Enhanced Gradient Boosting Machines Fusion based on the Pattern of Majority Voting for Automatic Epilepsy Detection

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***Abstract*—Automatic detection of epilepsy based on EEG signals is one of the interesting fields to be developed in medicine to provide an alternative method for detecting epilepsy. High accuracy values are very important for accurate diagnosis in detecting epilepsy and avoid errors in diagnosing patients. Therefore, this study proposes the Enhanced Gradient Boosting Machines Fusion (Enhanced GBM Fusion) for automatically detecting epilepsy based on electroencephalographic (EEG) signals. Enhanced part of GBM Fusion is the pattern of majority voting evaluation based on the fusion of five-class and two-class GBM, called Enhanced GBM Fusion. The raw signal is extracted using Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT), then feature is selected by using Genetic Algorithm (GA) before classification. This proposed method was evaluated using five classes (normal in open eyes, normal in close eyes, interictal with hippocampal, interictal, and ictal) from the University of Bonn. The experimental results show that the proposed Enhanced GBM Fusion can increase the accuracy of GBM Fusion of 99.8% to classify five classes of epilepsy based on EEG signal. However, the performance of Enhanced GBM Fusion cannot be generalized to other datasets.**

Keywords*—Epilepsy; enhanced gradient boosting machine fusion; electroencephalographic (EEG) signal; discrete wavelet transform (DWT); discrete fourier tansform (DFT); genetic algorithm (GA)

I. Introduction

Globally, WHO estimates that about five million people are diagnosed with epilepsy yearly. Low and middle-income countries are nearly three times more than high-income countries to be diagnosed with epilepsy [1]. This is feasible due to the increased risk of endemic conditions, variations in medical infrastructure, the availability of preventive public health programs, and accessible healthcare services.

Epilepsy is a chronic medical disorder with clinical symptoms and signs due to intermittent brain function disorders. It occurs due to abnormal or excessive electrical discharge from neuron paroxysms of various etiologies. Generally, epilepsy is attended in unpredictable, unprovoked recurrent seizures that affect a variety of mental and physical functions. Seizure is a spontaneous electrical hyperactivity activity of a group of nerve cells in the brain and is not caused by an acute brain disease. “Seizure” in epilepsy is an incurable disease. However, about 70% of people with epilepsy can be free from seizures with proper treatment. Neuroscientists generally predict seizures based on an abnormal electroencephalographic (EEG) pattern in the brain. An EEG is a device that records activity in the brain, including seizures.

A method with high accuracy is needed to detect whether the ongoing seizure is an epileptic seizure or a fake seizure. Visual examination of the EEG signal is necessary to determine the occurrence of epilepsy. Unfortunately, checking the EEG signal manually takes a long time, and sometimes the results are missed or false-alarm detections [2]. Automatic epilepsy detection has been studied since the 1970s in the form of literature in the hope of helping the medical world in detecting automatic epilepsy based on EEG data [3]. In general, automatic epilepsy detection can be categorized into two groups which are conventional approaches and Deep learning approaches.

Misdiagnosis of epilepsy is a fatal error because it can lead to inappropriate treatment and death. Therefore, a high accuracy value is essential in the automatic detection of epilepsy. The automatic detection of epilepsy from five classes of EEG data has been tried using various approaches, but not many of them achieve accuracy above 98%. This study presented a method for automatic epilepsy detection based on the motivation that the method can classify five classes of EEG signals with greater than 98 percent accuracy. This study utilized a combination of Discrete Fourier Transform (DFT) and Discrete Wavelet Transform (DWT) for feature extraction in the frequency and time-frequency domains. The output from the feature extraction by DFT and DWT is extracted again using a statistical feature and crossing frequency features. To obtain the best features that would be used for classification, feature selection based on a Genetic Algorithm (GA) is used in this study. This study proposes a method to enhance GBM Fusion that was previously used by Sunaryono et al. [4].

The distinguish of this study from the study conducted by Sunaryono et al. [4] is that this study proposes the Enhanced Gradient Boosting Machine Fusion, where the method will focus more on errors that occur in the classification results. Errors in this classification will be evaluated to see if there is a

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pattern in the errors. The pattern will be applied to the Enhanced Gradient Boosting Machine Fusion classification for higher accuracy. The workflow for the proposed method can be seen in Fig. 1. By using the proposed method, this study hopes to have good accuracy results (above 98%) and the study also hopes to contribute to helping the medical world to detect epilepsy automatically so that people with epilepsy can be diagnosed accurately and quickly.

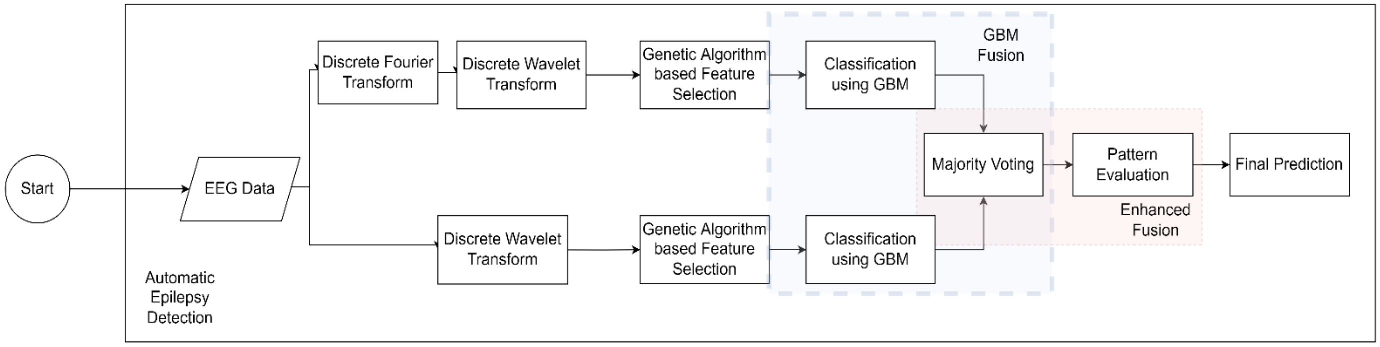


Fig. 1. Flowchart of the Proposed Method.

The remaining sections are organized as follows. Section II provides related works. The Section III outlines the materials and methods utilized in this study. In Section IV, the experimental result and discussion are presented. In Section V, the conclusion is reached.

II. Related Work

This section provides literature study based on the University of Bonn dataset: Wu et al. [5] carried out their research using the Complete Ensemble Empirical Method (CEEMD) to decompose signal data into 12 IMFs and one residue. XGBoost was used as a classification method where the results detected an accuracy higher or equivalent to 99% in 12 cases of two and three classes. Ullah et al. [6] use a Pyramidal One-Dimensional Deep Convolutional Neural Network (P-1D-CNN) as an architecture to perform feature extraction to classify three classes. To improve accuracy, the author added majority voting on the architecture, which has significantly increased the accuracy of P-1D-CNN. This architecture yields an accuracy of 99.1 ± 0.9% in the two and three-class cases.

Türk and Özerdem [7] performed Continuous Wavelet Transform (CWT) as a feature extraction method on EEG signals to get a time-frequency 2-D scalogram image. The scalogram images were used as input for CNN classification. The classification result with the highest accuracy was 99% for three classes and 93.6% for five classes. Wang et al. [8] propose the Discrete Wavelet Transform (DWT) method as a feature extraction method and uses the Gradient Boosting Machine and Grid Search Optimization to optimize the hyperparameters. The study resulted in an accuracy of 96.5% for classifying three classes using a dataset from the University of Bonn.

Sunaryono et al. [4] also suggested using Discrete Wavelet Transform (DWT) in automatic epilepsy detection. Gradient Boosting Machine fusion (GBM Fusion) method is proposed to increase the accuracy of classifying three classes to 99.45%. The proposed fusion combines the results of the classification of 2 classes and three classes using majority voting.

Singh and Dehuri [9] produced 100% accuracy in two and three classes case. Also, they produced 93.33% in five classes case with a hybrid technique using DWT-based Singular Value Decomposition fuzzy *k*-nearest neighbor (SVD-F*k*NN) classifier. On a substantial scale, DWT-based SVD decomposes the input EEG signals into sub-bands. The extracted feature is classified using several '*k*' values for the F*k*NN classifier.

Zhao et al. [10] implemented a 1-D DNN based on CNN for robust automatic epilepsy detection that consisted of three convolutional blocks and three fully connected layers. In addition, each convolutional block consists of five distinct layer types. The proposed method achieved an accuracy of 93.55% in the five classes problem. Zhao et al. [11] continue the research with proposed a method called SeizureNet based on CNN that utilizes two convolutional neural networks to extract features and a fully connected layer to learn high-level features. This method has achieved 95.84% accuracy in five classes case.

Sukriti et al. [12] used two entropy features, called refined composite multi-scale dispersion entropy (RCMDE) and multi-scale dispersion entropy (MDE) to detect seizure from EEG data with one way analysis of variance (ANOVA) as a feature selection method before being classified by Support Vector Machine (SVM). The best accuracy achieved is 96.67% in three classes case using RCMDE.

Zhang et al. [13] modeled a multi-scale non-local (MNL) network, 1 D CNN, to identify epilepsy automatically. Signal pooling and multi-scale non-local layers were added to boost CNN performance. The MNL network achieved 98.64% accuracy in classifying three classes case. Fast Fourier Transform (FFT) and PCA neural network (PCANet) are utilized by Li and Chen [14] as feature extraction method. From EEG signal, a frequency matrix was created using FFT, and the feature was extracted using PCANet. The extracted feature is classified using SVM. The proposed method achieves its best accuracy in classifying three classes case with a 99.6% accuracy score.

III. Material and Method

A. EEG Dataset

The data used is data that has been collected by the Department of Epileptology University of Bonn (UoB), Germany, which was obtained by Andrzejak et al. [15]. This data consists of an analog signal which is converted to 12-bit digital and then filtered by a bandpass filter in the range of 0.53 to 40 Hz. The datasets are grouped into five sets denoted by A, B, C, D, and E, where each class has different characteristics, as detailed in Table I. Each dataset has 100 single-channel EEG data segments, and each data has a duration of 23, 6 seconds for a total of 4097 samples. Sample signal for five datasets as shown in Fig. 2. This study evaluated the proposed automatic epilepsy detection using EEG waves from all sets.

B. Discrete Wavelet Transform

Discrete Wavelet Transform (DWT) is a technique for performing signal analysis that provides a representation of a signal in time and a signal that can be computed efficiently. In DWT, the signal to be analyzed will pass through the filter process with different frequencies and scales. DWT will divide the signal into two: high frequency using a highpass filter and low frequency using a lowpass filter. DWT has a more flexible frequency window function than CWT, where the DWT frequency window narrows when observing high-frequency information and widens when analyzing low-frequency resolution. As defined in equation 1, for example, the parameter m is an integer that controls the dilation of the wavelet, the parameter m, k are an integer that controls the translation of the wavelet, s_0 is a preset scaling parameter, and its value is greater than 1. 0 is a translation parameter that has a value greater than zero and is the parent of the wavelet.

$$\Psi_{m.k}(t) = \frac{1}{\sqrt{s_0^m}} \Psi\left(\frac{t-kt_0 s_0^m}{s_0^m}\right) \quad (1)$$

In this study, DWT is used to decompose the EEG data obtained through the discrete Fourier transform process. Various wavelet families and wavelet levels are used in DWT to provide a scaling function. The wavelet decomposition L-level determines the signal's frequency band according to its level. The output of DWT were the coefficient vectors.

C. Discrete Fourier Transform

DFT is a technique to perform feature extraction using the frequency domain. DFT is beneficial because DFT makes it possible to find the spectrum of a signal with a finite duration. Since DFT treats the data periodically, it will express the input data's periodicity along with each periodic component's relative strength. The method proposed in this study uses the implementation of Fast Fourier Transform (FFT) since FFT is an efficient algorithm to compute DFT. The use of FFT is to divide the original EEG data into five frequency sub-sections, namely gamma (>30 Hz), beta (between 12 and 30Hz), alpha (between 8 and 12 Hz), theta (between 4 and 8 Hz), and delta (< 4Hz) using DFT as described in equation 2.

TABLE I. Dataset Overview

Dataset	Patient Status	Setup	Phase
A	Healthy	Surface EEG	Open Eyes
B	Healthy	Surface EEG	Close Eyes
C	Epilepsy	Intracranial EEG	Interictal Hippocampal Position
D	Epilepsy	Intracranial EEG	Interictal Epileptogenic Zone
E	Epilepsy	Intracranial EEG	Ictal

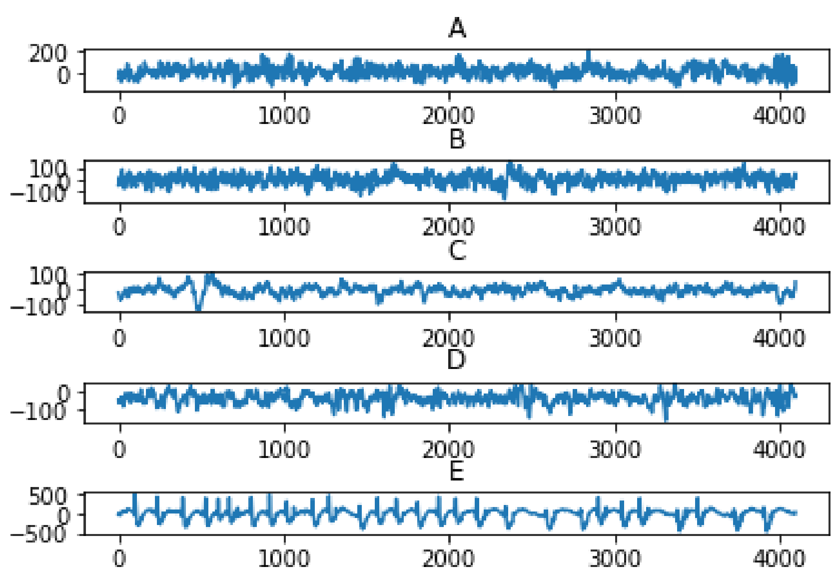


Fig. 2. Dataset EEG Samples.

$$F_n = \sum_{k=0}^{N-1} f_k\, e^{-\frac{2\pi i n k}{n}},\ n \in [0, N-1] \quad (2)$$

The transformed data is filtered using a band-pass filter to produce $F_\gamma(n), F_\beta(n), F_\alpha(n), F_\theta(n)$, and $F_\delta(n)$ signals at the respective sub-band frequencies. The EEG signal that has been in the form of frequency will be transformed again into the time domain using Inverse DFT to get an EEG signal that has been decomposed in the time domain as described in equation 3.

$$f_s(k) = \frac{1}{N}\sum_{n=0}^{N-1} F_s(n) e^{\frac{2\pi i n k}{n}}, n \in [0, N-1], s = \gamma, \beta, \alpha, \theta, \delta \quad (3)$$

D. Statistical Feature

Information on data distribution can be obtained from percentiles by dividing the data into 100 equal parts. To get the percentile of p^{th}, the elements of the coefficient vector are ordered from smallest to largest. Eq (4) is used to get the n^{th} index of the p^{th} percentile, and N represents the length of the vector coefficient.

$$n = \frac{p}{100}(N+1) \quad (4)$$

The result was five statistical signal features retrieved from the results of each DWT coefficient vector, namely, the 95th percentile, 75th percentile, 50th percentile, 25th percentile, and 5th percentile. Thus, 5(L+1) statistical features were retrieved from all coefficient vectors of the DWT L-level decomposition result.

E. Crossing Frequency Features

Zero-Crossing Frequency (ZCF) is a condition where the two elements of the vector coefficient have a frequency that crosses zero or changes signs from positive to negative and vice versa. ZCF was chosen to replace Zero Crossing Rate (ZCR) because ZCF has a more straightforward calculation and the exact duration data. This work extracted ZCF from the coefficient vector of DWT results to capture the signal's frequency information. Suppose N is the span of the coefficient vector, $v(k)$ is the k^{th} component of the coefficient vector, and sgn is the sign function, then ZCF can be obtained by equation 5.

$$ZCF = \frac{1}{2}\sum_{k-1}^{N-1}\left|sgn\big(v(k+1)\big) - sgn\big(v(k)\big)\right| \quad (5)$$

This study also uses the Mean Crossing Frequency (MCF) to complete the signal frequency information that ZCF has obtained. MCF is described as the frequency of two subsequent components of the vector cross m; if m is the average value of the coefficient vector, MCF can be calculated by using equation 6.

$$MCF = \frac{1}{2}\sum_{k-1}^{N-1}|sgn(v(k+1) - m) - sgn(v(k) - m)| \quad (6)$$

With the L-level of decomposition, a total of 2(L+1) crossing frequency features were obtained from the coefficient vector of the DWT result.

F. Feature Selection using Genetic Algorithm

Genetic Algorithm (GA) is an optimization algorithm that is a population-based search algorithm that uses the concept of survival of the fittest. GA is inspired by natural selection[16]. A new population is generated by repeated iterations of the genetic operator on the individuals present in the population. The critical elements of GA are chromosome representation, selection, crossover, mutation, and computation of fitness functions. The Fitness function determines the ability to compete of an individual. The fitness value determines the probability of selecting an individual for reproduction. The selection phase is to choose parents based on their fitness values to carry their genes to the next generation. Crossover is the phase where the parents reproduce, and the crossover point is chosen randomly from the parents' genes. Offspring is made by exchanging genes between parents. Of the many offspring made, several offspring can experience mutations with a low random probability. This happens to maintain diversity in the population and prevent premature convergence.

GA dynamically changes the search process through crossover and mutation probabilities to achieve the optimal solution. GA has better global search capabilities because GA can modify the encoded gene. Besides that, GA can also evaluate many individuals and generate several optimal solutions. As stated by Katoch et al. [17], offspring derived from crosses of parental chromosomes have a high probability of deleting the genetic scheme of parental chromosomes. The cross formula is defined as equation (7).

$$R = \frac{G + 2\sqrt{g}}{3G} \quad (7)$$

G is the fixed number of generations determined by the population and g is the number of generations.

A classification with many features will increase the complexity of the training process. Many features also do not always result in good classification [18]. In this study, GA is used as a feature selection method to eliminate features that will not be used in the classification. Firstly, feature selection technique using GA was began by randomly creating the initial population of chromosomes, which are binary mask vectors of length comparable to the number of features. The genes on the chromosomes could take on the value 0 or 1. If the value of the i^{th} gene was 0, then the i^{th} feature was disregarded for classification; else, the feature was chosen. Feature selection using A fitness function was used to determine the quality of each chromosome. The fitness function for feature selection using GA makes use of the accuracy rate of a classifier that has been trained with chromosome-specific features. Until the final requirements are reached, the population is iteratively modified through crossover, mutation, and selection.

G. Gradient Boosting Machine Fusion

To construct new base-learners to be maximally correlated with the negative gradient of the loss function, which is related to the entire ensemble, is the principle of the Gradient Boosting Machine (GBM) [19]. Unlike the Decision Tree and Random Forest algorithms, the random forest combines several decision tree outputs to generate predictions. In GBM, each decision tree predicts from the previous error decision tree [20]. Therefore, GBM is a classification method that always tries to reduce errors. If $y = z(s(t))$ is an estimate of functional dependence, then for the loss function model, $\Psi(y, z)$, is formulated in eqution (8).

$$\hat{z}(s(t)) = \hat{y} = \arg min \Psi(y, z) \quad (8)$$

To optimize the function, ŷ is used as a parameter in the function as $in\ \hat{y} = \sum_{i=1}^{M} \hat{y}_i$. This is what distinguishes GBM from other machine learning. In GBM, a "greedy stagewise" approach is derived from the weak-learners increment function. The function is formulated in equation (9).

$$(p_t, \theta_t) = \arg \min_{p,\theta} \sum_{i=1}^{N} \Psi(y_i, \widehat{f_{t-1}}) + ph(x_i, \theta) \quad (9)$$

In this study, GBM Fusion is used to classify multi-class models. To improve the classification results where several classifiers would be trained as basic classifiers to classify EEG signals into five and two classes. After classifying five classes and two classes, the best results will be taken through majority voting using equation (10), suppose C is a class.

$$C(x_o) = \arg max_{k \in \{0,1,2,3,4\}} \left(\sum_{i=1}^{4} I_k \begin{matrix} s \in \{0,1\} \\ or\ s \in \{0,2\} \\ or\ s \in \{1,2\} \\ or\ s \in \{1,3\} \\ \dots \\ or\ s \in \{3,4\} \end{matrix} \right) \sum_{i=1}^{4} I_k(y_s^i) \quad (10)$$

H. Enhanced GBM Fusion

This study enhances the research of Sunaryono et al. [4] by evaluating the pattern of errors in the majority voting to improve the classification performance of automatic epilepsy detection in five classes case. The steps below were utilized to train Enhanced GBMs fusion and predict the class label for unknown data using Enhanced GBMs fusion.

- Obtain the decomposed signals $f_\gamma, f_\beta, f_\alpha, f_\theta$, and f_δ by decomposing the original EEG signal using DFT.
- Perform DWT with L-level decomposition to the initial EEG data to produce the coefficient vectors C1.
- Perform DWT with L-Level of decomposition to the decomposed EEG data for frequency sub-band $\alpha, \beta, \gamma, \delta$ and θ to obtain the coefficient vectors as C_2.
- Obtain feature sets F_1 by extracting 2(L+1) crossing frequency features and 5(L+1) statistical features from the coefficient vectors C_1.
- Obtain feature sets F_2 by extracting 10(L+1) crossing frequency features and 2 5(L+1) statistical features from the coefficient vectors C_2.
- Perform feature selection using GA to F_1 and F_2 to determine which are the most important features.
- Train two 5-class GBMs, X1 and X2, utilizing the selected features from F_1 and F_2 as input features, respectively.
- Train twenty 2-class GBMs with the selected features from F_1 and F_2 to classify the EEG signal as either class 0 and class 1 (named F_1^{01} and F_2^{01}), class 0 and class 2 (named F_1^{02} and F_2^{02}), class 0 and class 3 (named F_1^{03} and F_2^{03}), class 0 and class 4 (named F_1^{04} and F_2^{04}), class 1 and class 2 (named F_1^{12} and F_2^{12}), class 1 and class 3 (named F_1^{13} and F_2^{13}), class 1 and class 4 (named F_1^{14} and F_2^{14}), class 2 and class 3 (named F_1^{23} and F_2^{23}), class 2 and class 4 (named F_1^{24} and F_2^{24}), class 3 and class 4 (named F_1^{34} and F_2^{34}).
- Suppose x_0 is an EEG signal without labels. Using F_1 and F_2, predict the class label of x_0 to obtain y_1 and y_2, respectively.

a) If y_i = 0, then predict the class label of x_0 using models F_i^{01}, F_i^{02}, F_i^{03}, and F_i^{04} to obtain y_i $y_i^{01}, y_i^{02}, y_i^{03}$, and y_i^{04} from each model, for i = 1, 2.

b) If y_i = 1, then predict the class label of x_0 using models F_i^{01}, F_i^{12}, F_i^{13}, and F_i^{14} to obtain y_i $y_i^{01}, y_i^{12}, y_i^{13}$, and y_i^{14} from each model, for i = 1, 2.

c) If y_i = 2, then predict the class label of x_0 using models F_i^{02}, F_i^{12}, F_i^{23}, and F_i^{24} to obtain y_i $y_i^{02}, y_i^{12}, y_i^{23}$, and y_i^{24} from each model, for i = 1, 2.

d) If y_i = 3, then predict the class label of x_0 using models F_i^{03}, F_i^{13}, F_i^{23}, and F_i^{34} to obtain y_i $y_i^{03}, y_i^{13}, y_i^{23}$, and y_i^{34} from each model, for i = 1, 2.

e) If y_i = 4, then predict the class label of x_0 using model F_i^{04}, F_i^{14}, F_i^{24}, and F to obtain y_i $y_i^{04}, y_i^{14}, y_i^{24}$, and y_i^{34} from each model, for i = 1, 2.

- Class x_0 was predicted by majority vote based on the result of 5-class and 2-class GBMs.
- Evaluate the pattern of errors from GBMs Fusion majority voting to disregard the pattern of errors.
- Class x_0 predicted using majority voting on the result of 5-class and 2-class GBMs but while disregarding the error pattern.

Suppose x_0 is some EEG signals that must be classified after the feature extraction and selection stage. x_0 is classified using two 5-class GBMs, and suppose the result is class 4 from F_1 and class 4 from F_2. Further classification with twenty 2-class GBM, because both results from F_1 and F_2 is class 4 then the model that will give output only the model $F_1^{04}, F_1^{14}, F_1^{24}$, F_1^{34}, F_2^{04}, F_2^{14}, F_2^{24}, and F_2^{34}, the given output is class 4, class 4, class 2, class 4, class 4, class 4, class 2, and class 4, respectively. The final prediction of class x_0 after majority voting is class 4. However, because x_0 has the original class 2, the prediction result of x_0 is wrong. Therefore, the 8 GBMs models that give results of class 4 are ignored so that the majority voting results become class 2.

I. Experimental Setup

Experiments for this study have been conducted to validate the proposed method for detecting epilepsy using EEG signals in three cases. In the first case, two 5-class GBMs were trained with F_1 and F_2 to classify EEG signals. In the second case, twenty 2-class GBMs were trained with F_1 and F_2 to classify EEG into two classes, namely class 0-1, class 0-2, class 1-2, class 1-3, class 2-4, class 0-3, class 0-4, class 1-4, class 2-3, and class 3-4. In the third case, Enhanced GBM Fusion was utilized to classify EEG signals into five classes, and the results will be compared to those of previous studies.

This experiment was run on a mid-spec computer with a specification of 2.2GHz Intel(R) Core(TM) i7-8750H, 16GB RAM, NVIDIA GeForce GTX 1050 Ti GPU, and Windows 10 Home Single operating system to ensure that the proposed method is implemented on everyday life. The proposed method uses the python programming language with several libraries, namely NumPy [21], DEAP [22], scikit-learn [23], and PyWavelets [24]. This experiment uses fold-cross validation in which the EEG data is randomly divided into ten sections with equal proportions for each section.

IV. Result and Discussion

A. *Classification of Five Class GBM*

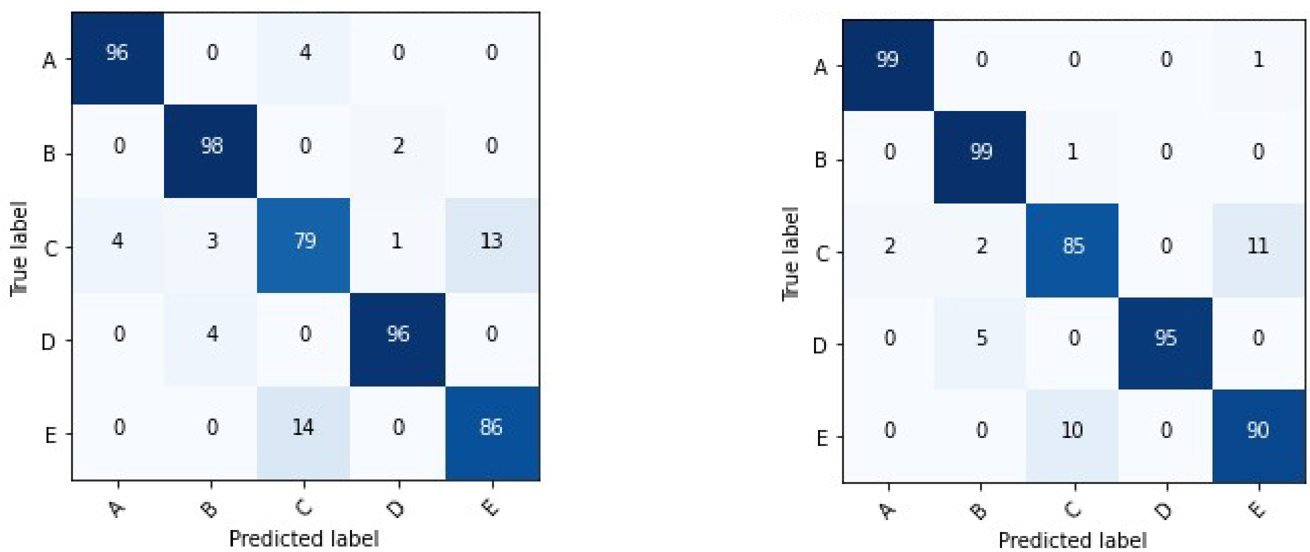
The accuracy of the 5-class classification using GBM with F_1 and F_2 has been summarized in TABLE II. The classification results using F_1 have a higher average of 91.13%, compared to F_2 with an average of 88.08%. The best result using F_1 feature is using Daubechies 6 (Db6) family wavelet with a decomposition level of 8 with the accuracy score of 91.99%. However, Db6 with a decomposition level of 8 needs more selected features to achieve the best accuracy than Symlet 16 (Sym16) and Symlet 20 (Sym20). For F_2 feature, the best result achieved is 93.6% by applying Biorthogonal 5.5 (Bior5.5) with the decomposition level of 3 while having the least original feature and having the lowest decomposition level compared to the rest as in Table II. The F_2 data has the same number of features after feature selection, while in F_1 data, more selected features are needed to get the highest accuracy results.

As shown in Fig. 3, confusion matrix was utilized to evaluate EEG signals that were incorrectly classified by F_1 using Db6 wavelet with decomposition level 8 and F_2 using bior5.5 wavelet with decomposition level 3. 5 classes model A-B-C-D-E FFT-Sub-band-Wavelet had a better classification result in class A, B, C, and E, while from 5 classes model A-B-C-D-E Wavelet had a better classification in class D.

The experimental results showed that raising the decomposition level of DWT does not necessarily increase the classification accuracy of 5-class GBM. These results also demonstrated that conducting DFT as added feature extraction method prior to DWT to generate features set F_2 does not always increase the accuracy of classification for 5-class GBM.

TABLE II. Summary of Five Class GBM Classification

Classifier	***Wavelet***		***Original Feature***	***Selected Feature***	***Accuracy with selected Feature***
	Family	***Level***			
F_1 Classifier	Db6	8	63	29	91.99
	Sym16	5	42	21	90.39
	Sym20	5	42	24	91.00
F_2 Classifier	Bior5.5	3	140	65	93.60
	Symll	5	210	65	89.20
	Db15	7	280	65	87.80



(a) Five Classes Model a-b-c-d-e. (b) Five Classes Model -a-b-c-d-e Fft-Subband-Wavelet.

Fig. 3. Confusion Matrices of 5-Class GBM using each Features.

B. Classification of Two Class GBM

The result of the classification of 2-class GBM using F_1 and F_2 features have been summarized in Table III and Table IV, respectively. The wavelet family and decomposition level used in F_1 and F_2 are the same for each class classifier. In the experiment before using the feature selection, the accuracy results using F_2 data have higher accuracy results with an accuracy of 95.08% compared to F_1 data with an average of 93.99%, as in TABLE III and TABLE IV. The only F_1 feature before feature selection with higher accuracy against F_2 is using F_1^{14} classifier using rbio2.4 wavelet family and decomposition level of 6 with an accuracy score of 90.73% against F_2^{14} with an accuracy of 90.04% by applying the same wavelet family and decomposition level. In the experiment using feature subset, the average accuracy of the F_1 and F_2 features increased with an average accuracy of 99.19% in both data, with the highest accuracy being 100% and the lowest being 94%, as shown in TABLE III and TABLE IV, respectively. These results demonstrated that using feature selection most of the time can improve classification accuracy. The experimental results also showed that conducting frequency sub-band decomposition prior to DWT to generate features set F_2 can improve the classification accuracy of 2-class GBM.

C. Enhanced GBM Fusion Classification

Previously, the results of the 2-class model accuracy were obtained using F_1 and F_2, where the results from these models were combined and used in GBM Fusion and Enhanced GBM Fusion using majority voting. The classification results using GBMs Fusion resulted in an accuracy of 97.2% in the classification of 5 classes, with 14 misclassifications listed in Table V. Table V shows that the misclassification results mainly occur in the data with the highest majority voting value of 3, 5, or 8. This value will be used as a value of 0 during the enhanced GBM Fusion classification. The accuracy of 99.8% in the 5-class classification was also successfully achieved using Enhanced GBM Fusion by leaving one misclassification result at index 440 with confusion matrix as in Fig.4. This happened because the majority voting result in Enhanced GBM fusion at index 440 was 3 in the 5th row, which means the prediction result in the index 440 is class 4, which should be class 0. As shown in Fig. 4, all the EEG signals from class B, class C, class D, and class E were correctly predicted by Enhanced GBMs Fusion. Only one signal from class A was misclassified as a class E.

TABLE III. SUMMARY OF TWO CLASS GBM CLASSIFICATION USING F_1

Classifier	Family	Level	Original Feature	Selected Feature	Accuracy with Original Feature (%)	Accuracy with Selected Feature (%)
F_1^{01}	Db24	2	21	4	95,12	100
F_1^{02}	Db5	4	175	78	93,87	98,5
F_1^{12}	Db38	1	14	7	90,54	100
F_1^{13}	Db10	2	105	63	98,03	99,49
F_1^{24}	Sym15	5	210	106	98,46	94
F_1^{03}	Db1	1	14	6	96,98	100
F_1^{04}	Db18	2	21	12	92,5	100
F_1^{14}	Rbio2.4	6	49	15	90,73	100
F_1^{23}	Bior1.3	4	35	14	91,28	100
F_1^{34}	Coif14	4	35	11	92,46	100
Average Accuracy (%)					93.99	99.19

TABLE IV. SUMMARY OF TWO CLASS GBM CLASSIFICATION USING F_2

Classifier	Family	Level	Original Feature	Selected Feature	Accuracy with Original Feature (%)	Accuracy with Selected Feature (%)
F_2^{01}	Db24	2	21	4	95,65	100
F_2^{02}	Db5	4	175	78	94,84	98,5
F_2^{12}	Db38	1	14	7	92,96	100
F_2^{13}	Db10	2	105	63	99	99,49
F_2^{24}	Sym15	5	210	106	98,99	94
F_2^{03}	Db1	1	14	6	98,98	100
F_2^{04}	Db18	2	21	12	92,71	100
F_2^{14}	Rbio2.4	6	49	15	90,04	100
F_2^{23}	Bior1.3	4	35	14	94,68	100
F_2^{34}	Coif14	4	35	11	93	100
Average Accuracy (%)					95.08	99.19

TABLE V. CLASSIFICATION ERROR FROM GBM FUSION

Index	Model	Expected Result	Classification Result
37	[0 0 2 0 8]	2	4
150	[8 0 2 0 0]	2	0
165	[8 0 2 0 0]	2	0
192	[0 0 2 0 8]	2	4
213	[0 0 8 0 2]	4	2
292	[0 8 2 0 0]	2	1
370	[0 8 0 2 0]	3	1
397	[0 8 2 0 0]	2	1
426	[0 8 0 2 0]	3	1
437	[0 0 8 0 2]	4	2
440	[2 0 5 0 3]	0	2
452	[0 0 8 0 2]	4	2
458	[0 0 8 0 2]	4	2
487	[0 8 0 2 0]	3	1

Table VI is comparison proposed method with the results of previous studies, the highest accuracy of five classes classification by the previous studies is 97.39% by Sunaryono et al. [4], which means that this study has an increase in the five-class classification by 2.41% from the best results in previous studies. The proposed method has the potential to classify five classes for the detection of epilepsy. However, this method is limited with the dataset that is used. The effect of this limitation that is this method still lack validation from other datasets.

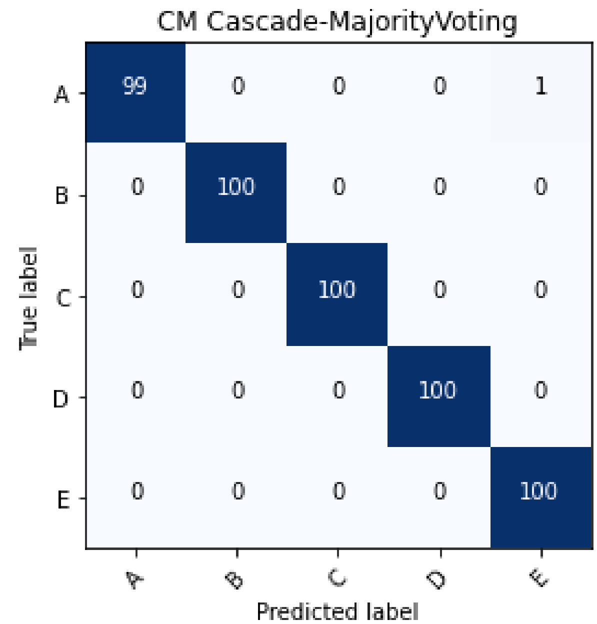


Fig. 4. Confusion Matrix of Enhanced GBM Fusion.

TABLE VI. COMPARISON TABLE WITH PREVIOUS STUDIES

Dataset	Method	Study	Accuracy (%)	This Study Accuracy (%)
A-B	GBM Fusion	[4]	**100**	**100**
	CNN+Scalogram	[7]	95.5	
A-C	GBM Fusion	[4]	**100**	98.5
	CNN+Scalogram	[7]	96.5	
A-D	GBM Fusion	[4]	**100**	**100**
	CNN+Scalogram	[7]	**100**	
A-E	MNL Network	[13]	99.52	**100**
	CNN+Scalogram	[7]	99.5	
	Symlet Wavelets, PCA, GBM-GSO	[8]	**100**	
	GBM Fusion	[4]	**100**	
	DWT, Fuzzy Approximate Entropy, SVML	[25]	**100**	
	FFT-based PCANet, SVM	[14]	**100**	
	RCMDE, SVM	[12]	**100**	
B-C	GBM Fusion	[4]	**100**	**100**
	CNN+Scalogram	[7]	99	
B-D	GBM Fusion	[4]	**100**	99.49
	CNN+Scalogram	[7]	**100**	
B-E	GBM Fusion	[4]	**100**	**100**
	Symlet Wavelets, and PCA, GBM-GSO	[8]	**100**	
	CNN+Scalogram	[7]	**100**	

	FFT-based PCANet, SVM	[14]	**100**	
	MNL Network	[13]	99.11	
C-D	GBM Fusion	[4]	94	**100**
	CNN+Scalogram	[7]	85.71	
C-E	MNL Network	[13]	98.02	98.99
	Symlet Waveletsand PCA, GBM-GSO	[8]	98.4	
	GBM Fusion	[4]	**100**	
	CNN+Scalogram	[7]	98.50	
	FFT-based PCANet, SVM	[14]	**100**	
D-E	FFT-based PCANet, SVM	[14]	99	**100**
	Symlet Wavelets, and PCA, GBM-GSO	[8]	98.1	
	LMD+GA+SVM	[26]	98.1	
	GBM Fusion	[4]	99.49	
	CNN+Scalogram	[7]	98.50	
	MNL Network	[13]	97.63	
	MDE, SVM	[12]	96.5	
A-B-C-D-E	MEMD + ANN	[27]	87.2	**99.8**
	GBM Fusion	[4]	97.39	
	ToC + DNN	[28]	97.2	
	CNN+Scalogram	[7]	93.60	
	SeizureNet	[11]	95.84	
	DWT-SVD-F*k*NN	[9]	93.33	
	1-D-DNN	[10]	93.55	
	MNL Network	[13]	93.55	

V. Conclusion

In this study, Enhanced GBM Fusion is proposed to be an automatic epilepsy detection method from EEG signal data. The proposed method obtains an accuracy value of 99.8% in classifying five classes A-B-C-D-E on a dataset from the University of Bonn. EEG signal data were decomposed using DWT and DFT as feature extraction methods. The decomposed signal is used to extract the crossing frequency feature and statistical feature. Genetic Algorithm is used as a feature selection method to get discriminatory features to improve the classification performance. For the whole experiment, the proposed method can improve the accuracy compared to normal GBM in classifying EEG signals. With the results that have been obtained, this study can be a reference for the medical world to detect epilepsy automatically so that people with epilepsy can be diagnosed accurately and quickly.

The drawback of the proposed method is that the determination of patterns on Enhanced GBM Fusion to improve performance must be done by hard coding. The performance of the proposed method may not be comparable to that of other datasets.

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This study is a follow up research from Sunaryono et al. [4] with the title of “Gradient boosting machines fusion for automatic epilepsy detection from EEG signals based on wavelet features”.

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