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APPLICATION OF CONTINUOUS WAVELET TRANSFORM AND SUPPORT VECTOR MACHINE FOR AUTISM SPECTRUM DISORDER ELECTROENCEPHALOGRAPHY SIGNAL CLASSIFICATION

The article's ***subject matter*** *is to classify Electroencephalography (EEG) signals in Autism Spectrum Disorder (ASD) sufferers. The* ***goal*** *is to develop a classification model using Machine Learning (ML) algorithms that are often implemented in Brain-Computer Interfaces (BCI) technology. The* ***tasks*** *to be solved are as follows: pre-processing the EEG dataset signal to separate the source signal from the noise/artifact signal to produce an observation signal that is free of noise/artifact; obtaining an effective feature comparison to be used as an attribute at the classification stage; and developing a more optimal classification method for detecting people with ASD through EEG signals. The* ***methods*** *used are: one of the wavelet techniques, namely the Continuous Wavelet Transform (CWT), which is a technique for decomposing time-frequency signals. CWT began to be used in EEG signals because it can describe signals in great detail in the time-frequency domain. EEG signals are classified into two scenarios: classification of CWT coefficients and classification of statistical features (mean, standard deviation, skewness, and kurtosis) of CWT. The method used for classifying this research uses ML, which is currently very developed in signal processing. One of the best ML methods is Support Vector Machine (SVM). SVM is an effective super-vised learning method to separate data into different classes by finding the hyperplane with the largest margin among the observed data. The following* ***results*** *were obtained: the application of CWT and SVM resulted in the best classification based on CWT coefficients and obtained an accuracy of 95% higher than the statistical feature-based classification of CWT, which obtained an accuracy of 65%.* ***Conclusions.*** *The scientific contributions of the results obtained are as follows: 1) EEG signal processing is performed in ASD children using feature extraction with CWT and classification with SVM; 2) the combination of these signal classification methods can improve system performance in ASD EEG signal classification; 3) the implementation of this research can later assist in detecting ASD EEG signals based on brain wave characteristics.*

Keywords: *Autism Spectrum Disorder (ASD); Continuous Wavelet Transform (CWT); Electroencephalography (EEG); Support Vector Machine (SVM).*

1. Introduction

1.1. Motivation for research

Autism Spectrum Disorder (ASD) is a neurological disorder that affects the development of children who are different in general, with disorders in the development of complex and varied brain functions [1]. Therefore, people with autism will find it difficult to do various things that result in the development of poor neurological functions. To determine the neurological condition of ASD, it can be done by recording signals in the brain using Electroencephalography (EEG) [2, 3]. EEG signals strongly correlate with ASD to detect abnormalities in nerve cells in the brain [4]. The development of an effective and efficient method for classifying EEG signals in people with ASD is needed to help patients or healthcare providers perform specialized treatment.

In November 2021, J. Zeidan et al. conducted a study of studies published in Medline that estimated the prevalence of ASD since 2012. Ninety-nine estimates from 71 studies were published, revealing variations in the global prevalence of ASD across regions. The median prevalence was 100 per 10,000 individuals, ranging from 1.09/10,000 to 436/10,000 [5].

EEG is a device that records all types of electrical activity from the brain and other physiological activities such as heart, ocular, muscle, or noise from the environment (electrical equipment/cables) [6]. A non-invasive or bioelectric method obtains the EEG recording

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system, making it safer because it does not require surgery on the brain [3]. The output of the EEG sensor electrodes obtained electrical activity from brain wave patterns in the form of signals that can interpret abnormalities or diseases experienced by people with autism through their brain activity. Currently, clinical EEG equipment can be found in health institutions that monitor brain electrical activity and assist doctors in making decisions [4].

1.2. State of the Art

Research related to EEG signal processing for ASD has been conducted before using EEG to detect ASD disorders with feature extraction using wavelets [7, 8]. Many EEG studies involve Brain Computer Interference (BCI) to detect ASD brain functionality [9]. Previous studies have developed BCIs using face recognition to find more effective computations [10]. Research also uses BCI to control wheelchairs and automate software for household appliances, which uses the wavelet function, namely Continuous Wavelet Transform (CWT), as feature extraction [11, 12].

The performance of this classification system is highly dependent on the model used; therefore, selecting appropriate feature extraction techniques is very important to provide optimal classification results [13, 14]. This study utilizes the wavelet technique CWT, which is used to decompose time-frequency signals. Research has been conducted on decomposing EEG signals of ASD [15] and analyzing the uniqueness of EEG features in wheelchairs with BCI [11]. CWT is starting to be used in EEG signals because it can describe the signal in great detail in the time-frequency domain [15].

Various techniques have been used to develop EEG signal classification models in ASD. M. I. Al-Hiyali et al. used functional connectivity patterns from resting-state functional Magnetic Resonance Imaging (rs-MRI) signals with Convolutional Neural Networks (CNN), which achieved an accuracy of 89.8% [16]. S. Alhassan et al. showed an energy-efficient approach that reduces energy consumption by transmitting processed EEG data. This study applies the SVM, Logistic Regression (LR), and Decision tree (DT) methods with accuracy reaching 96% [17]. N. Kumar et al. proposed a wavelet-based feature extraction technique that obtained 96% accuracy with ANN and 85.46% accuracy with Support Vector Machine (SVM) in classifying EEG signals in patients with epilepsy [18]. F. A. Alturki et al. proposed the latest technique for feature extraction using Common Spatial Pattern (CSP), which succeeded in obtaining the best accuracy of 98.62% from the combination of the CSP+LBP+KNN method [19].

EEG signal research using BCI is widely performed with classification using Machine Learning (ML) algorithms [20]. ML and Deep Learning (DL) can be implemented using complex Artificial Neural Network (ANN) architectures. As its development has increased significantly, it has been implemented in various fields of technology to overcome various challenges [21]. The application of ML and DL to mental workload and Motor Imagery (MI) has received great attention in recent years, where as much as 75% of DL research uses CNNs with various learning algorithms, and 36% of ML research achieves competitive accuracy using SVM algorithms [22]. To date, Artificial Intelligence (AI)-based algorithms can improve EEG analysis and diagnosis [14].

Signal processing techniques, such as filtering and normalization, have been used to process the input data before fed to ML algorithm [23]. Some studies have used SVM to classify EEG signals in patients with ASD [17, 18, 24]. The research on the application of SVM in ASD with a small dataset that shows the best accuracy of 95% [1] and the difference in EEG signals that diagnose epilepsy with ASD [25]. Research on SVM classification has been used for statistical feature classification (mean, mean power, standard deviation, absolute mean ratio, skewness, kurtosis), which obtained the best overall performance with an overall accuracy of 96% [26]. F. Salehi et al. demonstrated the efficiency of the SVM algorithm by classifying the EEG signal dataset of ASD, which resulted in a significant performance improvement of 96% [27].

T. Heunis et al. researched EEG signals to detect ASD by comparing classifiers from ML, namely Linear Discriminant Analysis (LDA), Multilayer Perceptron (MLP), and SVM based on the Principal Component Analysis (PCA) feature extraction method, which resulted in the highest accuracy of 95% from SVM classifier [28]. This study uses the feature extraction method with CWT and classification with SVM with the object of EEG signals in children with ASD and normal children.

1.3. Objective and Approach

Figure 1 shows the EEG classification system used in this study, where the EEG signal is first pre-processed to reduce noise and artifacts from the original signal using Independent Component Analysis (ICA) and then input to the feature extraction process using CWT to decompose the time-frequency signal. The obtained CWT coefficients are then used to calculate the statistical feature values of mean, standard deviation, skewness, and kurtosis. The feature extraction results obtained will be used as attributes for the SVM classification process.

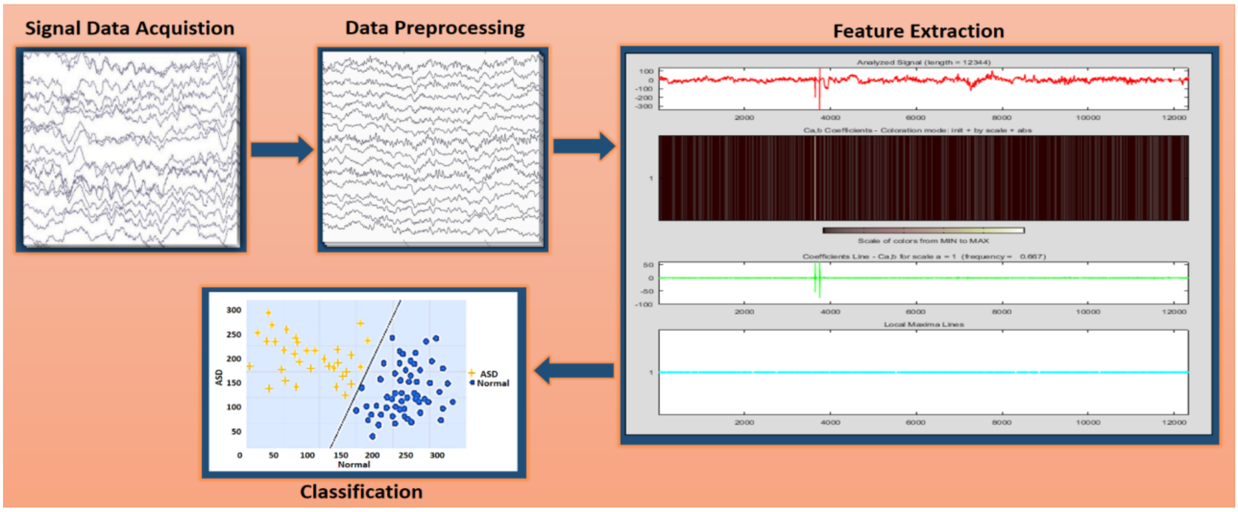

Fig. 1. EEG classification system

This study's major contributions can be summarized as follows:

1. CWT and SVM feature extraction methods are applied to datasets with ASD and normal contexts to improve accuracy.
2. CWT coefficients with four statistical features (mean, standard deviation, skewness, and kurtosis) are implemented.
3. CWT and SVM for EEG signal classification in patients with ASD are integrated for the first time.
4. The effectiveness of the method proposed in this study to classify EEG signals in people with ASD is proved by comparing the value of statistical features and CWT coefficients using the SVM classifier.

2. Materials and Methods

This study describes an approach for classifying people with ASD using EEG signals. The main methods used include the use of SVM as a classifier and CWT as a feature extraction technique. The evaluation of the model performance is done through confusion matrix analysis. A significant aspect of this research is the comparison of two feature approaches: feature extraction from CWT coefficients and statistical features. This comparative analysis identifies a more effective approach for classifying individuals into appropriate groups. Thus, this research focuses on applying CWT and SVM methods in EEG analysis to support the development of more accurate diagnostic methods for identifying people with ASD.

Initial processing of EEG recorded data uses Brain-Computer intelligence (BCI) to display EEG signals. Next, noise or artifacts outside the EEG signal are minimized using ICA. Then, the preprocessing results with ICA are used as input in the feature extraction process to obtain two feature values, namely, the CWT coefficients and statistical features (mean, standard deviation, skewness, and kurtosis) of CWT. In particular, the values of the CWT coefficients are used to calculate four statistical feature values: mean, standard deviation, skewness, and kurtosis. The two feature extraction results will be classified using SVM separately to measure the performance of the two features, namely between the CWT coefficients and the combination of CWT coefficients on statistical features, using a confusion matrix.

2.1. Dataset

This study uses secondary collected EEG signal data from research conducted by King Abdulaziz University (KAU), Jeddah, Saudi Arabia [29]. The data consisted of 16 class subjects, with 8 subjects for the normal class and 8 subjects for the ASD class. The tapes were recorded using 16 channels, including the Frontal (frontal part of the brain) channels Fp1, Fp2, F7, F3, Fz, F4, and F8. Then Temporal (middle part of the side) channels T3 and T5. Next is Central (top center), namely channels C3, C4, and Cz. Pz, O1, and ozs are the brain's Parental (upper back) and Occipital (lower back) parts.

2.2. Independent Component Analysis (ICA)

ICA is one of the best algorithms for removing noise/artifacts outside the brain signal from EEG recording [30]. The working principle is to divide a set of signals that have been mixed into a set of new components [31]. Noise/artifacts are unwanted potentials that alter brain impulses and usually come from physiological and non-physiological sources. Non-physiological sources are generated outside the human body, such as electronic EEG recording devices and cables. Physiological sources, such as heartbeat, eyes, and muscles, are generated from inside the body [32].

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N. Tulyakova et al. developed a local adaptive filtration method for non-stationary signals to find an effective algorithm to reduce non-stationary noise [33]. This research uses the ICA method, which has proven to be an effective data-based method for analyzing EEG signals, separating signals from brain activity from other sources (noise/artifacts) [34]. B. Kaliraman et al. showed that using ICA on EEG signals is very influential in producing more optimal performance [32]. The mixed signal is represented as $x = (x_1, ..., x_m)^T$, and the hidden component is a random vector $s = (s_1 ,..., s_n)^T$. Where m is the m-th signal, the hidden component is the m-th signal. Then, m is the mth signal and n is the n-th hidden component. The following equation model of ICA can be seen in Eq 1:

$$x_i = a_{i,1}\, s_1 + \cdots + a_{i,k}\, s_k + \cdots + a_{i,m}\, s_n\,, \qquad (1)$$

where x_i is the component of the random data vector $x = (x_1, ..., x_m)^T$ plus the independent component s_k with k = 1,..., n and a_i, 1 is the mixture matrix. Eq. 1 can be rewritten in the vectorial form shown in Eq. 2, where x is the signal of interest.

$$x = \sum_{i=1}^{n} a_i s_i. \qquad (2)$$

The ICA method can remove artifacts from EEG recordings, but its implementation still depends on the bulk of the data used. ICA will be more accurate as the number of electrodes used in EEG signal recording increases [31].

2.3. Continuous Wavelet Transform

CWT is one of the decomposition methods. CWT obtains the correlation coefficient between the original signal and the mother wavelet. The signal is decomposed into a time-frequency domain by adjusting the shape of the mother wavelet [35]. CWT can organize waves on various time scales. Fourier transformation decomposes the signal into sine and cosine functions of infinite length [36]. The basic idea of the method is performed by Fast Fourier Transform (FFT) of each time window continuously to obtain an overview of the frequency range in the target zone (reservoir) [37].

This study uses the CWT method for feature extraction, which is the process of converting raw data into numerical features without destroying the information contained in the original raw data set. This feature extraction plays an important role in ML in obtaining optimal results [36].

The working principle of CWT is to select a suitable wavelet basis function and obtain a series of basis functions at various intervals through translation and scale transformation. Then, the EEG signal generated and integrated through the appropriate intervals will be used to obtain the time and frequency characteristics of the EEG signal [38].

The image is analyzed using the Fourier Transform function, which has a signal that is different from the original signal because it has undergone a signal transformation process. The advantage of CWT is its ability to describe the signal in detail in the time-frequency domain. CWT is the convolution between the signal and the wavelet function. The CWT equation is written in the following equation

$$\gamma(\tau, s) = \int_{s,\tau} f(t)\Psi^*(t)dt. \qquad (3)$$

The * sign in Ψ* in Eq. 3. symbolizes complex conjugation [39]. There are several choices of wavelet functions, namely market, Mexican hat, Daubechies, market, samlet, and Shannon. Xiao et al. compared wavelet basis functions, where the market wavelet was selected as the most suitable basis function for EEG signal wavelets [38]. The basic wavelet function can be mathematically defined as follows:

$$\Psi_{\tau,s}(t) = \frac{1}{\sqrt{|s|}}\Psi\left(\frac{t-\tau}{s}\right). \qquad (4)$$

In Eq. 4, a mathematical representation of the wavelet function Ψ is given by considering the time (translational) shift τ and the scale s. The wavelet function Ψ is defined as 1 divided by the square root of the absolute value of the scale s, multiplied by Ψ, whose argument is the difference between t and τ divided by the scale s.

Figure 2 shows the steps of feature extraction using CWT. The ICA result data are decomposed to present the signal in the time and frequency domains. The output is a signal with a time window of 4 s, whose values are then determined using the wavelet function in Eq. 4. The wavelet calculates the convolution of the original signal (Eq. 3), which results in the CWT coefficients. The CWT coefficients are used to calculate the four statistical feature values.

2.4. Statistical features

The steps of obtaining statistical features are follows:

1. Mean is the average value $\bar{x}$ of the total amount of data x_i divided by the total amount of data n

$$\bar{x} = \frac{x_1 + x_2 + x_3 + x_4 + \cdots + x_n}{n} = \sum_{i=1}^{n} \frac{x_i}{n}. \qquad (5)$$

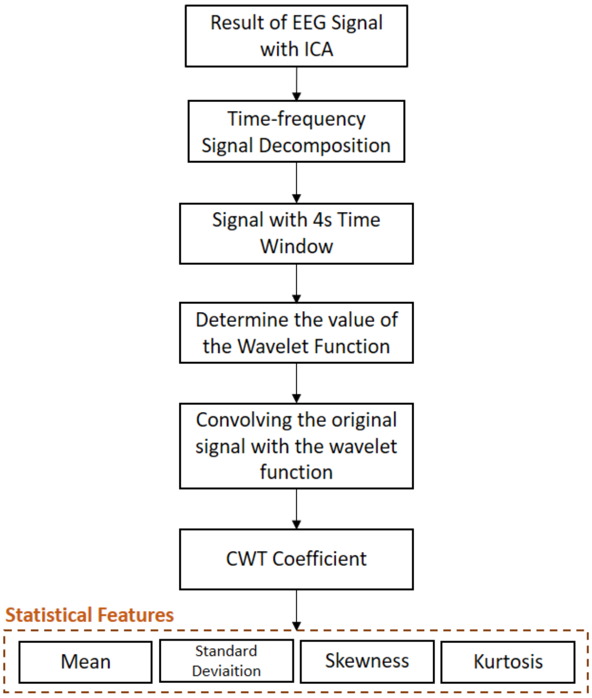

Fig. 2. Feature extraction using CWT

2. Standard Deviation σx is a value used to determine the distribution of data in a sample and determine how close the data is to the mean value $\bar{x}$. A large spread of data against the mean value results in a large x value, and vice versa [39]

$$\sigma x = \frac{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})}}{(n-1)}. \quad (6)$$

3. Skewness Sw is also called a measure of the slope of a data distribution. Skewness values indicate normal data when the values are between -2 and 2 [40]. The curve resulting from the skewness calculation can point positively or negatively if the data are not normally distributed

$$Sw = \frac{\sum_{i=1}^{N}\left(x_{iEEG} - \bar{x}_{iEEG}\right)^3}{N\left(\sqrt{\frac{\sum_{i=1}^{N}(x_{iEEG} - \bar{x}_{iEEG})^2}{N-1}}\right)^3}. \quad (7)$$

4. Kurtosis Kr is a parameter of the relative sharpness of a signal with respect to a normal distribution. In a normal distribution, kurtosis has the same range of values as skewness which ranges from -3 to 3 [40]. A curve is called symmetrical if the degree of skewness is zero

$$Kr = \frac{\sum_{i=n_s}^{n_e}\left(x_{iEEG} - \bar{x}_{iEEG}\right)^4}{N\left(\sqrt{\frac{\sum_{i=1}^{N}(x_{iEEG} - \bar{x}_{iEEG})^2}{N-1}}\right)^2}. \quad (8)$$

2.5. Support Vector Machine (SVM)

SVM is one of the most powerful classification techniques based on statistical theory and ML, capable of modeling complex data by finding linear combinations of features [41], where the features consist of 16 channels of brain wave frequency measurements so that the samples are separated into appropriate classes. This SVM-based ML model is most widely used in mental health disorders [36]. SVM uses a supervised learning algorithm where the applied kernel trick performs a transformation on the dataset, and this transformation provides a plate form to find the optimal boundary that determines the classification result. SVM can work with large amounts of data, detect data patterns, and form appropriate partitions to classify data into different classes [42].

The goal is to find the best hyperplane that separates two or more classes. The hyperplane separates classes by forming a linear straight line [43]. SVM uses kernels to find SVM classifiers in higher dimensions [32]. The hyperplane equation is as follows

$$\vec{w}\vec{x} + b = 0. \quad (9)$$

Equation 9 shows the relationship between the normal vector w, data point x, and intersection b. When the equation is satisfied, the data point is on the line defined by the normal vector and the intersection. This equation is the foundation for modeling and analyzing data using normal lines and vectors.

The path of the x position is determined to separate two classes, i.e., a negative class or a positive class. Before determining the hyperplane between the two classes, determine the margin distance or separator between the hyperplane and the two classes. The margin m equation can be seen in the following equation

$$m = \frac{1}{2}\|w\|. \quad (10)$$

Each class member's role in determining the margin is a support vector. In determining a good hyperplane in separating two classes, the margin must be maximized by minimizing the value of w, as shown in the following equation:

$$Max = \frac{2}{\|w\|} \rightarrow \min_{\vec{w}} \quad \tau(w) = \frac{1}{2}\|\vec{w}\|^2. \quad (11)$$

In other words, maximizing the margin on the decision boundary is equivalent to minimizing the length of the normal vector w of the hyperplane. To eliminate the square root, the normal vector must be squared because it has two classes to be separated.

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Next, the support vector will be combined with kernel tricks, hence the name SVM. The function of the SVM kernel itself is to make classification decisions where the SVM kernel works in the same way as higher-dimensional data points, converting low-dimensional data into high-dimensional data so that it can turn into data points that can be separated linearly.

$$f(x) = w \cdot x + b,$$
$$\mathrm{f(x)} = \sum_{\mathrm{i=1}}^{\mathrm{m}} \alpha_{\mathrm{i}} \mathrm{y_i} \mathrm{K(x, x_i)} + \mathrm{b}. \tag{12}$$

Eq. 13 represents the function f(x) in the context of SVM. This function results from the sum of m support vectors multiplied by the weights α_i, the data class y_i, and the kernel function $K(x, x_i)$. This equation is used in SVM to classify a new data point x based on a linear combination of support vectors with appropriate weights and kernel functions.

By using the support vector in determining the margin, the class member whose position is closest to the hyperplane. A support vector is a very difficult object to classify because its position almost overlaps with that of other classes. To maximize the hyperplane with good accuracy regeneration, even though it uses soft margins, kernel functions can be used to transform data into a higher dimensional space (kernel space), which is useful for linearly separating data.

The kernel function serves the classification system by providing convenience in the SVM defense process to determine the support vector by knowing the kernel function used. The types of kernels are Linear kernel which is the simplest kernel used in the case of text classification; Polynomial kernel, used for image classification; and Radial Basic Function (RBF), used for valid data [14, 17].

SVM research has been conducted by comparing linear, polynomial, and Gaussian RBF kernel types, where the best classification result is the Gaussian RBF kernel with an accuracy of 80.55% in predicting student graduation cases [44]. Therefore, this research combines SVM with Gaussian RBF for EEG data classification in ASD, which can solve the problem of data classification that cannot be linearly separated [44]. RBF is also known to have good performance, and the training results have a small error value compared to other kernels. The RBF kernel is mathematically represented as follows

$$K(x, x_i) = exp(-\gamma \cdot \|x - x'\|^2). \tag{13}$$

Note that calculating the Euclidean distance between two data points to measure how close the data is to each other. Data is divided into training and testing data before performing the classification process using the SVM algorithm. In the training data stage, namely by generating a model, while in the testing data, the model validation process. The output of both parts will result in a classification between ASD and Normal.

Figure 3 is the classification process of SVM, where the dataset is divided into training data (70%) and testing data (30%). The training data will go through the learning process first by determining the margin between the hyperplane and the two classes (Eq. 12). Then to find the best hyperplane by minimizing the value of w to maximize the margin (Eq. 13). By finding the maximum value of the margin, then determine the hyperplane equation of the data variable (Eq. 11). To improve the performance of the hyperplane, SVM is combined with kernel tricks that allow data transformation to a higher kernel space using RBF.

2.6. Confusion matrix

A confusion Matrix is a matrix that shows the actual and predicted classification data. The Confusion Matrix is n x n, where n is the number of different classes [45]. Classification performance is evaluated using Receiver Operating Characteristic (ROC) parameters [1], such as true positive TP, true negative TN, false positive FP, and false negative FN to calculate accuracy, recall (sensitivity), specificity and overall F1-score using the following equations:

$$\mathrm{Accuracy} = \frac{\mathrm{TP + TN}}{\mathrm{TP + FP + TN + FN}} \cdot 100\%\,, \tag{14}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP + FN}} \cdot 100\%\,, \tag{15}$$

$$\mathrm{Specificity} = \frac{\mathrm{TN}}{\mathrm{TN + FP}} \cdot 100\%\,, \tag{16}$$

$$\mathrm{F1{-}score} = 2\,\frac{\mathrm{TP}}{\mathrm{2\,TP\ + FP\ + FN}}\,. \tag{17}$$

The explanation of each character used in the confusion matrix is as follows:

- TP is data with the number in the True actual class, namely positive data, and correctly classified as a positive prediction class;
- TN is data with the number in the True actual class, which is negative data and is correctly classified as a negative prediction class;
- FP is data with the sum of the False class, which is negative data but classified as a positive prediction class;
- FN is data with the sum of the False class, which is positive data but classified as a negative prediction class.

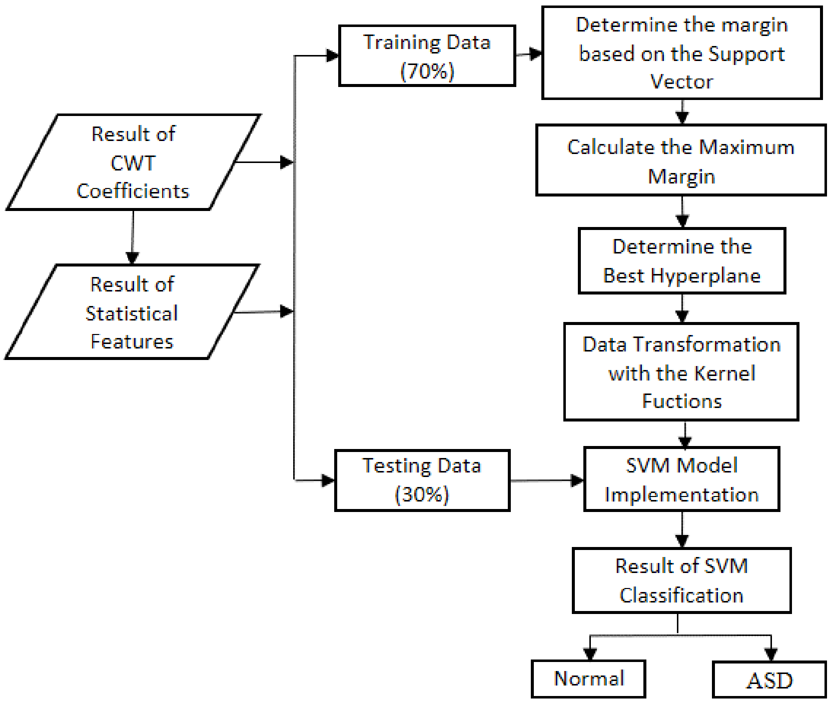

Fig. 3. Classification process using SVM

3. Results and Analysis

This section explains the results obtained in this study through several processes of the method applied.

3.1. Independent Component Analysis result

At this stage, pre-processing is performed using the ICA method to minimize noise/artifacts outside the brain signal during EEG recording. The data used is with 8 ASD data subjects and 8 normal data subjects. Sixteen data subjects will first go through the initial data pre-processing stage with ICA. The results of pre-processing produce data from EEG signals in both classes that minimize most of the noise and artifacts outside the EEG signal, as shown in Fig. 4.

Figure 4 (a) shows brain activity from the original EEG recording data signal in the normal class. Then, the EEG signal goes through the pre-processing stage using ICA in the MATLAB program so that a signal without noise and artifacts is obtained in Fig. 4, (b) for the normal class. Figure 4(d) shows the signal obtained from Fig. 4(c) after passing the pre-processing stage. The signal before pre-processing still has spectra outside the brain signal called noise and artifacts. The spectrum can be affected by eyeball movement, hand movement, and other factors. ICA will minimize the signal by filtering outside the 0.5-60 Hz range, and both signals coming from EOG and ECG. Then, the signal is sampled at as much as 256 Hz to clean the noise in the original signal. Furthermore, the signal is converted into numerical data containing the frequency and time values of each channel in the normal and ASD classes.

3.2. Feature extraction result of Continuous Wavelet Transform

The feature extraction results from the signal produce a new feature that distinguishes between the shape of one object and another through input parameters/values with the provision of wavelet function values to be identified or classified. Feature extraction is used to characterize the signal by studying neurological activity and reducing the dimensions of the signal so that it can be used as input in the next process. This study uses feature extraction with CWT, obtained after the pre-processing technique stage using ICA, which produces 16 channels of EEG data features for each normal and ASD subject.

The feature extraction results are obtained as CWT coefficient values by decomposing the time-frequency signal. Then, the signal is cut (window) with time for the first 4 s of each data. Next, we determine the value by wavelet transformation (Eq. 4). Then, we analyze the CWT function by calculating the convolution of the original signal with the wavelet function (Eq. 3). The process of transformation and convolution of the signal produces the CWT coefficient value, which is used as the classification input. Consisting of 16 channels against 16 classes, it can be seen in Table 1.

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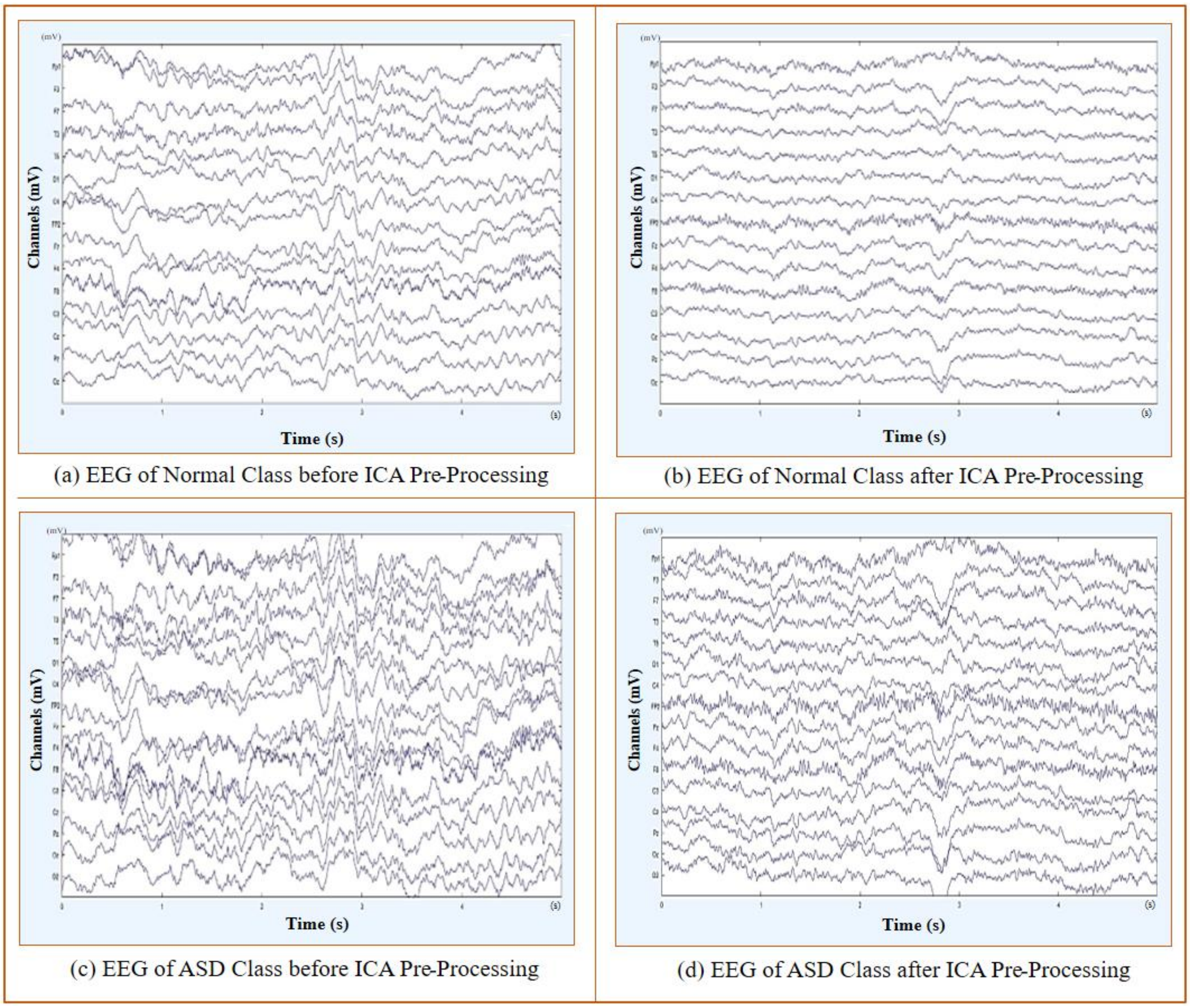

Fig. 4. The preprocessing result of EEG signal: (a) Normal class before ICA; (b) Normal class after ICA; (c) ASD class before ICA; (d) ASD class after ICA

Table 1

Feature extraction results from CWT

Data (Hz)	FP1	F3	T3	...	Oz	Class
1	10.44	23.11	14.50	...	0.45	Normal
2	10.44	34.43	11.14	...	0.43	Normal
3	10.44	40.32	12.20	...	0.03	Normal
...	...	...	...	...	...	...
19998	68.26	9.78	6.68	...	1.17	ASD

Table 1 shows the head data resulting from the feature extraction data from the CWT coefficient of 16 channels. The wavelet convolution result for the CWT coefficient value is obtained with a matrix length of 16 x 19998 features stored in CSV format. Then, the statistical feature value is calculated on the basis of the output of the CWT coefficient value. The calculation of statistical features is used as a parameter or characteristic value that is more specific to the feature extraction process to learn or recognize objects from one another.

The following are the results of the distribution of statistical features, namely the mean, standard deviation, skewness, and kurtosis values. The results of feature extraction on all channels are shown in Fig. 5.

Figure 5 shows the results of the mean value of the entire EEG channel with two different classes of normal and ASD, where the blue graph represents the normal class data and the orange graph represents the ASD class. The example of the distribution of statistical values is only on one data point to show the difference in values in different classes. The mean value generated in both classes is obtained from -10 Hz to 10 Hz. The largest mean value in the normal class is obtained in channel Fz with a value of 9.74 Hz, which has a large mean value that is not much different from the ASD class of 9.18 Hz in channel C4. In both classes, it can be seen that both classes have average values that are not far away for each channel data and only in the range of -10 to 10 Hz.

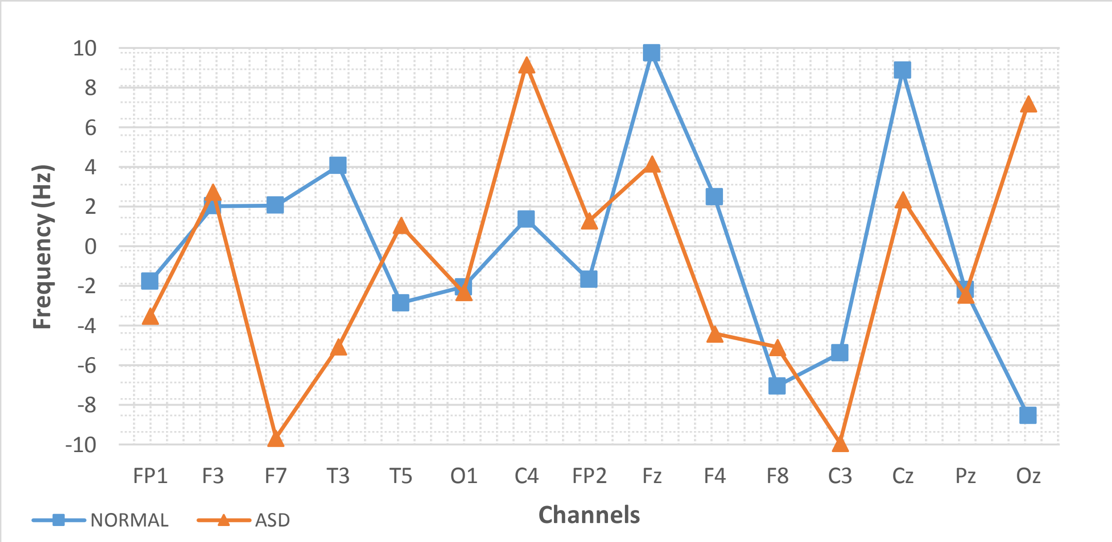

Fig. 5. Statistical feature of mean

After showing the mean value in both classes, the next statistical feature distribution is also found in the standard deviation obtained from (Eq. 6). Standard deviation is used to determine the extent of data spread in a sample with an average value (mean). Each data from both classes has a different standard deviation. Figure 6 below shows the distribution of statistical values on one dataset to show the difference in values in different classes. The standard deviation values of all channels in the two classes are shown in Fig. 6.

Figure 6 shows the standard deviation values of the 16-channel EEG for both classes. It can be seen that the standard deviation value in the normal class graph is different from that of the ASD class. In the ASD class, the resulting standard deviation value does not have a large range, whereas in the normal class, the channel feature value has channel data with a larger data range in some cases. For example, on channel FP2, with a value of 1.717 Hz, the standard deviation rises on channel Fz, which3 is 3.353 Hz. Furthermore, in the ASD class, the resulting standard deviation value is between 1-2 Hz for all channels. From these two cases, it is said that the normal class has a standard deviation value of several larger channels, which means the wider and further the spread of the data. In contrast, in other data that have a low standard deviation value, it is closer to the average.

The skewness statistical feature is obtained from Eq. 7, which is used to obtain the slope graph of the data. The following are the results of the distribution of the skewness statistical values of all channels in the two classes. Figure 7 shows the skewness value in each channel of the EEG signal for both classes.

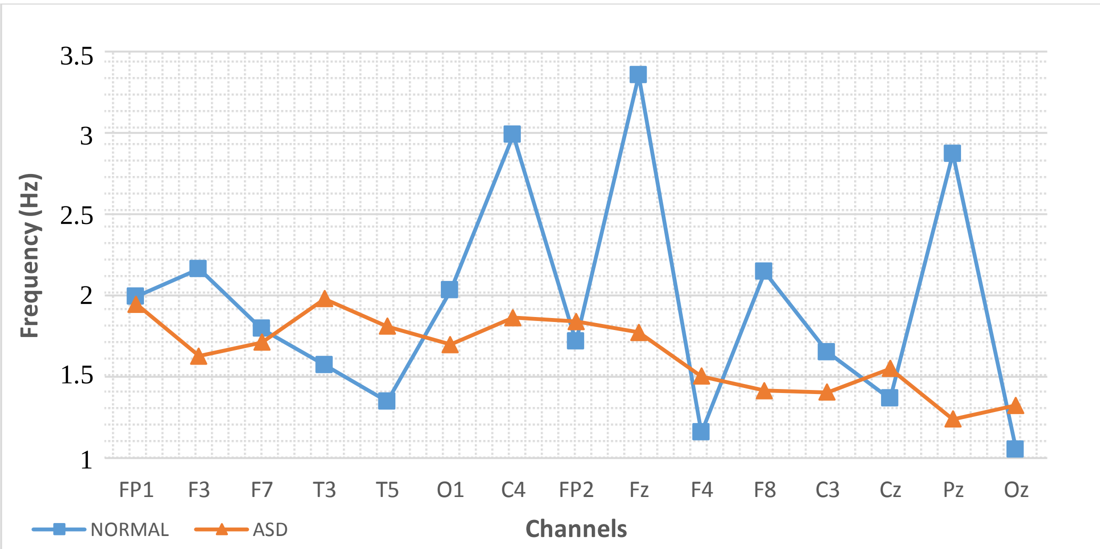

Fig. 6. Statistical feature of the standard deviation

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The skewness value with a blue graph is for the normal class, while the orange graph is for the ASD class. The skewness value that shows normal data is when the value obtained is from -2 Hz to 2 Hz.

In the normal class, the overall value obtained ranges from -2 Hz to 2 Hz, for example, in channel F3, which is 0.076 Hz, FP2, which is 0.114, and C3, which is 0.421 Hz. This does not apply to channel T5, which obtained a skewness value below -2, namely -2.594 Hz. In ASD class data, it is not much different from normal class data, which obtained almost the entire skewness value between -2 and 2 Hz. Channel T5 is 0.012 Hz, FP2 is 0.937 Hz, and channel Pz is -0.732 Hz; the skewness value outside the normal system data range occurs in channel Oz with a value of 2.013 Hz. This shows that in both classes, there is 1 channel with a skewness value that is not normally distributed because it has a value outside the range of -2 to 2 Hz. At the same time, the skewness value for other channels indicates that the data is normally distributed.

The kurtosis statistical feature is obtained from Eq. 8, which is used to determine the curvature of the data. The following are the results of the distribution of kurtosis statistical values of all channels in the two classes, as shown in Fig. 8.

Figure 8 shows the results of the kurtosis value of the entire channel on one dataset with two different classes of normal and ASD, where, like the previous feature, the blue graph is the normal class data and the orange graph is the ASD class. The distribution of kurtosis feature values in both classes has kurtosis values with different ranges for several channel cases. In the normal class, the value obtained in channel F7 is 0.086 Hz, channel T3 is -0.672 Hz, and in channel T5, the kurtosis value is 8.338 Hz.

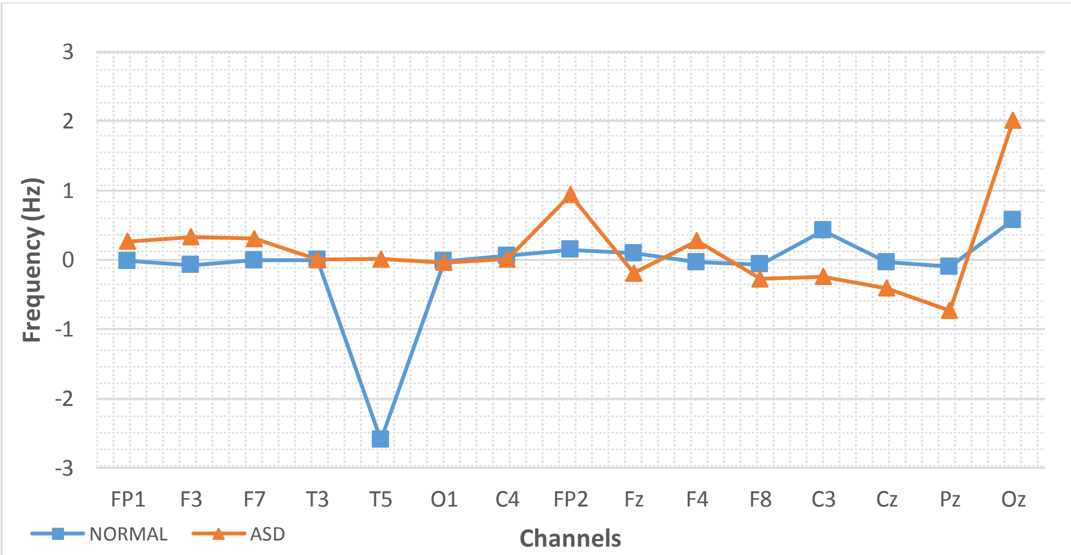

Fig. 7. Statistical features of skewness

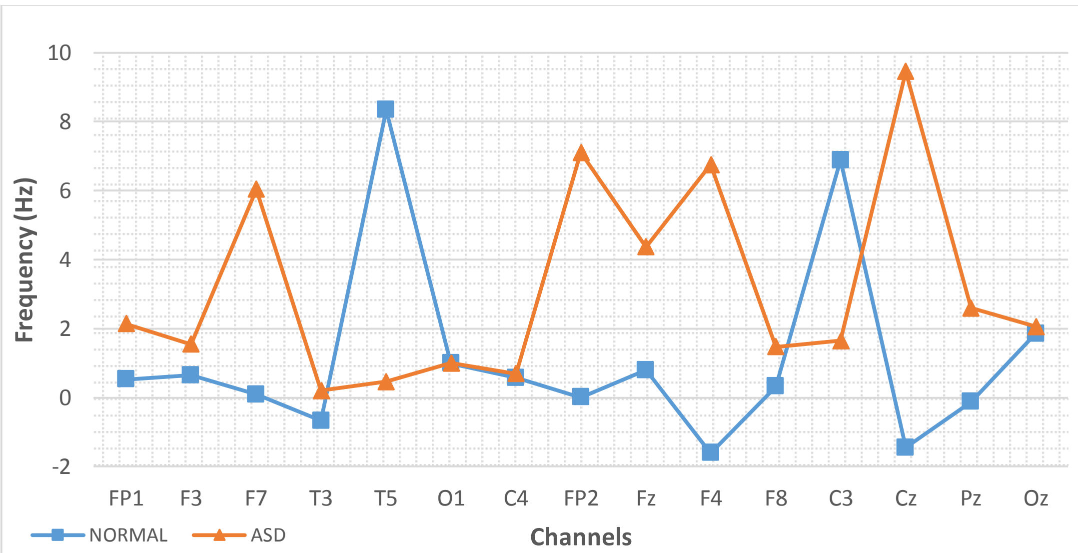

Fig. 8. Statistical feature of kurtosis

In ASD data, the value obtained in channel F8 is 1.473 Hz, C3 is 1.646 Hz, then the kurtosis value gets bigger in channel Cz, which is 9.448 Hz. The results of the kurtosis calculation obtained have a large kurtosis value (some data is too high), so the data distribution is said to be abnormal, or the level of data curvature is getting bigger. As for other kurtosis values that obtain values in the range of -3 Hz to 3 Hz, it can be interpreted as the resulting data distribution that is normal (normal curve).

3.3. Support Vector Machine results

At this stage, the classification used includes all data extracted using CWT features. Before the classification technique is performed using SVM, the data are divided into 70% training data and 30% testing data. The data used for classification are the output of the results of two feature extraction processes, namely, extraction with CWT coefficients and merging with the distribution of statistical feature values.

3.3.1. Classification with Continuous Wavelet Transfrom coefficient

The number of features on one object is 1250 x 16 data, with the amount of training data being 13998x16, consisting of 875 data features taken for one subject. The testing data amounts to 6000 x 16 data features consisting of 375 features for one subject. The following are the results of the CWT coefficient classification shown in Fig. 9.

Figure 9 shows the classification results of normal and ASD classes using SVM with RBF kernel function, which can separate the two pieces of data more accurately by determining the hyper-plane in separating the two classes. The normal class is plotted in green, while the ASD class is plotted in red. As for the area in the ASD class, the dataset is depicted with a region that is also red and normal with a green image region. The amount of data in the training process is 13998 data, and the testing is 6000 data.

In separating ASD and normal classes in SVM, we determine the hyperplane in separating the two classes. On the X axis with normal data and the Y axis with ASD data where previously the training data produced models for both classes, then tested with testing data to validate the model with new data. Therefore, from the two processes of separating the two pieces of data, the classification results using SVM with the help of the RBF kernel function obtained a good accuracy percentage of 95%.

3.3.2. Classification of statistical features from Continuous Wavelet Transform

The results of CWT feature extraction data with statistical features, namely Mean (Eq. 6), Standard Deviation (Eq. 7), Skewness (Eq. 8), and Kurtosis (Eq. 9). Each data has a feature value of 16 channels. Furthermore, the classification results with the support vector are obtained from training and testing data as much as 70% and 30% of the total data. The following are the results of the classification of the statistical features from CWT, as shown in Fig. 10.

Figure 10 shows the classification results of testing data for normal and ASD classes using SVM on EEG data against four statistical features. It can be seen that the normal class has a green plot, while the ASD class has a red plot. Then, in the ASD class, the dataset is depicted with a region that is also red and normal with a green image region.

The SVM kernel type used in this research is Gaussian RBF with kernel function (Eq. 11) to transform the data to a higher dimensional space to avoid overlap between the two classes. This is proven based on the algorithm of the amount of data in the training process, which is 44 data and testing 20 data. From the separation

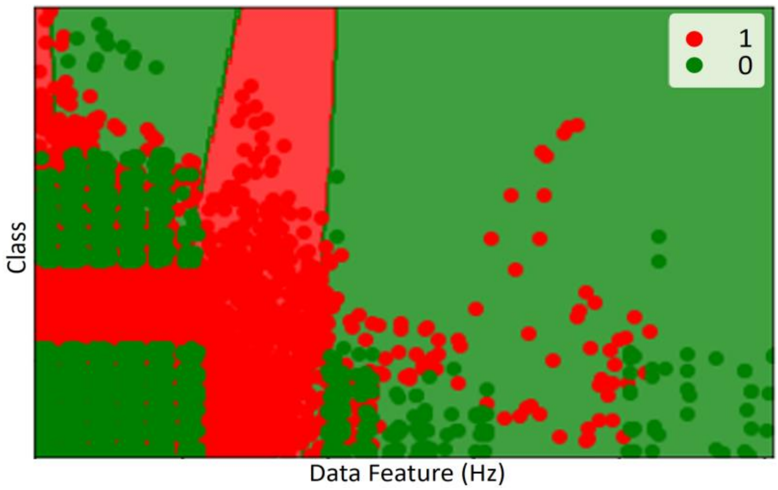

Fig. 9. SVM classification results with CWT coefficient feature

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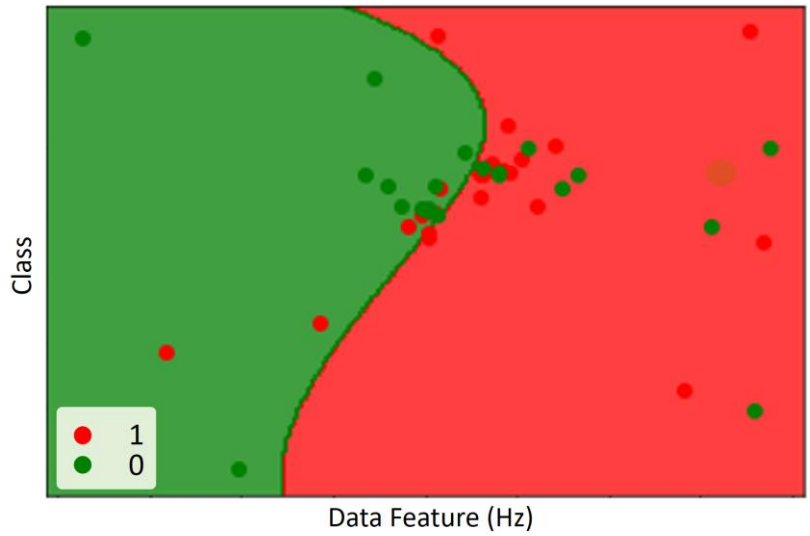

Fig. 10. SVM classification results against the statistical feature distribution of CWT

process between ASD and normal data, the classification results using SVM are obtained with an accuracy of 65%.

3.4. Analysis of the confusion matrix

3.4.1. Continuous Wavelet Transform coefficients

An analysis of the performance of the CWT coefficient classification system based on the evaluation parameters of the confusion matrix is shown in Fig. 11. Figure 11 shows the result of obtaining the value of performance analysis on classification with CWT coefficients, with a feature length of 6000 data. TP is obtained with a value of 2887, FP is 96, FN is 194, and TN is 2823. The number of values obtained by TP is ASD data predicted to be true ASD as much as 2887 data features. Then, FP is normal data predicted as ASD as much as 96 data features. Next, FN obtained 194 data features where ASD data was predicted as normal. The last is TN, where normal data is predicted correctly as normal with 2823 data features. The results of the evaluation parameter calculation analysis on the CWT coefficient classification are shown in Fig. 12.

Figure 12 shows the results of calculating the evaluation parameters on the confusion matrix obtained from the CWT coefficient feature classification. The accuracy value is obtained with a TP value of 2887 data features, FP is 96 data, FN is 194 data, and TN is 2823 data, using (Eq. 15), which gives a value of 95%. Then, the calculation of recall (Eq. 16) is with a value of 95%. Furthermore, the calculation of Specificity (Eq. 17) is 97%, and the calculation of F1-Score (Eq. 18) is 95%.

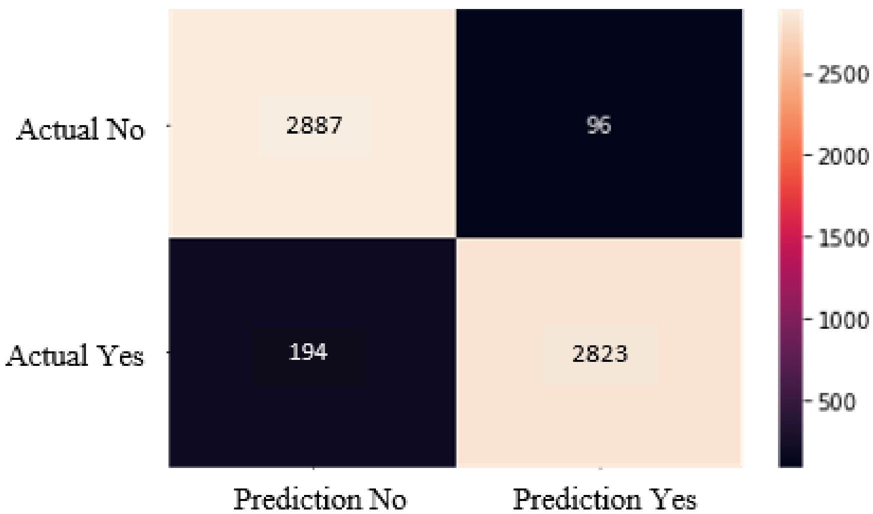

Fig. 11. Confusion matrix value for CWT coefficient classification

The results of this analysis prove that the testing process carried out with testing data on the classification model is good because it obtains a percentage of the results of the evaluation analysis on confusion with an accuracy value of 95%.

3.4.2. Statistical feature of Continuous Wavelet Transform

Analysis of the performance of the statistical feature classification system of CWT based on the evaluation parameters on the confusion matrix, as shown in Fig. 12.

Figure 12 shows the result of obtaining the value of the performance analysis on the classification of statistical features from CWT with 20 data features.

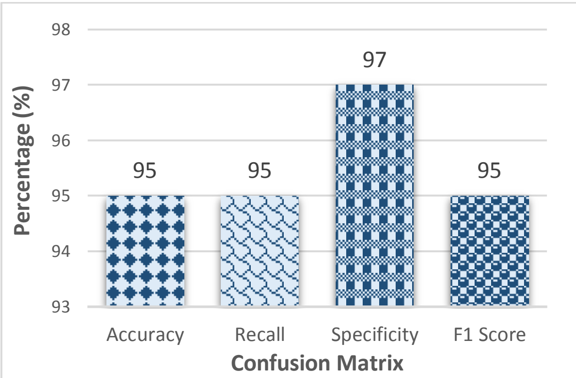

Fig. 12. Confusion matrix value on CWT coefficient classification

The value for TP is 9, the FP value is 0, the FN value is 7, and the last is the TN value 4. TP is obtained on the basis of the results of ASD data that is predicted to be true ASD data with 9 data features; FP is normal data predicted as ASD, which is 0. Then, FN is ASD data predicted as normal with as many as 7 data features, and TN is normal data predicted to be normal with as many as 4 data features. From these cases, the FP and FN values are the most influential because of an error in predicting the corresponding data. The resulting FP is zero, which means that the system predicts no error in detecting normal data that is considered ASD.

As seen in Fig. 13, the dark color shows the lowest value, and the value increases with the lighter color. The value is based on the testing data used to test the model results from the training data totaling 20 features. The results of the value obtained from Fig. 13 are then used to calculate the value of the evaluation parameter in the confusion matrix displayed in Fig. 14.

Figure 14 shows the results of the calculation of parameter evaluation on the confusion matrix obtained in the classification of statistical feature values from CWT, obtained for accuracy values with TP values of 9 data features, FP is 0 data. FN 7 data and TN 4 data, using (Eq. 15), obtained a value of 65%. Then, the recall calculation (Eq. 16) has a value of 65%. Furthermore, the specificity calculation (Eq. 17) obtained the highest result of 100%, and finally, the F1-Score calculation (Eq. 18) obtains a value of 62%. The results of this analysis prove that the system can categorize ASD and normal classes with calculation analysis using recall and specificity is the best because it can predict the correct data, namely in recall with correct data ASD of all children predicted ASD. Likewise, in specificity, namely correct data normal of all children predicted normal. Therefore, it is true that there is no detection error in children who are normal but declared ASD.

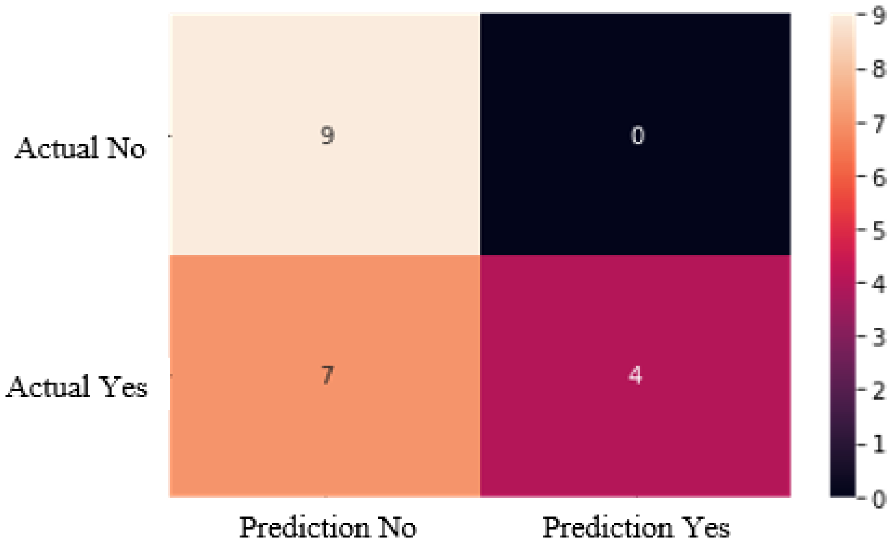

Fig. 13. Confusion matrix results on the statistical features of CWT

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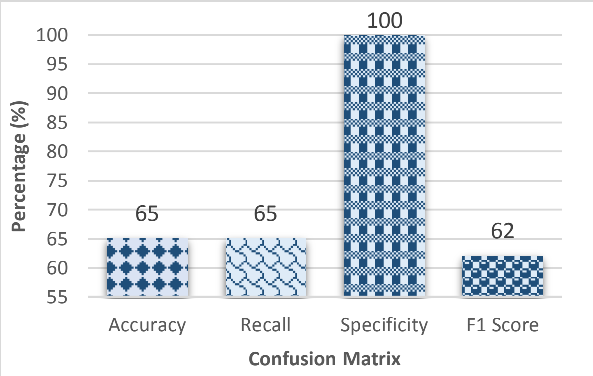

Fig. 14. Confusion matrix value
on the statistical feature classification of CWT

4. Discussion

The results of calculating system evaluation parameters with the confusion matrix value of the SVM classification scenario by comparing system performance between the two scenarios are shown in Table 2.

Table 2

Comparison of the evaluation analysis
of the two classifications

Classification	Accuracy	Recall	Specificity	F1-Score
CWT Coefficient	95%	95%	97%	95%
Statistical Feature	65%	65%	100%	62%

Table 2 shows the results of SVM classification performance for the two classification scenarios. It can be seen that the value of the evaluation analysis on the largest confusion matrix is the CWT coefficient feature-based classification, where the highest percentage value is obtained compared to the statistical feature-based classification of CWT, with an accuracy value of 95%; recall 95%, specificity 97%, and F1 Score 95%. The selection of the calculation value of the confusion matrix parameter is not based on the accuracy value alone because if the FP value with the resulting FN has a very close value, then the system's reference is said to be successful through the accuracy value alone. This applies to calculating the confusion matrix for the classification of statistical features where the FP value with a value of 0 is far apart or asymmetrical with a false negative value of 7. Furthermore, the specificity was chosen because it has a high value caused by the non-occurrence of FP, which is expected to result in no misdetection of children who are normal but are declared ASD.

Based on the classification stage with two scenarios, the greater the data features, the better the accuracy obtained. This proves that SVM classification based on CWT coefficient feature values is more accurate and effective at classifying both classes because it has more data feature values than classification based on statistical feature values from CWT.

Conclusions

This study successfully integrated CWT and SVM to improve the classification accuracy of children with ASD. The proposed method yields 95% accuracy. In addition, this study evaluates the application of CWT with statistical features, namely mean, standard deviation, kurtosis, and skewness. The experimental results show that combining CWT and statistical features produces an accuracy of 65%. The number of data features is directly proportional to the quality of accuracy, where the more data features used, the better the accuracy. This is because the feature classification of the CWT coefficient has many features; therefore, the classification system can distinguish between the two classes.

In future research, this study indicates several research directions that can be carried out, such as the development of more effective and efficient classification or feature extraction methods, the exportation of the use of Deep Learning (DL) techniques in EEG signal analysis, and the use of larger and diversified datasets to test the performance of the proposed methods more broadly.

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All the authors have read and agreed to the published version of this manuscript.

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ЗАСТОСУВАННЯ НЕПЕРЕРВНОГО ВЕЙВЛЕТ-ПЕРЕТВОРЕННЯ ТА МАШИНИ ОПОРНОГО ВЕКТОРА ДЛЯ КЛАСИФІКАЦІЇ СИГНАЛІВ ЕЛЕКТРОЕНЦЕФАЛОГРАФІЧНОГО РОЗЛАДУ СПЕКТРУ АУТИЗМУ

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Предметом статті є класифікація сигналів електроенцефалографії (ЕЕГ) у хворих на розлад аутистичного спектру (РАС). Мета полягає в тому, щоб розробити модель класифікації з використанням алгоритмів машинного навчання (ML), які часто використовуються для реалізації в технології Brain-Computer Interfaces (BCI). Завданнями, які необхідно вирішити, є: попередня обробка сигналу набору даних ЕЕГ для відділення сигналу джерела від сигналу шуму/артефакту для отримання сигналу спостереження, який не містить шуму/артефакту; отримання ефективного порівняння ознак для використання як атрибута на етапі класифікації; розробка більш оптимального методу класифікації для виявлення людей з РАС за сигналами ЕЕГ. Використовувані методи: один із методів вейвлетів, а саме безперервне вейвлет-перетворення (CWT), що є технікою для розкладання частотно-часових сигналів. CWT почав використовуватися в сигналах ЕЕГ, оскільки він може дуже детально описувати сигнали в частотно-часовій області. Сигнали ЕЕГ класифікуються за двома сценаріями: класифікація коефіцієнтів CWT; класифікація статистичних характеристик (середнє значення, стандартне відхилення, асиметрія та ексцес) CWT. Метод класифікації цього дослідження використовує ML, який зараз дуже розвинений у обробці сигналів. Одним із найкращих методів ML є Support Vector Machine (SVM). SVM – це ефективний контрольований метод навчання для розділення даних на різні класи шляхом знаходження гіперплощини з найбільшим запасом серед даних спостереження. Було отримано наступні результати: застосування CWT і SVM призвело до найкращої класифікації на основі коефіцієнтів CWT, отриманої точності на 95% вище, ніж класифікація CWT на основі статистичних ознак, яка отримала точність 65%. Висновки. Наукова новизна отриманих результатів полягає в наступному: 1) здійснює обробку сигналу ЕЕГ у

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дітей з РАС за допомогою виділення ознак за допомогою CWT та класифікації за допомогою SVM; 2) поєднання цих методів класифікації сигналу може покращити продуктивність системи в класифікації сигналу ЕЕГ РАС у попередніх дослідженнях; 3) реалізація цього дослідження може пізніше допомогти у виявленні сигналів ЕЕГ РАС на основі характеристик мозкових хвиль.

Ключові слова: розлад спектру аутизму (ASD); безперервне вейвлет-перетворення (CWT); електроенцефалограма (EEG); опорна векторна машина (SVM).

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