Classify Epileptic EEG Signals Using Extreme Support Vector Machine for Ictal and Muscle Artifact Detection

Baiq Siska Febriani Astuti, Santi Wulan Purnami, R. Mohamad Atok, Wardah Rahmatul Islamiyah, Diah Puspito Wulandari, and Anda Iviana Juniani

Abstract—EEG signals aids in diagnosing various wave signals recorded by the activities of the brain. It also produces unavoidable artifacts, in the recording process. The purpose of this study therefore is to detect ictal and artefact signals, with the aim of reducing interpretation errors especially those related to the muscle which are quite difficult to distinguish. The data used are EEG signal recording results obtained from Rumah Sakit Universitas Airlangga. It consisted of two classes, namely ictal and muscle artefact. The signal decomposition method used is a wavelet transform, known as DWT. While the extraction feature utilized, consist of quartile, maximum, minimum, mean and standard deviation. This study also utilized the SVM with linear, polynomial, RBF and ELM (ESVM) kernels. Research results shows that the ESVM classification time is faster than the SVM and other kernels. However, the values of accuracy, sensitivity, specificity and AUC are not better.

Keywords—ESVM, SVM, wavelet transform, ICTAL, muscle artifact, epilepsy.

I. Introduction

Epilepsy is a complex collection of brain symptoms which involves varied manifestations due to occurrence of various matters. It is defined as a seizure, which is a temporary event caused by excessive or non-neuronal activity in the brain [1]. Epilepsy is detected by utilizing Electroencephalogram (EEG), a complex signal that carries information from the brain and human nerve functions. EEG signals helps in diagnosing seizures, where each pattern differs from another. Before now, its visual assessment recordings were subjectively acquired from professionals trained to detect epilepsy like a doctor. The information is used for clinical diagnosis and is likely to be used to treat patients suffering from epilepsy. EEG produces various signal waves resulting from recording brain activity. The signal produced has different amplitude in ictal, preictal, postictal, aura, and in open/closed eyes. In addition, the EEG produces waves of artifacts that are generally caused by patients like eye, muscle, and heart movements using machines that release electrodes. Signal artifacts tend to have large amplitude and are often mistaken for a seizure (ictal).

The appearance of artefact signals during recording using EGG is quite difficult to withdraw. It resembles various types of EEG signal patterns. Therefore, it makes misunderstandings to regularly occur in signal interpretation [2]. Varieties of signal artifacts resemble a seizure signal. Therefore, in this study, the researchers aim at detecting the muscle artifact and ictal signals.

Support Vector Machine (SVM) and Artificial Neural Network (ANN) are often applied to solve the problem of EEG signal classification [3]-[9]. Based on several previous studies, both techniques are used with various types of preprocessing methods to produce a good performance in solving problems related to epilepsy cases. One of such techniques is the Single Hidden Layer Feed Forward Network (SLFNs), which comprises of methods used to minimize training error and the norm of output weight within Extreme Learning Machines (ELM) [10].

The classification process using the SVM method requires quite a long time to analyze, however, it is one good method that produces high accuracy values when conducting classifications. Therefore, this study, aims to improve the performance of the SVM method to be more effective and efficient, by combining it with the famous ELM technique with high processing speed.

II. Literature Review

A. Wavelet Transform

A wave is ordinarily described as an oscillating function of time or space such as sinusoid. A wavelet is a "small wave" which has its energy contemplated in time to give a device for analysis of transient, nonstationary, or time-varying appearances [11]. Some of the mother wavelets are commonly utilized such as db wavelet, morlet wavelet, haar wavelet, mexican hat wavelet, coifiet wavelet etc. The wavelet transforms protrude in terms of algorithmic elegance and efficiency [12]. Wavelet transform is a tool used to cut data or functions into different frequency components and study each component with a resolution harmonized to its scale [13]. Wavelet transform formula as follows [14]:

$$\psi_{a,b}(t) = |a|^{-\frac{1}{2}} \psi\left(\frac{t-b}{a}\right) \qquad (1)$$

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where a is the scaling parameter and b is the shifting parameter that determines the location of the time from the wavelet. The function $\psi_{(a,b)}$ is defined as a temporary wavelet ψ also called the mother wavelet [13].

Wavelet transforms are grouped into two, namely Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). The CWT coefficients are evaluated for a continuous variation (infinitesimal additions) both of factors namely translation and dilation. According of equation (1), the CWT can be defined as follows [4-5]:

$$CWT(a,b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|a|}} \psi\left(\frac{t-b}{a}\right) dt \qquad (2)$$

where ψ, a, b, and $x(t)$ are the wavelet function scaling, shifting parameters and signal to be processed, respectively. Assuming the function scaling and shifting parameters are converted to the power of two, the wavelet analysis will be more valuable. Therefore, DWT is defined below as follows [4-5]:

$$DWT(j,k) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|2^j|}} \psi\left(\frac{t-2^j k}{2^j}\right) dt \qquad (3)$$

where parameters a and b are replaced with 2^j and $2^j k$, respectively. This Continuous Wavelet Transformation has two disadvantages, namely redundancy and impracticability.

B. Feature Extraction

Feature extraction is a procedure used to produce new features that are used as independent variables in solving EEG signal classification problems. This procedure is carried out after translating the signals using the wavelet transformation method where the technique used in this study has been previously described. Some of the feature extractions used in this work is as follows [3], [15].

1) Quartile

This is a condition that divides a group of observations into four parts, with the value denoted by Q_1, Q_2, and Q_3. This value has a variety of meanings where Q_1 means that data falls under 25%, Q_2 means that it is below 50% while Q_3 means that the data falls below 75% [16].

2) Maximum value

This is the highest value among the wavelet coefficients of each sub-band EEG signals.

3) Minimum value

This is the smallest value held between the wavelet coefficients of each sub-band EEG signals.

4) Mean

Mean is the average of each wavelet coefficient calculated from each sub-band.

5) Standard deviation

This is a value that describes the distribution of the value of the wavelet coefficient of each sub-band.

C. Support Vector Machine

Support Vector Machine (SVM) was first introduced by Vapnik in the 1960s as a classification method and has become a method often used in research because of its development in engineering and theory coupled with its existence in regression and estimation [17]. SVM has become an alternative method used to solve classification problems in machine learning and data mining. It is not like traditional statistical methods which empirically reduce errors but SVM aims to minimize error limits by maximizing the hyperplane margin used in solving classification problems [18]. SVM examines a hyperplane using support vector and margins described by the support vector. The hyperplane is a dividing line between classes, while margin is the shortest distance from a hyperplane with both sides of the class [19]. SVM is not only powerful but also known for binary classification tasks in machine learning for high dimensional feature vector due to its accuracy and capability to deal with a large number of predictors.

Suppose a case consists of two classes, given a data set D with $S = ((\mathbf{x}_1, y_1),(\mathbf{x}_2, y_2),\cdots,(\mathbf{x}_i, y_i))$, where $\mathbf{x}_i$ has a connection with $y_i (\boldsymbol{x}_i \subseteq \mathbb{R})$. Every y_i is categorized +1 and -1 with $y_i \in \{+1, -1\}$. Figure illustrations are from two different classes separated by a hyperplane as shown below [19]:
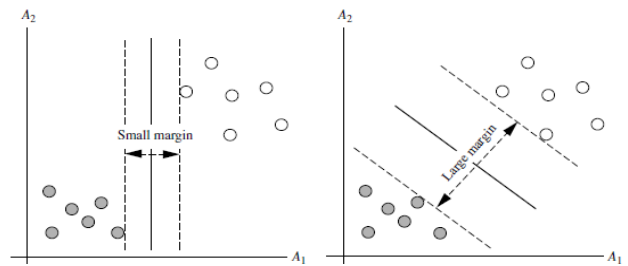

Fig. 1. Illustration of a hyperplane that might be on a classification.

The two forms of a hyperplane as shown in Fig. 1 produces different error values, however, there is no guarantee that they will show the same results when separating new data [20]. The hyperplane formula is written as follows:

$$\mathbf{x}^T \mathbf{w} + b = 0 \qquad (4)$$

where $\mathbf{w}$ is a weight vector which is $\mathbf{w} = [w_1, w_2, \ldots, w_3]$, n is number variables and $\mathbf{x}^T$ is a matrix containing independent variables which is $\mathbf{x}^T = (x_1, x_2, \ldots, x_n)$. In addition, b is a scalar which has a bias.

In the case of non-linear, a different kernel is required to form a hyperplane. The kernel function is represented as $R^n \times R^n$ or regularly written as $K(x,x') = (\Phi(x), \Phi(x'))$. Some of the frequently used kernel's functions are as follows [21], [22]:

1) Kernel Linear

$$K(\mathbf{x}, \mathbf{x}') = \mathbf{x}'\mathbf{x} \qquad (5)$$

2) Kernel Polynomial

$$K(\mathbf{x}, \mathbf{x}') = (\mathbf{x}'\mathbf{x} + 1)^d \qquad (6)$$

3) Kernel Radial Basis Function (RBF)

$$K(\mathbf{x}, \mathbf{x}') = \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}'\|^2}{2\sigma^2}\right) \qquad (7)$$

D. *Extreme Support Vector Machine*

Extreme support vector machine (ESVM) is a combination of methods of Support Vector Machine and Extreme Learning Machine. Extreme Learning Machine (ELM) is one of the available methods in Single Hidden Layer Feedforward Networks (SLFNs). The essence of ELM, which is the hidden layer on SLFNs, is not activated. Compared to other traditional computational techniques, it provides better results with a faster learning ability and least human intervention [23]. The performance of ELM is quite fast, but it does not look for the maximum hyperplane value. In otherwise, it minimizes the sum square error between classes, however it is not suitable for resolving classification cases. Therefore, it is necessary to combine SVM and ELM to obtain better results [24]. ESVM algorithm is as follows [24] [25]:

Input: Sample training: $x_i=\{x_{i1}, x_{i2},\ldots, x_{ip}\} \in \mathbf{R}^p$, $i=1,\ldots, n$. Label training: $y_i \in \{-1,+1\}$.

Output: Accuracy, Sensitivity, Specificity, AUC, Time, parameter.

1) Determine independent variables i.e. $A = [x_1, x_2, \cdots, x_n]^T$ and dependent variable $y = [y_1, y_2, \cdots, y_n]^T$.

2) Divide data into training and testing.

3) Randomly produce a hidden layer parameter matrix $\mathbf{w}^T \in \mathbf{R}^{m \times (m+1)}$ and choose an activation function, typically the signum function, to calculate $\Phi(\mathbf{w}^T, \mathbf{A})$ with formula as below:

$$\Phi(\mathbf{w}^T, \mathbf{A}) = \begin{bmatrix} \Phi(\mathbf{w}^T, \mathbf{x}_1)^T \\ \vdots \\ \Phi(\mathbf{w}^T, \mathbf{x}_m)^T \end{bmatrix} = \begin{bmatrix} g(\mathbf{w}_1^T, \mathbf{x}_1) \ldots g(\mathbf{w}_m^T, \mathbf{x}_1) \\ g(\mathbf{w}_1^T, \mathbf{x}_n) \ldots g(\mathbf{w}_m^T, \mathbf{x}_n) \end{bmatrix} \quad (8)$$

4) Generate E_Φ by computing $\lfloor \Phi(\mathbf{w}^T, \mathbf{A}), -\mathbf{e} \rfloor$ with e is an $m \times 1$ vector of ones.

5) Calculate $\begin{bmatrix} \mathbf{w} \\ b \end{bmatrix}$ by formula as follows:

$$\begin{bmatrix} \mathbf{w} \\ b \end{bmatrix} = \left(\frac{1}{c} + (\mathbf{E}_\Phi^T \mathbf{E}_\Phi) \right)^T \mathbf{E}_\Phi^T De \quad (9)$$

6) Classify new point using formula as defined follows:

$$\Phi(x)^T - b \begin{cases} > 0, \text{ then } x \in A+ \\ < 0, \text{ then } x \in A- \\ = 0, x \in A+ \text{ or } x \in A- \end{cases} \quad (10)$$

III. METHODOLOGY RESEARCH

A. *Data Description*

The data applied in this research was recorded by EEG signals in epilepsy patients. It was obtained from Rumah Sakit Universitas Airlangga (RSUA) which had been labeled based on epilepsy sources in the frontal and temporal lobes. Throughout the EEG signal recording process, the object of research was stimulated for instruction by opening/closing eyes, hyperventilation and strobe light flashes. Data

extracted from the results of EEG signal contained ictal and muscle artifact according to the notes given by medical personnel. EEG signal recording is carried out for 30 minutes and selected in such as way that it becomes a single signal data from an electrode with a duration of two seconds and with a sampling rate per of 500 per second, thereby, making the value 1000 points. The signal has filtered with a high pass value of 70 Hz.

B. *Proposed Methodologies*

EEG signal detection through several processes. The EEG signals which originally had a duration of 30 minutes, it will be cutting for two seconds according to the signal characteristics such as ictal or muscle artefact. The next process can be seen in Fig. 2. Fig. 2 presents the block diagram of the proposed method.
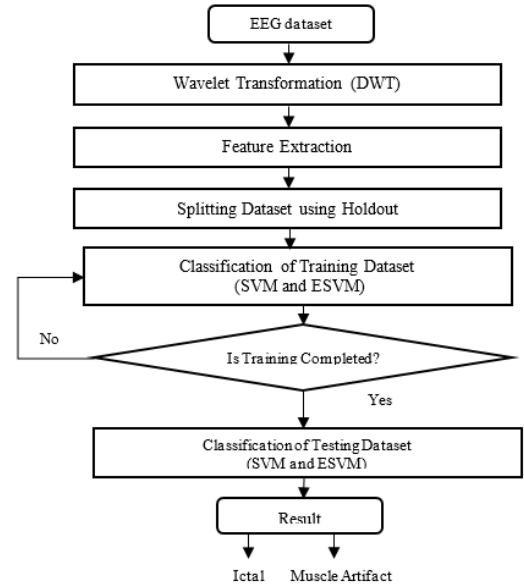

Fig. 2. Block diagram of the proposed epileptic EEG classification method.

IV. RESULTS

In this section, the performances of ESVM are compared with various SVM kernel such as Linear, Polynomial, and Radial Basis Function (RBF) on EEG signal datasets. All experiments on ESVM, SVM with kernel Linear, SVM with kernel Polynomial, and SVM with kernel RBF for detection EEG signals are carried out in MATLAB environment running in Intel CORE™i5 and 4 GB DDR3 memory. For classification of EEG, 2160 signals are used, with the dataset consisting of 992 ictal and 1168 muscle artifact respectively.

In this study, the decomposition technique used is the Discrete Wavelet Transform (DWT) method, while the mother wavelet used is Daubechies, especially db2. The EEG signals are decomposed with DWT at 7 levels. Furthermore, the next process is the signal extraction process where the decomposed signals are extracted into several features. This is followed by classifying the EEG signals. The process of distributing classification data is randomly carried out and uses a holdout approach of 10 repetitions.

Fig. 3 shows illustration results of signal recording using EEG. The blue signal shows the structure of the ictal while the red signal plot shows muscle artifact. Both are visually

difficult to distinguish because tools are required to reduce errors due to interpretation. Furthermore, in Fig. 3 shows the results of signal decomposition applying DWT.
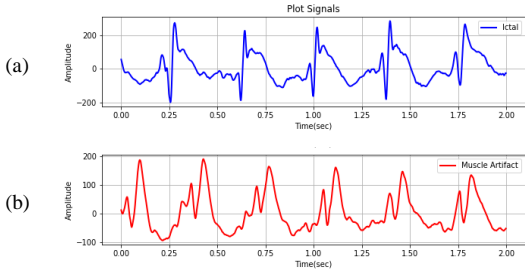

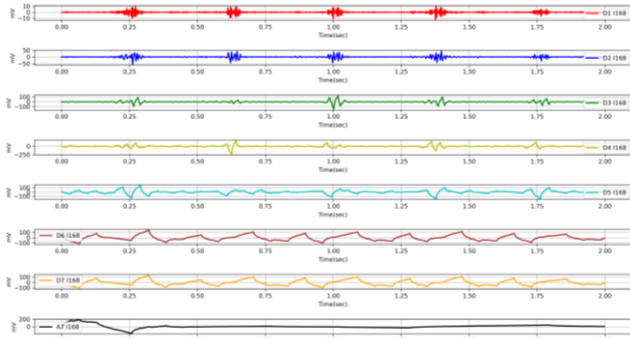Fig. 3. Illustration of EEG signals (a) ictal (b) muscle artifact.

Fig. 4. Illustration of EEG signals after decomposition using DWT.

The decomposition process is used to determine the additional highlight of the characteristics of the EEG signal, with the decomposition process carried out in seven levels. This process decomposes the signal into low and high pass filter sub-signals. The high signal was eliminated, and the low decomposed into two processes. The level 1 decomposition process produces sub-signals A1 and D1, while level two produces sub-band A1, D1, A2, D2 etc. The results of the EEG signal decomposition were shown in Fig. 4 above.

In addition, the decomposition process conducted the next extraction steps. It previously explained that the features used in this study include quartiles 1, 2, and 3, as well as maximum, minimum, mean and standard deviations. After decomposing and extracting constituents of level 7, 56 features were obtained. These were used as independent variables for the classification process.

TABLE I: MEAN OF ACCURACY, AREAN UNDER THE CURVE AND TIME CLASSIFICATION FOR TRAINING OF THE CLASSIFIER FOR VARIOUS HOLDOUT

Kernel	Holdout	Mean Accuracy	Mean AUC	Mean Time
Linier	50:50:00	0.94	0.94	0.01563
	60:40:00	0.94	0.94	0.02344
	70:30:00	**0.95**	**0.95**	0.00938
	80:20:00	0.94	0.94	0.00625
Polynomial	50:50:00	0.94	0.94	0.01878
	60:40:00	0.94	0.94	0.02034
	70:30:00	0.94	0.94	0.01565
	80:20:00	0.94	0.94	0.00939
RBF	50:50:00	0.92	0.92	0.05625
	60:40:00	0.92	0.92	0.03752
	70:30:00	0.93	0.93	0.0297
	80:20:00	0.92	0.92	0.02031
ELM	50:50:00	0.94	0.94	**0.00625**
	60:40:00	0.91	0.91	**0**
	70:30:00	0.91	0.91	**0**
	80:20:00	0.91	0.92	**0**

Table I shows the performance of the SVM method using several types of kernels. In SVM method with linear kernel $C = 0.1$, SVM with polynomial kernel $C = 0.1$ and $d = 1$, SVM with RBF kernel $C = 0.1$ and sigma = 300, while SVM with ELM kernel (ESVM) $C = 0.1$, hidden neuron = 1000.

Data in Table I were divided into training and testing using the holdout validation wherein Table I shows that the performance given by each kernel varies in each percentage in accordance to the amount. The ratio of the distribution of training and testing is seen in Table I. This table also describes the generalization ability of the proposed method and the statistical relevance of data using holdout validation. It is observed that the classification accuracy has monotonically decreased when more samples was used in training than in testing the dataset. At each given ratio, SVM with Linear kernel produces Accuracy and AUC higher than other methods, especially the proportion of data 70:30. While for other data proportions, SVM with a polynomial kernel produces an average accuracy and AUC in proportion of 0.94. It also describes that the proposed method is faster than the classifiers.

TABLE II: FERMORMANCE OF CLASSIFICATION VARIOUS SVM KERNELS

SVM Kernel	Training				
	Accuracy	Sensitivity	Specificity	AUC	Time (s)
Linear	0.952	0.964	0.941	0.953	42.57501
Poly	0.951	0.963	0.941	0.952	38.00001
RBF	0.946	0.975	0.922	0.948	**0.28594**
ELM	**0.967**	**0.989**	**0.948**	**0.969**	0.70784
SVM Kernel	**Testing**				
	Accuracy	Sensitivity	Specificity	AUC	Time (s)
Linear	0.943	0.967	0.924	0.945	0.01251
Poly	0.942	0.957	**0.930**	0.943	0.00782
RBF	**0.947**	**0.972**	0.927	**0.950**	0.0172
ELM	0.921	0.934	0.908	0.921	**0.00313**

The classification and misclassification result of various SVMs used in categorizing EEG signals are given in Table II. The performance of the proposed approach has also been compared with various SVM techniques. The classification performance provided by the ESVM method with training data is better than other kernels. Accuracy, sensitivity, specificity and AUC values are 0.967, 0.989, 0.948 and 0.969 respectively. However, the performance provided by ESVM during testing is not as good as others. This is because the ESVM gives a faster execution time compared to others which have only 0.00313. Based on the AUC value, the classifier method in this study is very nice for modelling EEG signal because its value is greater than 90%.
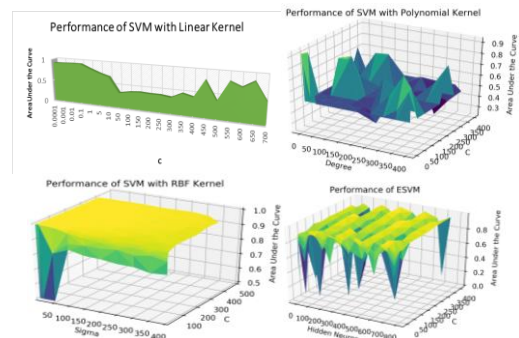

Fig. 3. Performance of SVM with Linier kernel, SVM with polynomial kernel, SVM with RBF kernel and ESVM.

The figure above shows a plot of the performance of various kernels. The performance of SVM method with various types of kernels in Fig. 5 is different on each parameter applied. The plot shows different performance EEG signal detection patterns in each parameter.

V. Conclusions

The classifier approach has successfully classified complete of EEG dataset with emphasis on ictal and muscle artifact detection. ESVM achieves 92.1% classification accuracy and AUC and the executions time for classifier faster than other classifiers, which is absolutely convinced that this method is successful. Experiments show that the executions time of SVM classifier with ELM kernel is faster than SVM with Linier kernel and Polynomial kernel.

Conflict of Interest

The author declare no conflict of interest.

Author Contributions

Baiq Siska Febriani Astuti has written paper and analyze the data. Santi Wulan Purnami and R Mohamad Atok offered a useful suggestion for the paper preparation and writing this paper. Wardah Rahmatul Islamiyah has prepared data. Anda Iviana Juniani and Indah P. Wulandari have a useful suggestion for a target of the paper.

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