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Hybrid One-Dimensional CNN and DNN Model for Classification Epileptic Seizure

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Abstract: Epilepsy is a common chronic brain disease caused by abnormal neuronal activity and the occurrence of sudden or transient seizures. Electroencephalogram (EEG) is a non-invasive technique commonly used to identify epileptic brain activity. However, visual detection of the EEG is subjective, time consuming, and labour intensive for the neurologist. Therefore, we propose an automatic seizure detection using a combination of one-dimension convolution neural network (1D-CNN) with majority voting and deep neural network (DNN). EEG signals features are extracted using discrete Fourier transform (DFT) and discrete wavelet transform (DWT) which then these features will be selected with XGBoost to minimize features classified with CNN. The proposed method experimental results show that it can detect epilepsy from EEG signals perfectly with an accuracy of 100%. However, the proposed method only yielded classified EEG signals from the University of Bonn Dataset as its results. The performance of the suggested approach might not be similar to other EEG datasets.

Keywords: Epilepsy, EEG signals, One-dimensional CNN, DNN.

1. Introduction

Epilepsy is a common chronic brain disease caused by abnormal neuronal activity and the occurrence of sudden or transient seizures [1]. According to WHO, there are around 5 million people with epilepsy every year [2]. People with epilepsy are two to three times more likely to die prematurely than people without epilepsy [3]. Electroencephalogram (EEG) is a non-invasive technique commonly used to identify epileptic brain activity. Visual detection of the EEG is subjective, time consuming, and labour intensive for the neurologist. Several hours are required for neurologists to scan one patient's EEG recording which is very burdensome for them [4]. This manual detection of epilepsy is the basis for making automatic epilepsy detection assisted by certain algorithms.

Convolutional neural network (CNN) is a classifier that is often used in classifying images and patterns. Several previous studies have used CNN in classifying epilepsy using EEG data. Jana, Sharma, and Agrawal proposed the use of 1-dimensional CNN where the patient's EEG data was first converted into spectrogram form using the Fourier transform and then inputted into CNN. Before being converted into a spectrogram, the raw EEG data was filtered using a Butterworth filter where the results became EEG data that was cut for 2 seconds. The dataset used is the CHB-MIT dataset. The accuracy produced using the model proposed by this author is 77.57% on average from the data for each significant patient [4]. One-dimensional pyramidal CNN was proposed by Ullah

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in classifying two epilepsy cases, namely 2 classes and 3 classes using the Bonn dataset. Batch normalization is added as an additional layer after the convolution layer to help provide fast convergence while avoiding special initialization of a parameter. Accuracy of 96.1% was obtained for the classification of 2 classes while for the classification of 3 classes an accuracy of 98.1% was obtained [5]. Wei Z introduced the use of CNN 12 Layer as the baseline for epilepsy classification, merger of the increasing and decreasing sequences (MIDS) to highlight the characteristics of waveforms, augmentation data and EEG data information. In Wei's study, the CHB-MIT Scalp EEG database dataset was used. An accuracy of 82.37% was obtained for the use of MIDS while an accuracy of 84% was obtained by a method that uses data augmentation [1]. Wei X shows the use of a 3-dimensional CNN where the dataset used is combined first into a new 3-dimensional form that is entered into the CNN model. Wei X compares the use of CNN 3D with 2D, where the accuracy of CNN 3D is 92.37% while the accuracy of CNN 2D is 89.91% [6]. Dwi Sunaryono proposed an epilepsy detection model using the gradient boosting machine (GBM) in which two classifications were carried out, namely classification 2 and 3 classes which were diffusion using majority voting. Feature extraction used is discrete Fourier transform (DFT) and discrete wave transform (DWT). After that, the feature selection process is carried out using genetic algorithm (GA) to find the most discriminatory features. Then the features are used as input for the two GBMs, then the results of the classification of each GBM are carried out by majority voting where these two processes are called the fusion process. The accuracy obtained is an average of 99.45% using GBM fusion with a number of experiments as much as 24.999 times [2]. Raul Sharma proposed a method to detect epilepsy with third order cumulant (ToC), generate two hidden layers for DNN with sparse autoencoder network with EEG dataset gained from University of Bonn. The method proposed by Raul Sharma yielded an accuracy of 97.20% for class A-B-C-D-E and 99.60% for class AB-CD-E [7]. Ahnaf Rashik Hassan proposed a method for classifying epilepsy with complete ensemble empirical mode decomposition with adaptive noise (CEEMDAN) for processing signal and used a classifier named adaptive boosting (AdaBoost) to classify epilepsy from University of Bonn Dataset. Method proposed by Ahnaf gained accuracies of 98.67%, 97.60%, 99.00%, 100%, and 100% for each class combination of A-D-E, AB-CD-E, C-E, A-E, D-E respectively [8]. Sreelekha Panda used empirical wavelet transform (EWT) to decompose EEG signals and deep ensemble network combining deep neural network (DNN) along with multi layer perceptron (MLP) to classify epilepsy which the dataset gained from University of Bonn. Shreelek method yielded accuracies of 98.93% for classifying A-D-E class, 94.43% for classifying A-E class, and 95.01% for classifying D-E class [9]. Umut Orhan introduced a new method for classifying epilepsy using multilayer perceptron neural network (MLPNN), discrete wavelet transform (DWT) for decomposing signal, and K-means to cluster each frequency sub-band gained from DWT. The accuracies yielded classifying EEG signals from University of Bonn are 96.67%, 95.60%, and 100% for each class combination of A-D-E, AB-CD-E, and A-E respectively [10]. U. Rajendra Acharya proposed a method to classify epilepsy with 13 layer of convolutional neural network (CNN). Dataset used is from University of Bonn. Accuracy obtained with the method proposed by U. Rajendra Acharya are 88.67% and 99.70% for both combination class of A-D-E and A-E [11]. Yilmaz Kaya classify EEG signal which gained from University of Bonn dataset with 1D-LBP to extract feature from EEG signal and used several classifiers which are BayesNet, support vector machine (SVM), artificial neural network (ANN), logistic regression (LR), and functional tree (FT). Proposed method by Yilmaz obtained accuracy of 95.50% for A-E class combination [12]. Yatindra Kumar also proposed a method to classify epilepsy with dataset gained from University of Bonn, discrete wavelet transform (DWT) to decompose signal, approximate entropy (ApEn) to calculate the values of approximation and detail coefficients gained from DWT, and artificial neural network (ANN) as a classifier. Yatindra method obtained an accuracy of 93.00% for D-E class combination [13]. All these studies yield good accuracy, and the use of CNN in EEG classification can still be developed more than has been done before.

Looking at the research of Jana, Sharma, and Agrawal using the 1D CNN Spectrogram method, the accuracy of the value is quite low, which is below the 80% accuracy level. The method used in this journal is to develop the use of 1D CNN using XGBoost as feature selection or to minimize features classified by CNN and the results of CNN classification that have been optimized using weighted majority voting are reclassified using deep neural network (DNN). The method for feature extraction proposed in this study also uses a combination of frequency domain and time-frequency domain for feature extraction by implementing discrete Fourier transform (DFT) and discrete wavelet transform (DWT). In Dwi Sunaryono's research, the feature extraction is the

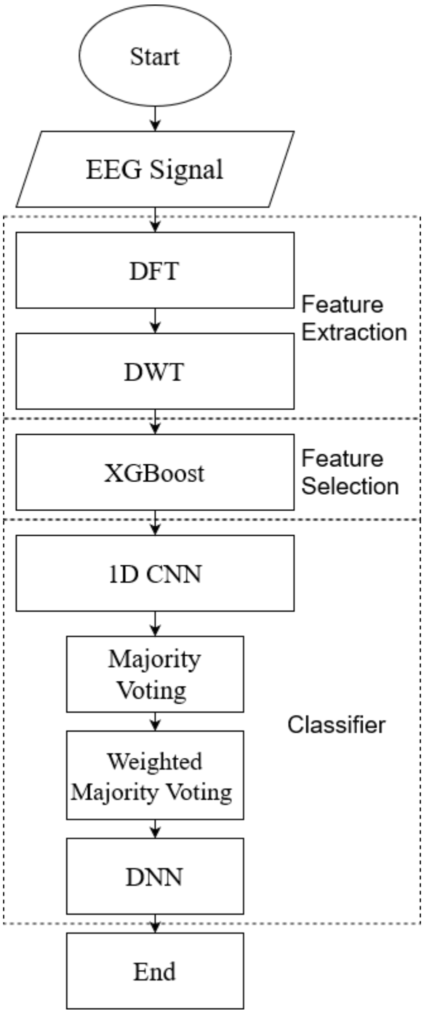

Figure. 1 Proposed method flowchart

same as the one proposed in this study, while Dwi Sunaryono's research uses genetic algorithm (GA) for feature selection, while the proposed method uses XGBoost. The flowchart for the proposed method can be seen in Fig. 1.

The structure of the sections in this journal is as follows. Section 2 describes the materials and methods proposed in this study. Furthermore, in section 3, the results and discussion of the results of the methods used are explained. Finally, the conclusion will be explained in section 4.

2. Materials and method

2.1 Dataset

The proposed method uses a dataset of EEG signals provided by the department of epileptology, University of Bonn (UoB), Germany, compiled by Andrzejak [14]. There are five sets in the dataset as shown in Table 1. Divided by class A, B, C, D, and E which consists of three phases, namely normal, interictal, and ictal. Class A and B normal EEG signals recorded with eyes open and closed. Classes C and D enter the interictal phase. What distinguishes the two is that class C shows defects in the brain (hippocampal), whereas class D EEG signals are collected from hippocampal formations and within the epileptogenic zone. Class E (ictal) consisting of EEG signals from epilepsy patients recorded during the preoperative evaluation process.

Table 1. Dataset overview

Class	Patient	Setup	Phase
A	Healthy	Surface EEG	Eyes Open
B	Healthy	Surface EEG	Eyes Closed
C	Epilepsy	Intracranial EEG	Interictal
D	Epilepsy	Intracranial EEG	Interictal
E	Epilepsy	Intracranial EEG	Ictal

2.2 Feature extraction

2.2.1. Frequency sub-band decomposition using discrete Fourier transform

Discrete Fourier transform is a transformation that deals with a finite-time discrete signal. The proposed method uses DFT to decompose the raw EEG signals into five frequency sub-bands. The five frequency sub-bands are: delta (0-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (12-30 Hz) and gamma (30-45 Hz).

Let $x(i)$, i = 0, 1, 2, …, N-1 be a discrete EEG signal in the time domain with N sample points. The X(i) EEG signal is converted into the frequency domain using DFT as defined in Eq. (1),

$$X(i) = \sum_{n=0}^{N-1} x(n)e^{-\frac{2\pi nj}{N}i}, i = 0, 1, \ldots, N-1 \quad (1)$$

where j = $\sqrt{-1}$.

To get the five frequency sub-bands, X(i) used different frequencies according to the delta, theta, alpha, beta, and gamma frequencies. So there are several variables from delta to gamma. $X_\sigma(i), X_\theta(i), X_\alpha(i), X_\beta(i), dan\ X_\gamma(i)$ each of which has a different frequency. The results of these variables will be converted into the time domain to get the results of the decomposed EEG signals using the inverse of the DFT defined in Eq. (2).

$$X_f(n) = \frac{1}{N}\sum_{n=0}^{N-1} X_f(i) e^{\frac{2\pi ij}{N}n},\ \ i = 0, 1, \dots, N-1, f = \delta, \theta, \alpha, \beta \quad (2)$$

2.2.2. Discrete wavelets transform

Wavelet transform is used to analyze signals in terms of time and frequency. The wavelet transform decomposes the signal into a set of coefficients known as wavelet coefficients. The proposed method uses dwt to be implemented by decomposing the EEG signal into rough approximations and detailed information using a lowpass filter and a high pass filter, respectively. The lowpass filter produces a rough estimate of the coefficients, while the high pass filter produces the detailed coefficients. Choosing the right amount of decomposition rate is important for DWT. For EEG signal analysis, the number of decomposition levels can be determined directly, based on the dominant frequency component and the number of decomposition levels [15].

2.2.3. Statistical features

The statistical feature is used to see the minimum value, maximum value, median, and standard deviation of a data. The proposed method uses the results of the discrete wavelet transform (DWT) which is extracted into five statistical features. There is 5th percentile, 25th percentile, 50th percentile, 75th percentile, and 95th percentile from the coefficient vector. The 5th and 95th percentiles are defined as the low and high points of the data. 50th percentile to determine the median. The 25th percentile (first quartile) and 75th percentile (third quartile) to determine the standard deviation. The statistical feature provides information on how big the box plot of the percentiles of a data is as in Fig. 2. If the box plot is short, it shows that there are many similar data points, because there are many data values in the short range of the box plot, vice versa. This study uses the percentile implementation in the NumPy library to extract statistical features.

2.2.4. Crossing frequency features

Zero-crossing rate (ZCR) looks at the signal changes in the available frames. The ZCR counts the number of times the signal changes value, from positive to negative and vice versa, divided by the length of the frame [16]. The proposed method uses zero-crossing frequency (ZCF) to extract from the resulting DWT coefficient vector to replace the ZCR because all EEG signals in the dataset have the same duration. ZCF calculation can be seen in Eq. (3).

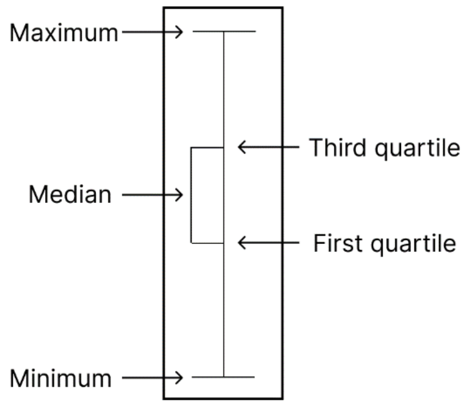

Figure. 2 Basic box plot

$$ZCF = \frac{1}{2}\sum_{i=1}^{N-1}\left|sgn\big(v(i+1)\big) - sgn(v(i))\right| \quad (3)$$

Where N is the length of the coefficient vector, $v(i)$ is the i^{th}element of the coefficient vector, and $sgn(v(i))$ is the sign function that can be seen in Eq. (4).

$$sgn\big(v(i)\big) = \begin{cases} 1, & v(i) \geq 0 \\ -1, & v(i) < 0 \end{cases}, \quad (4)$$

The proposed method also uses the mean crossing frequency (MCF). MCF is used if the signal lies only above or below the horizontal axis, this causes ZCF cannot be used. MCF also receives the DWT result coefficient, which results will be combined into ZCF. It can be seen in Eq. (5) that what distinguishes the calculation between ZCF and MCF is the mean in the variable m.

$$MCF = \frac{1}{2}\sum_{i=1}^{N-1}|sgn(v(i+1)-m) - sgn(v(i)-m)| \quad (5)$$

2.3 Feature selection using XGBoost

To determine the model prediction hypothesis, the feature set is one of several important factors. Feature selection works by taking or selecting some original features based on relevance and redundancy. The relevance of a feature is measured by the characteristics of the data, not by its value. The level of accuracy of the model hypothesis depends on the number of features, because the hypothesis space is directly proportional to the number of features. The greater the number of features, the greater the available hypothesis space [17]. Hypothesis space can be reduced and the accuracy of the model hypothesis will be increased by removing unused and irrelevant features.

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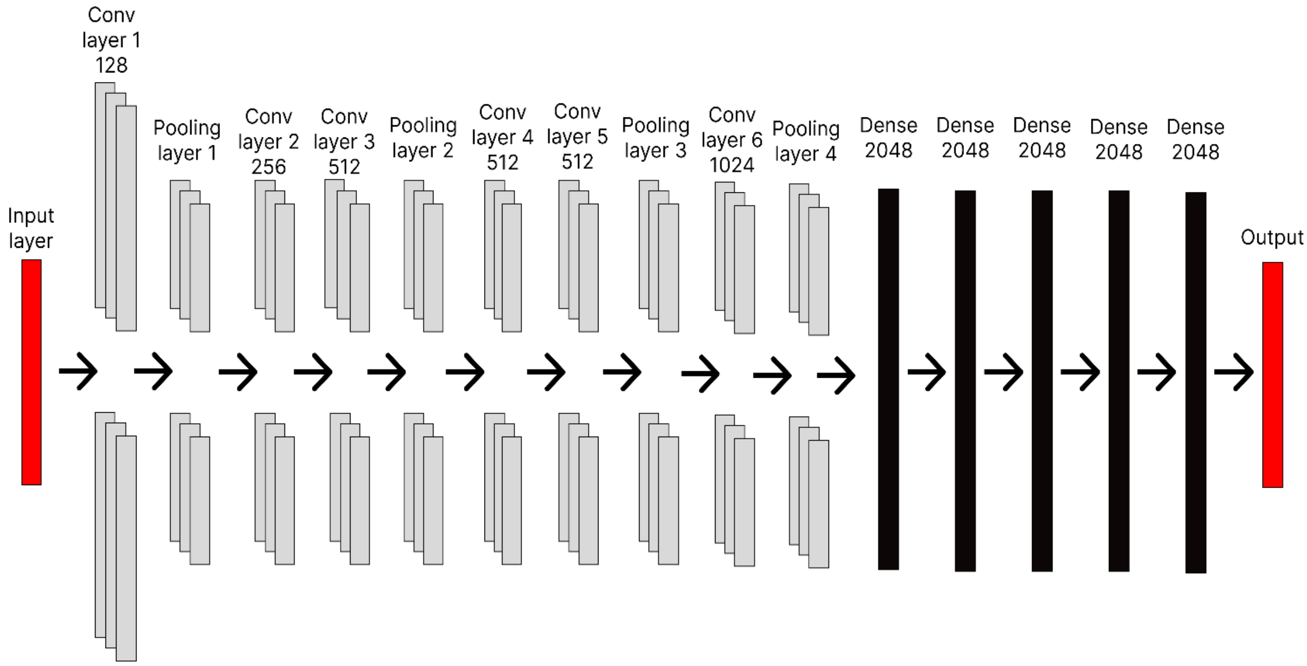

Figure. 3 Proposed convolutional multilayer 1D CNN architecture

The proposed method uses XGBoost to minimize features before they are classified into CNN. XGBoost processes the results of feature extraction from discrete wavelet transform (DWT) and statistical features then XGBoost will perform feature selection if the condition for the number of features is > 14 or the level of decomposition used is > 1. Level of decomposition also affects because it directly proportional to the number of features. For example, let x = level of decomposition. $if\ x = 3$, it means that x has arrays of three, $x = [0,1,2]$. There are 7 features (crossing and statistical) from each available array. It can be concluded that the number of features = the number of array levels multiplied by 7.

2.4 Classifier

2.4.1. Convolutional neural networks 1D

Convolutional neural network is a deep learning algorithm that processes mainly images but also numerical data to find patterns. CNNs generally consist of convolutional layers, pooling layers and fully connected layers (dense layers). Convolutional layers contain a number of convolution kernels and perform convolution calculations on the input signal. The convolution results are then nonlinearized by the activation function [18]. Convolutional layers have an important role in the process of 1D convolutional neural networks. The input image provided can be large in size so it will not be compatible for data processing. The convolutional layer helps to resize the image to be smaller by taking a few pixels from the source or input image and creating a new pixel that includes several pixels taken from the input image.

The proposed method uses the 1D-CNN structure as shown in Fig. 3. Several tests have been carried out before determining the number of convolutional layers needed and showing the final result with the highest accuracy using 6 convolutional layers and 4 pooling layers. Dropout classes are also used to prevent overfitting. The results of the CNN classification are optimized using majority voting to weighted majority voting. The following explains the use of filters, kernel size, and pool size from the convolutional layer and max pooling layer:

1. Convolutional layer with 128 filters and 2 kernel size,
2. Max pooling layer with 2 pool size,
3. Convolutional layer with 256 filters and 2 kernel sizes,
4. Convolutional layer with 512 filers and 2 kernel sizes,
5. Max pooling layer with 2 pool sizes,
6. Convolutional layer with 512 filters and 2 kernel sizes,
7. Convolutional layer with 512 filters and 2 kernel sizes,
8. Max pooling layer with 2 pool sizes,
9. Convolutional layer with 1024 filters and 2 kernel sizes, and
10. Max pooling layer with 2 pool sizes.

2.4.2. Deep neural network

Deep neural network (DNN) is a conventional multilayer with several hidden layers [19]. There is no definite size for the number of hidden layers in a DNN. Trial and error must be done in order to get the optimal structure to be used as a classifier. Activated forward propagation is used to export inputs (note-to-node) consecutively between the layers of the DNN, which is commonly made up of stacked multilayer perceptron's (MLPs). Through back-propagation of weights, the automatic (supervised) learning process of DNNs through gradient descent permits the reduction of the squared error in the projected outputs. In contrast to this architecture, CNNs are typically built with convolution, pooling, and fully connected layers. The convolution layers serve as filters for extracting discriminative features from inputs, while the pooling layer reduces the feature dimension for the sake of computational efficiency. Fully connected layers are responsible for the final fully connected configuration [20]. The proposed method develops the classification results from 1D CNN in the form of a weighted majority voting matrix by reclassifying it with a deep neural network (DNN) layer, the structure can be seen in Fig. 4. The DNN layers used are:

1. Convolutional layer with 128 filters and 2 kernel sizes,
2. Max pooling layer with 2 pool sizes, and
3. Dense layer with 16 units.

It might be argued that the benefits of efficiency and dependability that are connected with parallel hybrid networks cannot be overstated, particularly when it comes to classification challenges. Nevertheless, there are a number of factors that come into play and could result in an increase in the computing costs, a decrease in the transferability potentials of the model, and an increase in both the stochasticity and overfitting of the model.

2.5 Experimental setup

The proposed method is implemented using the python programming language with several python libraries, such as Numpy, Scikit-learn, PyWavelets. Experiments that have been carried out using 10-fold cross validation. Cross validation is useful for evaluating the proposed method by dividing the dataset into ten subsets. Each of these subsets has the same cardinality and exclusivity, so that each class has the same proportion in each subset. The testing and training process is carried out iteratively ten times. Each subset is used as one-time test data and the remaining subset as training data in each iteration [2].

This experiment was conducted using a computer with a processor specification Intel(R) Core(TM) i7-12700F (20 CPUs) ~2.1GHz, 32GB of Ram, NVIDIA GeForce RTX 3080 GPU, and Windows 11 Home operating system.

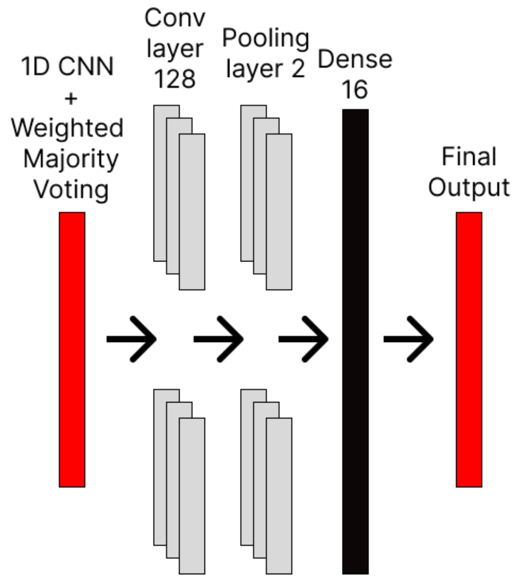

Figure. 4 The proposed hybrid 1D CNN and DNN model architecture

Table 2. Median value and standard deviation

Class	Median	Standard Deviation
A	-1.963	±35.039
B	8.746	±40.734
C	-8.623	±77.271
D	-21.464	±143.145
E	20.371	±251.345

3. Result and discussion

3.1 Classification results of three classes

Classification of three classes is divided according to the period of each occurrence, namely A for normal EEG signals, D for signals in the interictal period (before seizure), and E for ictal signals or when a seizure occurs. Fig. 5 shows examples of EEG signals for each class. The difference visually was most significant in the interictal period. If we refer to the median (greenline) and standard deviation (redline) of each class, it can be seen that normal signals tend to have values not exceeding from the upper limit of the standard deviation and values not exceeding from below the standard deviation. Meanwhile, in interictal signals (Fig. 5c, Fig. 5d) and ictal (Fig. 5e), many peaks are located far from the

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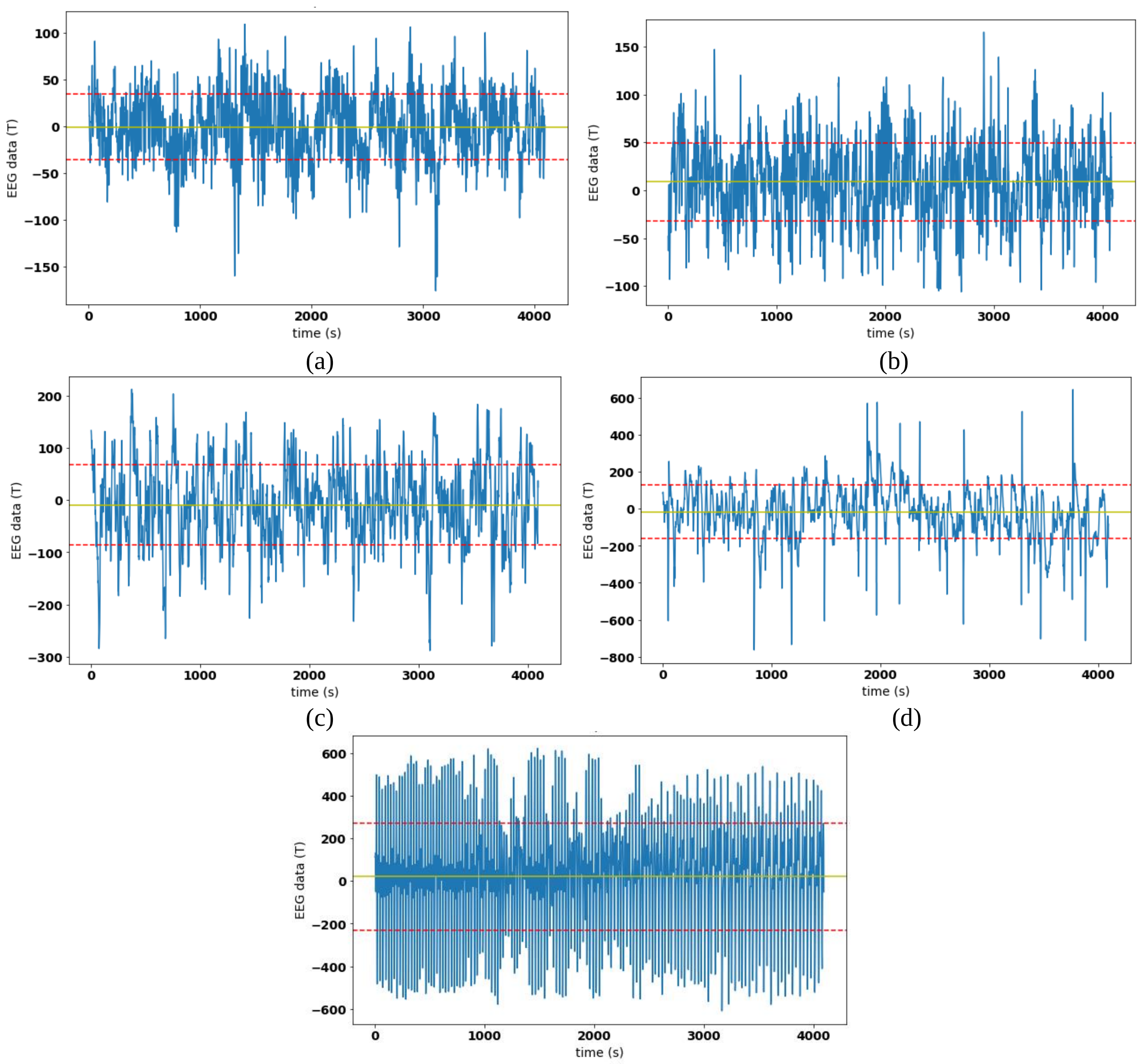

(e)

Figure. 5 Visualization of EEG signals: (a) class A, (b) class B, (c) class C, (d) class D, and (e) class E

upper limit with the highest value approaching more than 600 and below the standard deviation with the lowest value approaching more than -700. This shows that the normal signal tends (Fig. 5a, Fig. 5b) to be more stable than the other three classes.

Classification trials were carried out with different family scenarios and levels of decomposition and using 10-fold cross-validation. The highest test results from each combination of two classes and three classes are shown in Table 3. Classes A and E get 100% accuracy with family bior1.1 level 1, classes D and E get 100% accuracy with family db2 level 2, and Class A and D obtained 100% accuracy with family bior1.1 level 3. Each scenario did not have a significant difference with the lowest accuracy being 99.6% from the combination of 3 classes A-D-E. This proves that the classification using CNN and the XGBoost feature selection almost produces perfect results from each combination.

Table 3. Classification result from two classes and three classes combination before being optimized

Class	**Family**	**Level**	**Accuracy**
A-E	Bior1.1	1	100%
D-E	Db2	2	100%
A-D	Bior1.1	3	100%
A-D-E	Coif2	1	99.6%

The results of the family type trial and the level of decomposition of A-D-E class the highest accuracy is 99.63% with (bior6.8 level 3, bior6.8 level 5, coif1 level 2, coif1 level 3, coif1 level 5, coif2 level 1, coif3 level 4, coif3 level 6, coif5 level 2, coif8 level 3, coif16 level 3, db2 level 6, db2 level 9, db3 level 3, db3 level 4, db4 level 3). Among all the

Table 4. Classification result on three classes

Class	Methods	Accuracy
A-D-E (3 Class)	CNN + XGBoost	99.6%
A-D-E (3 Class)	Majority Voting	**100%**
A-D-E (3 Class)	Weighted Majority Voting	**100%**
A-D-E (3 Class)	Hybrid 1D CNN and DNN	**100%**

Table 5. Classification result from two classes and five classes combination before being optimized

Class	Family	Level	Accuracy
A-B	Db10	4	100%
C-D	Sym3	3	88.5%
B-E	Bior1.1	10	100%
C-E	Bior1.1	6	100%
A-C	Bior2.4	7	100%
B-D	Bior2.2	5	100%
B-C	Bior1.5	5	100%
A-B-C-D-E	Rbio1.5	1	94.6%

Table 6. Classification result on five classes

Class	Methods	Accuracy
A-B-C-D-E (5 Class)	CNN + XGBoost	94.6%
A-B-C-D-E (5 Class)	Majority Voting	96.4%
A-B-C-D-E (5 Class)	Weighted Majority Voting	97.0%
A-B-C-D-E (5 Class)	Hybrid 1D CNN and DNN	**98.0%**

families for class A-D-E, the selected type for this study is the coif4 family with 1 level of decomposition. A study stated that the difference in decomposition family type was not too significant compared to the decomposition level [20]. Judging

Table 7. Classification result from multi class combination before being optimized

Class	Family	Level	Accuracy
AB-E	Bior1.5	3	100%
CD-E	Bior2.2	2	100%
AB-CD	Coif10	5	100%
AB-CD-E	Bior3.5	5	99.8%

Table 8. Classification result from multi class combination

Class	Methods	Accuracy
AB-CD-E (3 Class)	CNN + XGBoost	99.8%
AB-CD-E (3 Class)	Majority Voting	**100%**
AB-CD-E (3 Class)	Weighted Majority Voting	**100%**
AB-CD-E (3 Class)	Hybrid 1D CNN and DNN	**100%**

from several test results, the lowest level of decomposition and has an accuracy of 99.63 is only the coif4 family type. The lowest level of decomposition is prioritized to produce the lowest number of features to obtain the highest accuracy.

In accordance with Table 4. The results of the combination of two classes and three classes become a model to be optimized using majority voting (MV), weighted majority voting (WMV), and classification by adding a DNN layer to WMV results. This shows that the MV classifier can increase the accuracy rate by 0.4%.

3.2 Classification results of five classes

The highest trial results from each combination of 2 classes and 5 classes are shown in Table 5. Almost all combination classes get a perfect accuracy of 100%, except C-D with an accuracy of 88.5% and five classes A-B-C-D-E with an accuracy of 94.6%. Class C-D has been trial and error 767 times with a combination of family wavelets and decomposition of different levels. The highest accuracy is using wavelet family sym3 and decomposition level 3. In addition, wavelets with family rbio3.5 decomposition level 3 and db1 decomposition level 12 obtain 88% accuracy.

To improve the classification accuracy of the five classes, this study conducted trials using the majority voting (MV), weighted majority voting (WMV), and CNN + DNN methods. From the results in Table 6 it can be seen that WMV outperforms the non-voting and MV methods. This proves that weighting with several three-class and five-class classification models can increase the accuracy of model predictions. In addition, optimization using CNN + DNN seems to outperform other methods with an accuracy of 98% increasing the prediction accuracy by 3% from WMV. This shows that the use of the DNN layer from the results of the WMV matrix has succeeded in studying the features in more depth and improving the performance of the classification model of the five classes.

3.3 Classification optimization five classes by three classes

Similar to the classification of three and five classes, accuracy is improved from Table 7 using the majority voting, weighted majority voting, and DNN layer methods. In accordance with Table 8 the results of the accuracy increase by 0.2%, and the three methods mentioned produce perfect accuracy of 100%.

3.4 Comparison with other methods

For comparison, several studies using different methods but using the same dataset University of Bonn (UoB) can be seen in Table 9. The numbers in bold indicate the highest accuracy in each case class. So far, previous studies have mostly focused on cases of three classes, namely normal, inter-ictal, and ictal. Thus, there are still few cases of classification of the five classes A-B-C-D-E. However, this proposed method has outperformed previous studies which also used deep learning with a difference of 0.8% and the GBM Fusion method with a difference of 0.61%.

In the case of three classes A-D-E, there is a significant difference between the proposed method and the previous study which only used CNN by 10.96%. This shows that the use of feature selection using XGBoost has proven to increase the level of accuracy and has succeeded in eliminating redundant and irrelevant features. In addition, compared to other ensemble methods it is not as significant as other methods but still outperforms. The superiority of the proposed method is also seen in other cases of the three classes (AB-CD-E) with perfect accuracy. This shows that the voting method using the hybrid 1D CNN and DNN classifier can improve the performance of the model for the detection of three classes of seizures.

Table 9. Comparison with other methods

Author	Class	Method	Accuracy
[7]	A-B-C-D-E	DNN	97.20%
[2]		GBM Fusion	97.39%
Proposed Method		**Hybrid 1D CNN and DNN**	**98.00%**
[8]	A-D-E	AdaBoost	98.67%
[9]		DNN + Ensemble	98.93%
[10]		K-means + MLP	96.67%
[11]		CNN	88.67%
Proposed Method		**Hybrid 1D CNN and DNN**	**99.63%**
[10]	AB-CD-E	K-means + MLP	95.60%
[8]		AdaBoost	97.60%
[7]		DNN	99.60%
Proposed Method		**Hybrid 1D CNN and DNN**	**100%**
[8]	A-E	AdaBoost	**100%**
[10]		K-means + MLP	**100%**
[11]		SVM	99.70%
[9]		DNN + Ensemble	94.43%
[12]		LBP	98.00%
Proposed Method		**CNN + XGBoost**	**100.00%**
[12]	D-E	LBP	95.50%
[13]		ANN	93.00%
[9]		DNN + Ensemble	95.01%
[8]		AdaBoost	**100%**
Proposed Method		**CNN + XGBoost**	**100%**
[8]	C-E	AdaBoost	99.00%
Proposed Method		**CNN + XGBoost**	**100%**

In the case of two classes, the method used in this study achieves perfect accuracy and outperforms most of the previous methods. When compared to other methods, this proposed method has the same accuracy as the AdaBoost method which is also an ensemble method. This can indicate that the ensemble method can improve model performance.

4. Conclusions

In the study of the epilepsy dataset from the University of Bonn, CNN-1D was used as the proposed method for detecting epilepsy from EEG signal data. Method proposed in this study are meant to increase the accuracy for classifying epilepsy. In the first scenario which classify three classes of A-D-E, we obtained 99.6% accuracy with only CNN and XGBoost. After the used of majority voting, the accuracy for classifying three classes of A-D-E is 100%. Additional method proposed to classify which are WMV and hybrid 1D CNN and DNN also obtained an accuracy of 100% for classifying A-D-E class combination. For the second scenario which classify EEG signals to 5 class A-B-C-D-E also increase accuracy for each proposed method used. For the first method which are CNN and XGBoost we obtained an accuracy of 94.6%, 96.4% after the used of MV, 97.0% after WMV is used, and 98.0% after we used Hybrid 1D CNN and DNN. It can be concluded that using the MV, WMV, and adding a DNN layer for classification can increase the accuracy level from 3 classes to 5 epilepsy classes. The disadvantage of using the proposed method is that the classification results depend on the wavelet family. Have to do several experiments on the combination of wavelet families and their level of decomposition in order to get maximum classification results and it takes quite a long time.

Conflicts of Interest

The authors declare no conflict of interest.

Author Contributions

Conceptualization, Dwi Sunaryono, Riyanarto Sarno, Joko siswantoro and Rahadian Indarto Susilo; methodology, Dwi Sunaryono and Joko Siswantoro; software, Diana Purwitasari and Naufal Rafi Akbar; validation, Dwi Sunaryono, Joko Siswantoro, and Shoffi Izza Sabilla; formal analysis, Dwi Sunaryono, Joko Siswantoro and Shoffi Izza Sabilla; investigation, Dwi Sunaryono and Joko Siswantoro; resources, Dwi Sunaryono and Naufal Rafi Akbar; data curation, Dwi Sunaryono and Naufal Rafi Akbar; writing—original draft preparation, Dwi Sunaryono and Naufal Rafi Akbar; writing—review and editing,Dwi Sunaryono, Joko Siswantoro, Shoffi Izza Sabilla and Naufal Rafi Akbar; visualization, Dwi Sunaryono and Naufal Rafi Akbar; supervision, Joko siswantoro and Shoffi Izza Sabilla; project administration, Dwi Sunaryono, Riyanarto Sarno and Shoffi Izza Sabilla ; funding acquisition, Riyanarto Sarno and Shoffi Izza Sabilla.

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