Application of Machine Learning Algorithm for Mental State Attention Classification Based on Electroencephalogram Signals

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***Abstract*—Technological developments provide a new work environment where the human role is reduced to that of a passive observer. Risk in the workplace might result from a person's incapacity to maintain attention and concentration while doing passive control activities. Passive brain-computer interface (BCI) can be used to monitor mental attention status in humans (focused, unfocused, and drowsy) using electroencephalogram (EEG) signals. This study proposes using BCI to detect the level of mental attention status based on EEG signals using machine learning. In designing the architecture of this study, the EEG signal data has been decomposed by the Discrete Wavelet Transform (DWT) decomposition process with 4 decomposition levels and using the Daubechies family (dB). The signal decomposition results are extracted using several statistical features, which are then used for machine learning model features. The Xtreme Gradient Boost (XGBoost) algorithm was used to perform the classification task. The XGBoost model produced accuracy results of 99% (best) on individual subject tests and 98% (average) on all subjects.**

Keywords—Electroencephalogram (EEG), Brain-computer interface (BCI), Discrete Wavelet Transform (DWT), Machine Learning, Xtreme Gradient Boost (XGBoost).

I. INTRODUCTION

Technological developments in automation provide a new work environment where the human role is reduced to that of a passive observer. A lot of work has been automated so that humans, as passive observers, are given passive control tasks. Operators must be capable of maintaining their attention and concentration while performing passive control duties [1]. Brain-computer interfaces are one of the finest methods for observing specific human conditions in such situations (BCI) [2]. Electroencephalogram (EEG) is widely used because it is cost-effective, easy to record, non-invasive, and allows the subject to have more freedom and mobility [1], [3]. For the reasons above, EEG signals are used to monitor the mental attention status of operators given passive control tasks by utilizing machine learning methods as classifiers of EEG signals. Extreme Gradient Boost (XGBoost) is an open-source library that can be used to perform the efficient, fast and scalable classification task of the Gradient Tree Boosting algorithm [4].

Various feature extraction techniques are used to process the EEG signals. Nadzeri Munawar et al. [5] compare Stationary Wavelet Transform (SWT) with Fast Fourier Transform (FFT), and Nugraha et al. [6] use FFT together with statistical characteristics for classification tasks, such as mean, median, variance, standard deviation, and mode. Statistical features and Crossing Frequency Features with Discrete Fourier Transform (DFT) are also used by Sunaryono et al. [7]. This study designed a classification system by combining the Wavelet Transform (WT) for EEG signal decomposition and using XGBoost as the classification method. Research [8]–[10] uses statistical features such as mean, standard deviation, kurtosis, and skewness as classification features obtained from signal decomposition results.

In previous studies, an algorithm was developed to gauge the level of mental attention state using EEG data represented in the time-frequency domain [1]. For its feature extraction stage, the system calculates the spectrogram of each EEG channel using the short-time Fourier Transform (STFT) and Blackman Window. The feature extraction stage produces a 252-dimensional feature vector. In the next step, the features that have been obtained are used for classification using the SVM model with a one-versus-the-rest approach. Three mental states are the target of the class in this research, namely passive focus, passive unfocused, and drowsy.

In this study, we apply several steps compared to previous studies, especially at the feature extraction stage using the Wavelet Transform (WT) to decompose the EEG signal. Then the decomposition results are taken for statistical features that produce a vector with dimensions of 280. In this study, we also conducted qualitative tests on several classification techniques such as XGBoost, Random Forest, and K-nearest neighbor to see the level of mental attention status (focused, unfocused, and exhausted). Our main contributions to this study include the following:

- Feature extraction uses Wavelet Transform (WT) to decompose EEG signals, and the decomposition results are processed to become statistical features.
- Conduct qualitative testing by comparing the machine learning classification model to data that has been extracted previously.

This paper is divided into several parts. The suggested approach, feature extraction, and calcification are detailed in Section 2, which also describes the materials and procedures employed in this work. In Section 3, the findings and analysis will be discussed. Conclusions from this research are presented in the last part.

II. MATERIAL AND METHOD

In this section, the features and steps that will be used in the proposed method will be discussed.

A. EEG Dataset

The EEG signal dataset utilized in this investigation was made accessible to the public by a study [1]. With a sample rate of 128 Hz and 14 channels, the Emotiv Epoc headset was used to record EEG data. This dataset was collected from 25 hours of EEG recordings while five individuals completed a low-intensity control task in an experiment. The "Microsoft Train Simulator" game is assigned to participants. Participants were required to steer a train for 35 to 55 minutes in every experiment to gather data.

There were 3 mental conditions were examined in this study: passive focus, passive unfocus, and drowsiness. A focused mental state means that participants can maintain focus and concentration while passively watching the train. The defocused state was defined as detached but awake supervision, in which the participants were not explicitly sleepy. The last state of the participant is in a state of drowsiness. These 3 mental conditions will be used as the target class in this study's classification.

B. Proposed Method

At this time, time-frequency analysis is known to work well to capture various information on non-stationary signals [8], [11]. A useful technique for examining numerous non-stationary signal components is multi-resolution analysis utilizing the wavelet transform. The Discrete Wavelet Transform (DWT) is utilized as a feature extractor, and K-Means is used as a divider to classify data into alert states or drowsiness. Statistical variables such as the mean, median, variance, standard deviation, and mode of the wavelet coefficients are employed for classification [8].

Classifying datasets having an imbalanced distribution, as an example of the minority class, presents challenges for the model to efficiently learn decision boundaries. In Yang et al. [12], In the majority of illness data sets, there are more samples in the negative group than in the helpful category. To rebalance the dataset and improve the model's validity, the distribution might be changed using particular data processing techniques. The minority class examples can be oversampled as one method of resolving this issue. Synthesizing new instances of the minority class is an improvement over duplicating existing instances of the minority class. The Synthetic Minority Oversampling Technique, or SMOTE, is the method that is most frequently employed to create new samples.

In most illness data sets, there are more samples in the negative group than in the helpful category. The distribution might be changed using particular data processing techniques to rebalance the dataset and improve the model's validity. The minority class examples can be oversampled as one method of resolving this issue. Synthesizing new instances of the minority class is an improvement over duplicating existing instances of the minority class. The Synthetic Minority Oversampling Technique, or SMOTE, is the most frequently employed method to create new samples.

C. Feature Extraction

In order to successfully analyze EEG signals, the feature extraction stage is crucial. A vector called a feature vector is created during feature extraction. Thus, the approach that transforms signals into feature vectors is the feature extraction method [13]. In this study, it is proposed to use a popular feature extraction technique, Discrete Wavelet Transform (DWT). To create feature vectors, use DWT based on the mean, standard deviation, kurtosis, and skewness.

The wavelet transforms analysis method examines frequencies at various resolutions [13]. Low-pass and high-pass filters are frequently employed to create digital signal representations of approach coefficients (A1) and details in the first level of decomposition (D1). The following equation may be used to define the DWT decomposition:

$$f(t) = \sum_{k=-\infty}^{k=+\infty} C_{n,k}\emptyset(2^{-n}t-k) + \sum_{k=-\infty}^{k=+\infty}\sum_{k=-\infty}^{k=+\infty} 2\frac{-j}{2} d_{j,k}\psi(2^{-j}-k) \quad (1)$$

Where n is the level, $d_{j,k}$ and $C_{n,k}$ are the approximation. n detail coefficients, and $\emptyset$ is the scale function. After parsing the initial estimate, the procedure is repeated. The total number of decomposed signals is n+1 at the conclusion of the operation. Since level 4 provides the best qualities for the signal features that have been effectively identified, Daubechies 4 (db4) was employed as the waveform function in this investigation.

In this study, the feature wavelet coefficients of each sub-band are extracted to classify EEG signals. From each DWT yield coefficient vector, four statistical features are extracted from all DWT yield coefficient vectors at each level of decomposition. The statistical features used are the mean, standard deviation, kurtosis, and skewness. The following equation obtains the mean of the wavelet coefficients in each sub-band:

$$\bar{S} = \frac{1}{N}\sum_{i=1}^{N} S_i \quad (2)$$

Where $\bar{S}$ is the mean value and N is the number of data points in the sample that contain the value S_i. The standard deviation of the wavelet coefficients in each sub-band is obtained by the following equation:

$$\sigma = \sqrt{\frac{1}{N}\sum_{i}^{N}(S_i - \bar{S})^2} \quad (3)$$

Where σ is the standard deviation value and N is the number of data points in the sample that contain the value S_i. Skewness is a statistic used to describe the distribution of data, whether skewed to the left, right, or symmetrically. The following equation obtains the skewness of the wavelet coefficients in each sub-band:

$$\text{Skewness} = \frac{\sum_i^N (S_i - \bar{S})^3}{(N-1) * \sigma^3} \quad (4)$$

Where N is the number of variables in the distribution, σ is the standard deviation value, S_i is random variable and $\bar{S}$is mean of the distribution. Kurtosis is a statistic used to describe whether the distribution of data tends to be flat or spiky. The kurtosis of the wavelet coefficients in each sub-band is obtained by the following equation:

$$\text{Kurtosis} = \frac{1}{N}\sum_{i}^{N}(\frac{S_i - \bar{S}}{\sigma^4})^4 \quad (5)$$

Where N is the number of variables in the distribution, σ is the standard deviation value, S_i is random variable and $\bar{S}$is mean of the distribution.

D. Classification

In 2016, Tianqi Chen discovered XGBoost, which is a refinement of Friedman's earlier Gradient Boosting Decision Tree (GBDT) algorithm. The fundamental idea behind XGBoost is to train the model with residuals. The mistake gets smaller over successive rounds, with the output from the most recent training tree serving as the input. In order to create ensemble learners, all weak pupils are given a linear weighting [12]. XGBoost can be used to make predictions and classifications; just like other methods, XGBoost can also be applied to various fields such as education, health, government, and others [4], [12], [14].

E. Methodology

The proposed method is explained in this section. The procedure of feature extraction and classification are included in the technique. The EEG signal labeling procedure is used to perform the feature extraction process. The EEG signal recorded during the first 10 minutes will be categorized as concentrated; during the next 10 to 20 minutes, it will be categorized as unfocused; after 20 minutes, it will be categorized as drowsy.

The WT approach is used throughout the feature extraction process to compress the signal while preserving the original signal. This procedure is carried out to lessen signal noise and to offer information for preserving the signal's data information's integrity. The length of the signal after the WT procedure is shorter than the original signal. With low-pass and high-pass filtering applied to the Time domain signal, WT divides the signal into sub-bands. Approximations are produced by low-pass filtering, while detailed coefficients are produced by high-pass filtering, which is then deconstructed at the following level using approximations from the previous level. The wavelet employed in this experiment was a fourth-order Daubechies Wavelet (DB4) level 4. An illustration of the decomposition process can be seen in Figure 1.

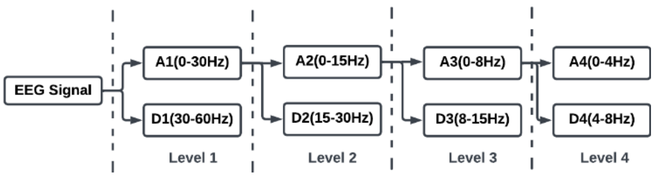

Fig. 1. Electroencephalogram signal decomposition via 4-level DWT

Decomposing the original signal into a set of coefficients that characterize the frequency content is possible. The original EEG signal will be decomposed, resulting in several sets of coefficients, including D1 (Gamma), D2 (Beta), D3 (Alpha), D4 (Theta), and A4 (Delta). Figure 1 shows that in level 1 decomposition, the EEG signal will be decomposed into A1 with a frequency range of 0-30Hz and D1 (Gamma) with a frequency range of 30-60hz. Furthermore, in level 2 decomposition, A1 will be decomposed into A2 with a frequency range of 0-15Hz and D2 (Beta) with a frequency range of 15-30hz. In level 3 decomposition, A2 will be decomposed into A3 with a frequency range of 0-8Hz and D3 (Alpha) with a frequency range of 8-15Hz. Finally, in level 4 decomposition, A3 will be decomposed into A4 (Delta) with a frequency range of 0-4Hz and D3 (Theta) with a frequency range of 4-8Hz.

The results of the signal decomposition are taken as statistical features which consist of the mean, standard deviation, kurtosis, and skewness to produce a feature vector with dimensions of 280. The frequency of feature extraction is depicted in Figure 2.

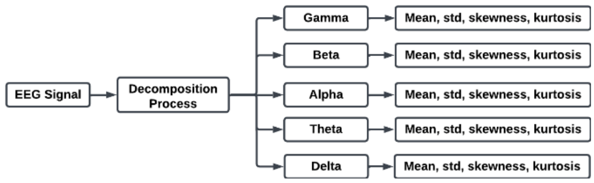

Fig. 2. Feature Extraction Process

In the proposed method used in this study, we use DWT and statistical features to obtain features in the classification model. Previous studies used STFT to obtain features in the classification model. For the analysis of non-stationary signals, such as EEG, the STFT feature extraction method is not suitable. With the STFT method, the resolution is constant across all frequencies. The wavelet decomposition of the EEG signal correlates with the non-stationary EEG signal and acquires the characteristics of the non-stationary signal [15]. In addition, classification techniques with other machine learning are also used to test the methods used quantitatively. This study has a drawback, namely in using more electrodes than previous studies, which only used seven electrodes, while this study still used 14 electrodes. The method proposed in this study can be described in general as illustrated in Figure 3.

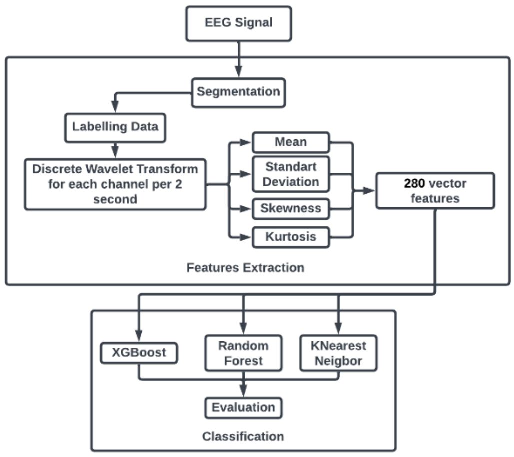

Fig. 3. Proposed Method

As can be seen in Figure 3, the proposed method consists of two parts: feature extraction and classification process using machine learning. In the feature extraction part, there is a segmentation process, namely cutting the EEG signal data for 2 second per segment. Furthermore, the data is labeled the "focused" label for the EEG signal in the first 10 minutes of the experiment, the "unfocused" label given to the EEG signal at minute 10 to minute 20, the "drowsy" label taken from the EEG signal at minute 20 until the experiment is complete. Furthermore, there is a decomposition process using DWT. The results of the decomposition set will be searched for statistical features such as mean, standard deviation, skewness, and kurtosis to produce a vector with a dimension of 280. Furthermore, the vector can be used as a feature in the machine learning classification model.

Machine learning models such as XGBoost, Random Forest, and KNN are used in the classification section. The model will be tested quantitatively using the feature vectors compiled in the previous process. The model will evaluate its performance using the confusion matrix to obtain the Accuracy, precision, sensitivity, and F1 score values for each model tested.

III. Result And Discussion

This study classified the EEG signal feature vectors using the XGBoost algorithm. In machine learning, hyper-parameter optimization is used to identify the ideal hyper-parameter for a given learning algorithm in order to get the greatest performance when tested on a validation set. This process uses the sklearn library with the GridSearchCV function to get the value of the n_estimators parameter, which is a parameter to determine the number of trees used, and max_depth, which is a parameter for the maximum depth of each tree in the XGBoost algorithm. Look for the n_estimators parameter values of 100 to 1000 with multiples of 100 and max_depth with values of 20, 30, and 40. Until the best combination results are obtained with parameter n_estimators = 400 and max_depth = 40.

In the experiment, we used 5-fold cross-validation to get the average accuracy value from 5 experiments. The dataset is separated randomly, with a ratio of 85:15 for training and testing. Following are the results of the 5-fold cross-validation:

TABLE I. The Results Of K-Fold Cross Validation Using The XGBoost Method With Data Train

Subject	*Split 1 (%)*	*Split 2 (%)*	*Split 3 (%)*	*Split 4 (%)*	*Split 5 (%)*	*Mean Score (%)*
Subject 1	95.833	96.569	93.750	94.118	95.221	95.098
Subject 2	95.693	93.706	94.406	94.755	93.823	94.477
Subject 3	96.105	95.876	95.986	95.528	96.445	95.988
Subject 4	**96.036**	**96.287**	**97.567**	**97.823**	**96.799**	**96.902**
Subject 5	96.469	96.355	97.836	96.355	97.377	96.879

From the experimental results above, we obtained an accuracy value of 97.823% (the best) and 96.902% (average) using the XGBoost method, which has been tuned to hyper-parameters. From the experimental results above, good classification results have been obtained with an imbalance dataset. The following table shows the class distribution:

TABLE II. Class Distribution On The Dataset Per Subject

Subject	*focused*	*unfocused*	*drowsy*
Subject 1	1500	1500	2440
Subject 2	1500	1500	2722
Subject 3	1500	1500	2816
Subject 4	1500	1500	2209
Subject 5	1500	1500	3453

Oversampling technique with the SMOTE method is used to synthesize samples from the minority class. In the case of this dataset, the minority class is the focused and unfocused class. After obtaining a balanced dataset, the hyper-parameter tuning process is repeated for the XGBoost method until the best combination is obtained with parameter values n_estimators = 700 and max_depth = 30. The following are the results of 5-fold cross-validation using balanced datasets:

TABLE III. K-Fold Cross Validation Results With The SMOTE-XGBoost Method

Subject	*Split 1 (%)*	*Split 2 (%)*	*Split 3 (%)*	*Split 4 (%)*	*Split 5 (%)*	*Mean Score (%)*
Subject 1	96.630	97.541	95.902	96.995	96.266	96.667
Subject 2	96.898	96.082	97.143	96.980	96.405	96.702
Subject 3	97.792	97.238	97.474	97.317	97.474	97.459
Subject 4	**97.284**	**96.680**	**97.887**	**98.692**	**97.887**	**97.686**
Subject 5	98.198	98.777	98.777	98.649	98.648	98.610

In the experiment above, the accuracy value was increased from 97.823% to 98.692% (the best) and 96.902% from 97.686% (average) after the oversampling technique was carried out using the SMOTE method on the dataset. This study conducted similar tests with several different classification algorithm approaches, namely the Random Forest and KNN methods, with the following results:

TABLE IV. Comparison Of The Performance Accuracy Of The Classification Method With Data Train

Method	*Subject's Accuracy (%)*					
	1	*2*	*3*	*4*	*5*	*Mean Score*
XGBoost	**96.667**	**96.702**	**97.459**	**97.686**	**98.610**	**97.425**
Random Forest	96.011	95.281	97.128	97.586	97.838	96.768
KNN	89.271	89.631	92.961	93.320	96.113	92.259

The table above shows a comparison of the performance of several methods to carry out the task of classifying EEG signal feature vectors. It can be concluded from the table above that XGBoost is better for classifying this dataset compared to the Random Forest method, with an accuracy of 96.768%, and KNN, with an accuracy of 92.259%.

Furthermore, an evaluation is also carried out using the confusion matrix to measure the performance of the multiclass classification machine learning model. Accuracy, precision, sensitivity, and F1 score can be calculated using the confusion matrix. The following is a classification report using test data:

TABLE V. SMOTE-XGBoost Classification Report With Data Test

Subject	*Class*	*Precision (%)*	*Recall (%)*	*F1-Score (%)*	*Accuracy (%)*
Subject 1	*Unfocused*	98	97	97	97
	Drowsed	97	98	97	
	Focused	96	96	96	
Subject 2	*Unfocused*	98	98	98	98
	Drowsed	97	97	97	
	Focused	95	96	96	
Subject 3	*Unfocused*	98	98	98	98
	Drowsed	98	99	98	
	Focused	98	97	98	
Subject 4	*Unfocused*	99	99	99	98
	Drowsed	99	97	98	
	Focused	96	98	97	
Subject 5	***Unfocused***	**99**	**99**	**99**	**99**
	Drowsed	**99**	**98**	**99**	
	Focused	**97**	**98**	**98**	

In the classifications report above, it can be seen in subject 5 for the accuracy value obtained 99% and for the average accuracy value for all subjects obtained 98% on test data using the XGBoost model. Classification of test data is also carried out using Random Forest and KNN machine learning models, with the following results:

TABLE VI. Comparison Of The Performance Accuracy Of The Classification Method With Data Test

Method	*Subject's Accuracy (%)*					
	1	*2*	*3*	*4*	*5*	*Mean Score*
XGBoost	**97**	**98**	**98**	**98**	**99**	**98**
Random Forest	97	96	97	98	98	97.2
KNN	91	91	94	94	97	93.4

The results in table 6 show no significant difference from the accuracy value given by the XGBoost and Random Forest models. For the KNN model, a slightly lower value is obtained than the XGBoost and Random Forest models, with an average value of all subjects of 93.4%.

IV. Conclusion

This study used WT as a preprocessing process to extract EEG signal features. The WT preprocessing process was carried out with 4 levels of decomposition and using the 4th-order Daubechies (DB4) type. Statistical features are obtained from the wavelet coefficient obtained from the EEG signal so that a feature vector with dimensions of 280 is obtained. From the 280-dimension vector, XGBoost classification is carried out with n_estimators = 700 and max_depth = 30. This classification method produces an accuracy value of 99% (best) and 98% (average). It has been demonstrated that the oversampling strategy used with the SMOTE method improves the performance of the classification model when dealing with datasets having an unbalanced class. In the preprocessing step, it has been demonstrated that combining WT with statistical variables like mean, standard deviation, skewness, and kurtosis produces a vector that performs well as a classification feature for the amount of mental attention status.

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