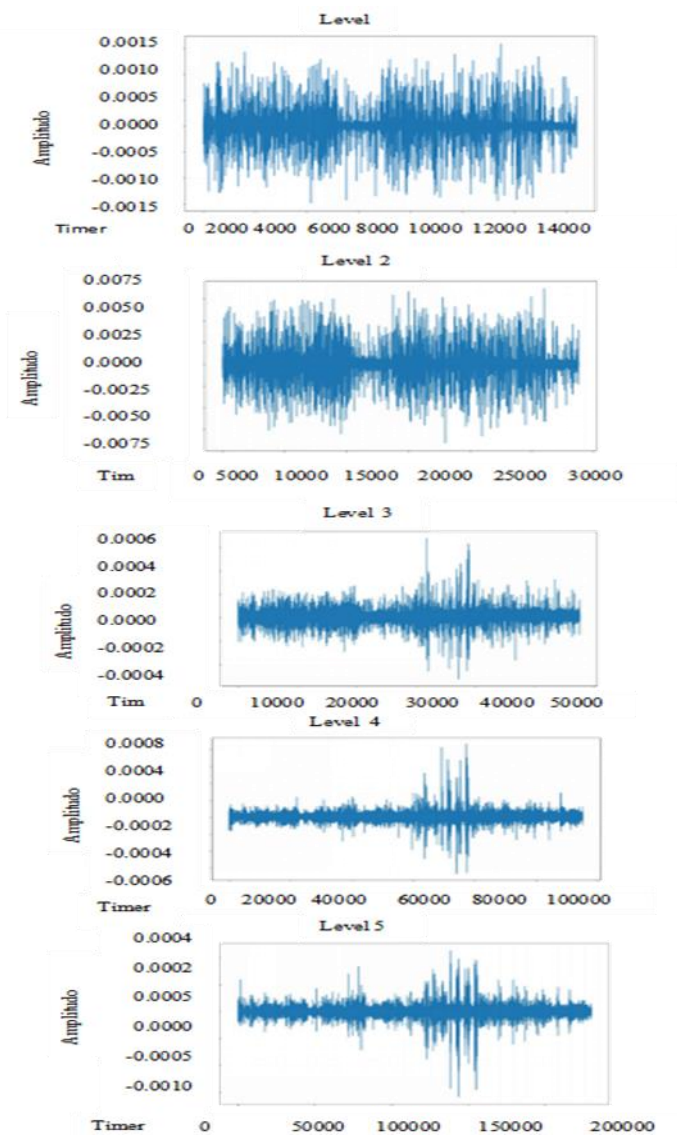


Fig 5. Signal after decomposition using Db4 DWT

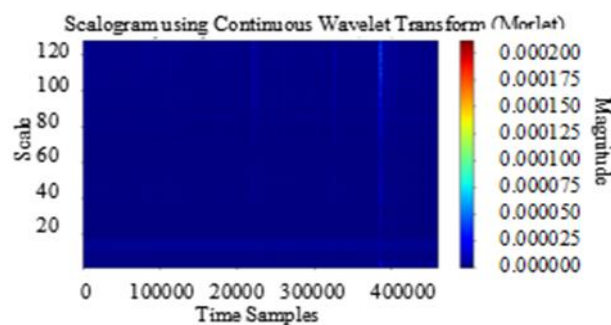
(Yovi - pasien 1) testing the first patients pengujian ke. kejan atau normalkah. The testing of this research in the DWT section is shown in Figure 5, where a five-level decomposition is used for testing the first patients (pasient 1) in normal conditions and during seizures. The signal is divided into low and high-frequency components in this decomposition process. Wavelet Transform is a method that accurately captures information by providing the signal's time and frequency domain information [24]. DWT is used to analyze signals in the time-frequency domain, one of which is DWT decomposition. Research on the performance of DWT for epilepsy seizure detection has achieved high accuracy compared to conventional methods [25]. DWT has been used to detect abnormal waves in EEG signals of epilepsy patients [16].

Figure 5. a shows the result of DWT decomposition during normal testing on patient 1 and Figure 5. b shows the result of DWT decomposition during seizure testing on patient 1 too. This research uses Using the Daubechies4 (Db4) Wavelet with five levels of decomposition. Based on test results the frequency range of each level in DWT depends on the number of levels and the original signal's sampling frequency. In this case, the original sampling frequency is 128 Hz, and the number of levels is 5. The frequency range of each level can be calculated as follows: level 1: 64-127Hz, level 2: 32-63Hz, level 3: 16-31Hz, level 4: 8-15Hz and level 5: 4-7Hz. Therefore, the frequency range of the output data after DWT at level 5 is 4-7 Hz.

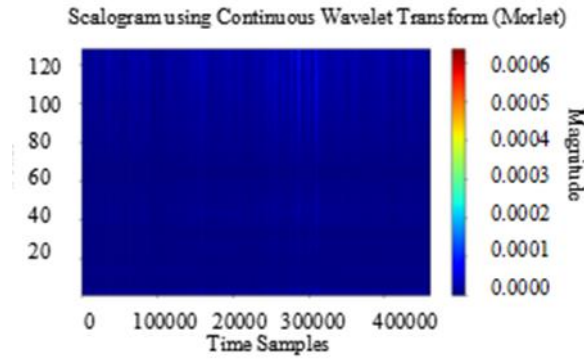
EEG signals were extracted using the Daubechies4 (Db4) Wavelet form. Due to the non-stationary and asymmetric nature of EEG signals, the Db4 Wavelet form is more suitable for extraction processes, considering that Db4 is more reliable in handling asymmetric and orthogonal signals. Db4 each has four low-pass filter coefficients and high-pass filter coefficients [26]. The DWT method, with the type of mother wavelet has used Daubechies 4 with five decomposition levels [27].

Akurasi klasifikasi menggunakan DWT terbukti berhasil dengan nilai 99,7% [100], penggunaan DWT untuk deteksi kejang telah dilakukan 40 buah penelitian dan menggunakan CWT dengan 21 buah penelitian (translate) [28]. [100] Acharya UR, Sree SV, Ang PCA, Yanti R, Suri JS. Application of non-linear and wavelet based features for the automated identification of epileptic EEG signals. *Int J Neural Syst* 2012;22(2):1250002.

Visualization of Signals in a Scalogram



(a)



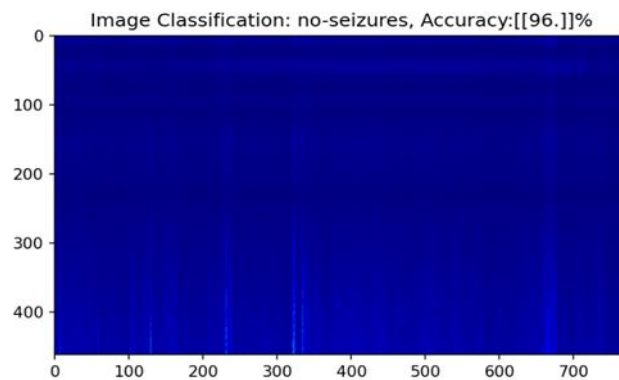
(b)

Fig 6. Visualization of signals in a scalogram (a) Normal (b) Epileptic Seizure

Scalogram illustrates how the frequency energy in a signal changes over time, which is useful for analyzing non-stationary signals where the frequency characteristics change [21]. Deep learning can be utilized to classify EEG signals to detect epilepsy seizures [29], employing data mining and machine learning techniques [30]. Many machine learning algorithms have been found have good generalization ability and can even solve the problems having small training samples [47].

The testing on the CNN part can be seen in Figure 7, examining the first patient under normal conditions and during seizures.

		Actual /Ground Truth		
		Seizures of epilepsy	No Zeizures	Anxious states
Predicted	Seizures of epilepsy			
	No Seizures			
	Anxious states	0	0	23



(a)

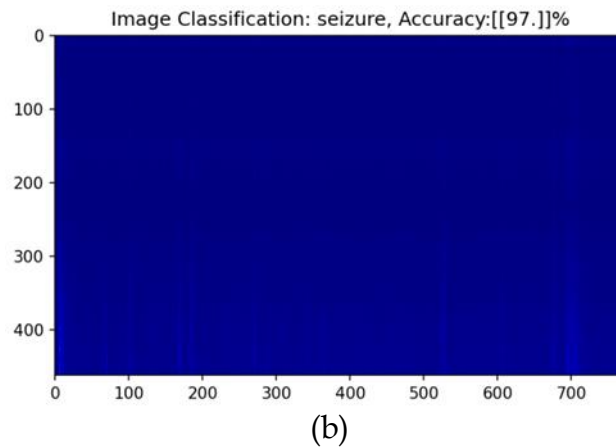


Fig 7. Visualization of signals in a CNN (a) Normal (b) Epileptic Seizure

Moreover, the performance of the CNN classifier can be greatly enhanced by the appropriate selection of hyperparameters such as number of filters, filter size, kernel size, pooling size, learning rate, epochs, activation function, optimizer, and batch size. The application of CNN to the representation of EEG from the amplitude data of all electrodes has shown significant potential in classifying EEG signals between healthy subjects and those with epilepsy. With an overall classification accuracy of 99.48%, CNN demonstrates its ability to accurately detect epileptic seizures [31]. Detecting epileptic seizures with reliable accuracy in EEG signals, the method employed involves in-depth an using 1D CNN [32].

CONCLUSIONS AND RECOMMENDATIONS

The paper presents a method for automated detection of epileptic seizures using EEG signals, wavelet decomposition, scalogram. The study demonstrates the effectiveness of this approach through experiments with EEG data from epilepsy patients. It contributes to ongoing research on automated epilepsy detection and emphasizes the significance of utilizing advanced technology in healthcare. The paper references various techniques preprocessing, decomposition, wavelet transform, and scalogram for seizure detection and classification EEG signals. In the DWT process, the original signal with a sampling frequency of 128 Hz is processed with five levels. The data produced in the frequency range of 4-7 Hz at the fifth level is extracted as features and input into a CNN for classification. Studies in this field focus on EEG signal detection for epilepsy prediction and the application of advanced signal processing techniques for automatic seizure detection With an accuracy of 97%.

FURTHER STUDY

Every zation of the proposed epileptic seizure detection system. First, the dataset used in this research is limited to specific EEG recordings, which may not fully represent the variability of brain signals across different patients, age groups, and clinical conditions. As EEG signals are highly non-stationary and patient-dependent, this limitation may influence the robustness of the classification model.

Second, the implementation of the Discrete Wavelet Transform (DWT) is limited to the Daubechies 4 (Db4) wavelet with five decomposition levels. Although this configuration provides good results, other wavelet families and decomposition levels may offer better feature extraction performance. Additionally, the scalogram representation used in this study is based on a specific configuration, which may affect the quality of time-frequency visualization.

Third, the Convolutional Neural Network (CNN) model used in this study still depends on selected hyperparameters such as the number of layers, kernel size, and learning rate. Suboptimal parameter selection may limit the model's ability to achieve maximum accuracy and generalization.

For future research, it is recommended to use larger and more diverse EEG datasets to improve model robustness. Further studies can also explore the use of different wavelet types, hybrid feature extraction methods, and advanced deep learning models such as CNN-LSTM or transformer-based architectures. Moreover, implementing the system in real-time applications and integrating it with clinical decision support systems would enhance its practical usability in medical environments.

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