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Classification of Electroencephalogram Signal of Sleeping Condition as Output of EEG Digital Device of Clinical Neurophysiology Laboratory of Immanuel Hospital Using Support Vector Machine

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ABSTRACT

Sleep disorders like insomnia is one of the main health problems. Sleep deficiency can increase the risk of diabetes, hypertension and cognitive and behavioral disorders. The brain produces electrical signals, when someone is doing any activity such as moving, waking up, sleeping, etc. This electrical signal can be recorded using an electroencephalogram (EEG). In this study, brain signals are read using Digital EEG of the Clinical Neurophysiology Laboratory of Imanuel Hospital. The result of EEG signal will be classified using machine learning of Support Vector Machine (SVM). EEG signal data was obtained from Immanuel Hospital in Bandung. Conditions to be classified are the conditions of wakefulness, drowsiness (stage-1), and sleeping (stage-2). The extraction of features uses Daubechies DB4 discrete wavelet transform. The decomposition level used in this study is level-1 and level-2. Based on the tests that have been carried out, the best parameter values obtained are C 10, Gamma 1, and Kernel Poly. Based on these parameters, the accuracy value was 78.8% for level-1, and 76.6% for level-2.

I. Introduction

In this study, a person's deep sleep (N2), wakefulness, and drowsiness (N1) are classified based on their EEG signals. It is expected that this study can help health workers in reading EEG signals, because there are very few doctors specializing in EEG who can read EEG signals; as a result, with the help of the system created here other health workers can read EEG signals. EEG signal data were obtained from Clinical Neurophysiology Laboratory of Immanuel Hospital, Bandung. The EEG signal was obtained directly from the output of the EEG digital device. The EEG signal as the output of the device will be in *.csv format and feature extraction. The feature extraction uses wavelet transform. Machine Learning with the Support Vector Machine (SVM) algorithm will be used to carry out the classification. This research will contribute to the multiclass classification, namely wakefulness, sleeping, and drowsiness conditions. Besides, the classification results using two different levels of wavelet decomposition, namely level-1 and level-2, will also be compared.

Sleep is a temporary unconscious state and a condition of rest for a human's body, in which what happens is not just resting with closed eyes, but the brain becomes gradually less responsive to external stimuli. Sleep is required by all living things because during sleep body organs are repaired. In general, humans need about 6-10 hours of sleep per day [1]. Broadly speaking, sleep conditions can be divided into two stages, namely Non-Rapid Eye Movement (NREM) and Rapid Eye Movement (REM) [2].

At present, sleep disorders are considered a health problem. Sleep disorders like insomnia are one of the main health problems [3]. In America, about 35% of the population experience sleep disorders.

Sleep deficiency can increase the risk of having several diseases, including diabetes, hypertension, dyslipidemia. In addition, deficiency of sleep can also disrupt the cognitive and behavioral function of a person [2].

During sleep, the brain experiences several stages of physiological change. Besides the brain, some physiological parameters of the human body also experience changes during sleep. Some biomedical signal recording devices, such as EEG, ECG, EMG, and EOG are required to record sleep activities and identify sleep disorders. A complete sleep record using a combination of EEG, ECG, EMG, and EOG recording devices along with a visual recorded data is called Polysomnography (PSG) [3].

EEG is a method of recording electrical signals produced by the brain. With the development of EEG devices which are more and more sophisticated, EEG is increasingly used in medical research, such as epilepsy and sleep studies, as well as research on psychology, for example research regarding perception, noble function, attention, and emotions [4]. Assessment on sleeping stages is a challenging task, both if the sleep is recorded completely on polysomnographic recordings and if it is only the recording of the brain waves using an EEG device.

EEG signal reading can only be read by specialists who understand the meaning of the signal forms. Hence, it is essential to use machine learning so that the conditions of the signal obtained can be classified. Machine learning is a field of science which is a part of artificial intelligence or often called as AI. Machine learning is commonly used in various fields, such as medicine, financial analysis, science analysis, etc. The technology of machine learning enables the machine to learn on its own so that it looks as if the machine had its own intelligence to solve certain problems [5].

Sleeping stage assessment is a challenging task; besides, manual assessment done by EEG experts or PSG takes a lot of time and they have variabilities in assessing. Consequently, both researchers and EEG and PSG signal recorder industry have developed various methods for automatically analyzing dataset of sleep recording. Most researchers conduct a classification of sleep stages by analyzing electroencephalography (EEG) signals in the time or frequency domain. Diykh et al. proposed another technique which uses the statistical features and the complex network equality is used to classify the EEG signal of a single channel into six stages of sleep. First, each 30 seconds of EEG segment is divided into 75 sub-segments, and then different statistical features are extracted from each sub-segment. Here, feature extraction is important to reduce the dimensions of EEG data and processing time in the classification stage. Second, every feature vector that is extracted, which represents an EEG segment, is transferred to a complex network. Third, the similarity of the complex tissue is extracted and classified into one of the six stages of sleep using Classifier K-Means. For further investigation, in the statistical features of the Extraction Phase, two statistical features are examined and ranked based on the complex network performance. To investigate the complex network classification capabilities which are combined with K-means, the extracted statistical features are also forwarded to K-Means and Supporting Vector Machines (SVM) for comparison. The result of the experiment shows that the proposed method achieves a better classification and a reasonable execution time compared to SVM, K-Means and other existing methods. The results of the study in this paper show that the proposed method can help neurologists and sleep specialists diagnose and monitor sleep disorders [6][7].

Aboalayon et al. proposed an efficient technique that can be implemented in the hardware to distinguish the stages of sleep which will help doctors in the diagnosis of sleep disorders. Aboalayon et al.'s research, based on EEG dataset which is different from PhysioNet, uses the Sleep-EDF database and is explained by scientists for the analysis and diagnosis of the sleep stages. In general, the EEG signal is decomposed into five bandwidths: Delta, Theta, Alpha, Beta, and Gamma to determine changes in the state of the brain. In this study, Butterworth band-pass filters are designed to filter and decompose the EEG into the sub-bands of the above frequency. Furthermore, various discrimination features including energy, standard deviation and entropy are calculated and extracted from each sub-band Δ, α, β, and γ. The extracted features are then fed to the classification of supervised learning; SVM can recognize the status of the sleeping stages and identify whether the signal obtained is in accordance with the wakefulness or sleep stage 1, which also fits the purpose of this study. The main novelty of this work is to identify the sleeping stage of the EEG signal dataset that is available to the public by using a series of feasible features, an easy filter implemented on any microcontroller device, and an efficient classification method. Thus, a doctor can track the stages of sleep to identify certain patterns, such as detecting fatigue, drowsiness, and/or various sleep disorders like sleep apnea.

The results of the experiment in various subjects verified 92.5% of the accuracy of the classification of the proposed work [8].

Through another research report, Aboalayon and Faezipour showed the advantages of their technique based on the filter that is easily implemented on any hardware devices and a decent discriminatory feature of the Electroensefalogram (EEG) signal using the one-for-all method of all Multiclass Support Vector Signals (SVM) to recognize the stages of sleep and identify whether the signal obtained is in accordance with Wakefulness (Wake, Stagel, Stage2, Stage3 or Stage4. The result of the experiment in several subjects reached 92% of the accuracy of the classification of the proposed work. The comparison between this technique and several of the latest works reported by other researchers also presents the performance of accuracy with high classification [9].

Research findings show that several diseases can be detected by quantitative analysis of sleep signals. Detecting and analyzing Cyclic Alternating Patterns (CAP) is an important part of sleep analysis. Although some methods have been recommended for automatic cap detection, no one can provide acceptable accuracy. In this paper, the entropy-based feature family is evaluated by Support Vector Machine (SVM), Neighborest Neighbor (KNN) and Linear Discriminant Analysis (LDA) to distinguish CAP from non-CAP. To assess the recommended feature set, the Sleep EEG from 4 healthy subjects and 4 patients are analyzed by the conventional as well as recommended features. The comparison result reveals that the recommended subset features can drastically outperform the previous features for both healthy groups and patients[10].

In Novie et al.'s research, the EEG signal classification using Support Vector Machine (SVM) for Drowsiness Detection produces two classes, namely Wakefulness and Drowsiness [11].

II. Literature Study

A. Sleep

Sleep is an unconscious state so that the body is less responsive to external stimuli, and is one of the needs for all living things. In general, humans need a sleep for about 6-10 hours per day [1].

Sleep stages can be divided into NREM (Non-Rapid Eye Movement), consisting of four stages (Stages 1 - 4) and REM (Rapid Eye Movement). Here are the stages of sleep [12]:

- Stage 1 (drowsiness). At this drowsy stage, the eye blinking is reduced. The distribution of the alpha waves shifts to the anterior, and the amplitude will be modest. Then, the theta slow waves arise in the frontosentral, temporal and posterior areas.
- Stage 2 (Light Sleep). At this stage, a person will begin to enter the light sleep or start sleeping. Vertex waves and spindles will appear when someone enters stage 2. Sleep spindles have a frequency between 11-16 Hz and a quite big amplitude at the initial part and will slowly decrease. Vertex waves are very sharp in the central area.
- Stage 3 (slow, stable sleep). At this stage, there will be a slow, stable sleep. Here a delta wave is found about 20% -50% of sleep recordings.
- Stage 4. At this stage the delta waves will increase and begin to dominate more than 50% of sleep recordings.
- Rapid Eye Movement. The typical picture of this stage is the emergence of rapid eye movement that can be detected with EOG leads. Sharp theta waves (saw-tooth waves) in the central region are found.

What happens while sleeping? Why do humans spend about one third of their lives sleeping? Sleep not only rests our bodies but also plays an important role in maintaining mental health. When people sleep, the way the tissue works and interacts changes dramatically in the brain. One part of the brain that plays an important role in the cycle of waking up – sleeping, namely the thalamus, has the role of controlling the process of sensory information into the entire cerebral cortex area through the thalamo-cortical pathway. Thalamus changes the "setting" of processing the external sensory information that he receives during sleep; thus, changing the way we respond to external stimuli during sleep. This is useful to maintain sleep conditions. Changes in the activity of this brain path are manifested in the recording of the electric brain activity.

Contrary to faster mixture frequency activity which is typical of the wakefulness condition, a sleeping brain produces slow amplitude waves and occasionally a higher frequency activity, called sleep spindles. Interestingly, this oscillation is associated with the effect of sleeping on the cognitive function. For decades, sleep spindles have fascinated researchers. The researchers found evidence that sleep spindles are directly related to memory processing during sleep [13].

A study conducted by Drago et al. reveals that sleep has been proven to increase creativity although the mechanism of this increase is not fully known. We have known that there are some physiological changes in the body during sleep. Based on these physiological changes, sleep can be classified into REM and Non-REM (NREM)sleep. Based on the percentage of slow waves in the EEG record of sleeping condition, NREM sleep is classified into 4 stages, namely Stages 1 – 4. During NREM sleep, an EEG picture showing a cyclic pattern that repeatedly appears during sleep is also found, and it is called Cyclic Alternating Pattern or abbreviated as CAP. Based on this pattern, the EEG picture can be divided into 3 three subtypes (A1 - A3). It is said that the differences in the ratio of CAP subtype are closely related to cognitive performance. Drago et al. concluded that NREM sleep is correlated with a low level of cortical arousal, and this actually enhances a person's ability to access the association's path that plays an important role in creative innovations [14].

B. Electroencephalogram (EEG)

Neuron cells found in the brain process information in the form of electrical potential. The information is forwarded to the synapses which are connections among neurons, and here the information is continued in the form of biochemical information. After passing the synapses, the information is then converted back into an electrical potential by the next neuron, and proceeds to the next neuron. Electroencephalogram (EEG) is a method to record electrical signals produced by brain neuron cells, by placing electrodes on the scalp [4].

By placing the electrode on the scalp, the EEG signal will be obtained. EEG signals can be divided into four main types of waves based on their frequency, namely [15]:

- Alpha waves (8-13 Hz). Alpha waves have a frequency range from 8 Hz to 13 Hz. This wave can be found in people who are still waking up (conscious), relaxed, and eyes being closed with the distribution in the occipital, parietal, and temporal areas.
- Beta waves (14-30 Hz). Beta waves have a frequency range from 14 Hz to 30 Hz. This wave can be found when a person is being relaxed or sleepy with the distribution in the frontal and central areas.
- Theta waves (4-7 Hz). Theta waves have a frequency range from 4 Hz to 7 Hz. This wave can be found in a state of sleep with the distribution in the anterior areas.
- Delta waves (0.5-4 Hz). Delta waves have a frequency range from 0.5 Hz to 4 Hz. This wave can be found in a deep sleep condition or being sound asleep with the temporal distribution.

The four main waves on EEG can be seen in Figure 1.

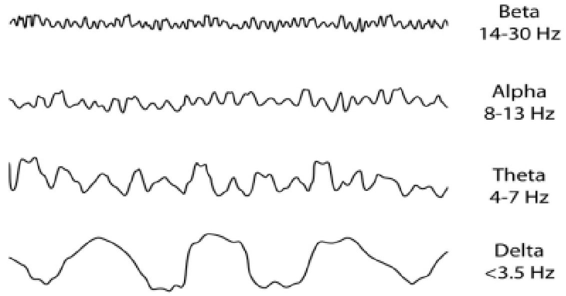

Fig 1. The main waves on EEG

Electroencephalogram (EEG) is a common basic signal used to monitor brain activities and diagnose sleep disorders. The manual assessment of the sleep stage is rather time-consuming for experts and is constrained by the assessors'reliability. Accordingly, a lot of researchers have designed various methods to assess the stages of sleep automatically in order to help speed up the process of EEG sleeping records. Some researchers reported their findings which have high reliability and accuracy so that they can help clinical services with accurate diagnosis. One of them is Mousavi et al.'s research, which uses the automatic sleeping stage annotation method which is called Sleepeegnet using a single channel EEG signal. Sleepeegnet consists of deep convolutionary neural networks or deep CNNS to extract time-invariant features, frequency information, and sequence-to-sequence models to capture the short term and long-term complex dependence between the epoch of sleep record and scores. The researchers used special methods to reduce the inaccurate evaluation of sleep record data by the network, and evaluate it with a variety of single EEG channel (e.g. FPZ-CZ and PZ-OZ EEG) from the Physionet Sleep-EDF dataset published in 2013 and 2018. The evaluation results show that the proposed method reached the best annotation performance with an overall accuracy of 84.26%, the macro F1 score of 79.66% and κ = 0.79. The model can be applied to other sleep EEG signals and it can help sleep specialists to arrive at an accurate diagnosis [16].

C. Electrode placement system 10-20

The 10-20 electrode placement system is the internationally standardized placement of scalp EEG electrodes. The placement of the electrodes will be at intervals of 10% or 20% of the distance between the points on a person's head. In the 10-20 electrode placement system there are labels and numbers that represent the location of the electrodes. There are several labels in the system, such as the letter "F", which represents the location in the frontal area, the letters "Fp", which represents frontopolar, the letter "P", which represents parietal, the letter "T", which represents temporal, the letter "C", which represents central, and the letter "O", which represents the occipital. Moreover, the numbers represent the position on the left or right side of the head. Electrodes with odd numbers represent the left head, while electrodes with even numbers represent the right head. In addition to labels and numbers, if the electrode has the letter "z", then the electrode represents the midline or central line on the head [4]. The 10-20 electrode placement system is illustrated in Figure 2.

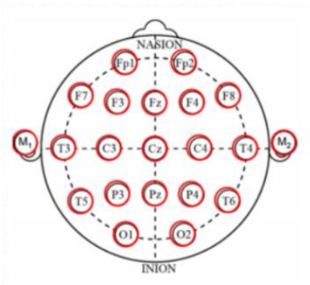

Fig 2. 10-20 Electrode System

D. Wavelet Transform

Wavelet Transform is a tool suitable for analyzing non-stationary signals such as EEG signals. The Wavelet Transform is multi-resolution which can divide the signals into different frequency spectrums [17]. Wavelet has two functions, namely translation and scale. Ψ(t) is a transforming function which can be referred to as the mother wavelet. Wavelets can be called small waves because the window function in wavelets has limited length, while the mother wavelet is the basic function that will be used for other window functions [18]. The formula for the mother wavelet can be seen in equation (1) [19].

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}}\psi\left(\frac{t-b}{a}\right) \qquad \text{for } a > 0 \text{ and } b \in R \tag{1}$$

in which: a is the scale parameter, b is the location parameter, ψ is the mother wavelet, and t is the time parameter. The scale function will show the shape of the wavelet. If the value of the scale is lowered, it will be denser and will get high-frequency information, whereas if the scale value is increased, it will be more tenuous and will get low-frequency information. The translation function will show the position of the wavelet [19].

Discrete Wavelet Transform (DWT) is often used because it can separate unwanted frequencies and can also decompose the signal into several decomposition levels [20]. The decomposition level can be illustrated in Figure 3.

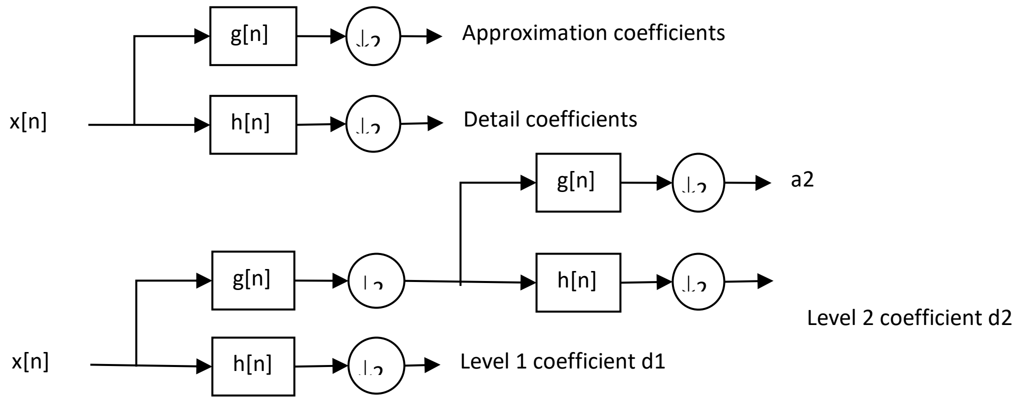

Fig 3. DWT decomposition level

In Figure 3, it can be seen that the input signal x[n] will be decomposed into two coefficients, namely the approximation coefficient g[n], and the detail coefficient h[n]. In the figure, level-2 decomposition is illustrated. The approximation coefficient is the signal obtained by convolution of the input signal with a low-pass filter, while the detail coefficient is the signal obtained by convolution of the input signal with a high-pass filter. In each of these decomposition processes, a down sampling will occur, which will reduce the input signal to half [20].

E. Support Vector Machine

Machine Learning is a field of science that is part of artificial intelligence or what is often called AI [5]. Machine Learning is used to train machines to learn various data so that they can help make decisions or can predict without the help of humans. Machine Learning can create mathematical models based on the data provided and can make decisions [13].

Machine Learning can be divided into two categories, namely supervised learning and unsupervised learning. In supervised learning, the algorithm is trained based on the previously labeled input data. The algorithm will compare the predicted output results with the actual output to get the error. Examples of this category are support vector machines, decision trees, and random forests [21]. In unsupervised learning, the algorithm will be trained based on the input data that is not previously labeled. Usually unsupervised learning is used for clustering and association. An example of this category is k-means [5].

Support Vector Machine is one of the machine learning algorithms in the supervised learning category. This algorithm is usually used to classify data and is often used to classify EEG signals [15]. The concept of SVM algorhythm is to find out the best hyperplane line that can separate the classes of data. Hyperplane is a dividing line between classes linearly [22]. Hyperplane can be found by looking for the margin or distance between the hyperplane and the closest data in each class. The closest data can be called a support vector. There are many hyperplanes to choose from, but the greater the margin is between the hyperplane and its support vector, the better the algorithm can distinguish the class of each data [23].

The kernel technique can be used for data that cannot be separated linearly. The kernel technique is a technique that transforms data into a higher dimensional space in order to separate non-linear data. There are various types of kernels that can be used, such as linear, rbf, polynomial, and sigmoid [24]. The equation below will show the formulas for each kernel [25].

$$RBF : K(x_i, x_j) = \exp\left(-\gamma \|x_i - x_j\|^2\right) \quad (2)$$

$$Polynomial : K(x_i, x_j) = (x_i . x_j + 1)^d \quad (3)$$

$$Sigmoid : K(x_i, x_j) = \tanh\left(\alpha x_i^T y + c\right) \quad (4)$$

With: γ is the radial basis constant, d is the order of the polynomial function, and α is the slope.

In the SVM algorithm, there are several parameters that can be tuned in order to improve the performance of the model. The parameters are the type of kernel, the value of C and gamma. As previously mentioned, the types of kernels that will be used are linear, rbf, polynomial, and sigmoid [26].

Parameter C is a parameter to add a penalty for any misclassified data. If the C value is small, the penalty for misclassification is low so that a decision boundary with a large margin is chosen. However, it will add the amount of misclassification. If the C value is big, SVM tries to minimize the number of misclassifieds so that it will produce a decision boundary with a smaller margin. The gamma parameter is used to set the distance from one training point. The gamma value will determine the similarity radius. The smaller the gamma value is, the greater the similarity radius is. Vice versa, if the gamma value increases, the similarity radius will be smaller so that the data must be close to one another because the similarity radius decreases to be considered the same class [26].

F. K-Fold Cross Validation

Cross Validation is a way to evaluate the capability of a model that has been trained. This cross validation process will divide the training data into several parts depending on the number of selected K. If K is selected by 5, then the training data will be divided into 5 parts. First of all, this process will use the first fold as validation data and the remaining four folds will be used for model training. After that, it will alternate with the second fold, third fold, and so on. After the process is complete, the average accuracy value will be obtained from each of these experiments. This cross validation will produce more valid accuracy [27].

G. Confusion Matrix

Confusion Matrix is a way to visualize the performance of the model that has been obtained by machine learning algorithms. This method is used to conclude the prediction result of the model. In the confusion matrix, there are four kinds of values, such as TP (True Positive), FP (False Positive), FN (False Negative), and TN (True Negative). Based on these four types of values, several metrics can be determined as follows:

$$Akurasi = \frac{TP+TN}{TP+TN+FP+FN} \quad (5)$$

$$Presisi = \frac{TP}{TP+FP} \quad (6)$$

$$Recall = \frac{TP}{TP+FN} \quad (7)$$

$$Specificity = \frac{TN}{TN+FP} \quad (8)$$

$$F1 - score = 2x\frac{precision\ x\ recall}{precision+recall} \quad (9)$$

H. Feature Scaling

Feature Scaling is a way to change the range of feature values. Using scaling can improve the performance of machine learning algorithms. "MinMaxScaler" is a method for scaling features that changes the range of values in features without changing the shape of the data distribution. The range of these features will be 0 to 1 [28]. The formula of MinMaxScaler can use Equation (10) [29].

$$x_{scaled} = \frac{x-\min(x)}{\max(x)-\min(x)} \quad (10)$$

I. Pipeline

Pipeline is a framework that can be used to automate various processes. This pipeline can also be combined with machine learning algorithms. Various processes that are put into the pipeline will be carried out sequentially, depending on which process is put first into the pipeline [30].

J. GridSearchCV

GridSearchCV is a tool that can be used for hyperparameter tuning, namely to find the best parameter for the model that is being worked on. This tool can provide the best parameter depending on the accuracy after trying all the combinations of the given parameters. These results include the k-fold cross-validation process and the number of folds can be chosen so that the results given will be more valid. The results to be given are the average accuracy value after cross-validation. These tools can be combined with pipeline functions; as a result, they can automate most of the machine learning process [31].

III. Experiments

In this chapter, the design of the system of classification of a wakefulness, sleep, and drowsiness conditions based on EEG signals will be explained.

A. System Block Diagram

In this study, a band-pass filter will be given to the EEG signal which is still a signal in .eeg format. After being given a filter, the signal will be converted into .csv (dot csv) format and then feature extraction will be carried out in the form of a 1-D discrete wavelet transform with decomposition levels 1, 2, 3, and 4. The type of wavelet chosen is Daubechies db-4. After this process, classification will be done using a support vector machine (SVM) algorithm and the output will be obtained in the form of certain conditions, such as wakefulness, sleeping, or drowsiness. This block diagram can be seen in Figure 5.

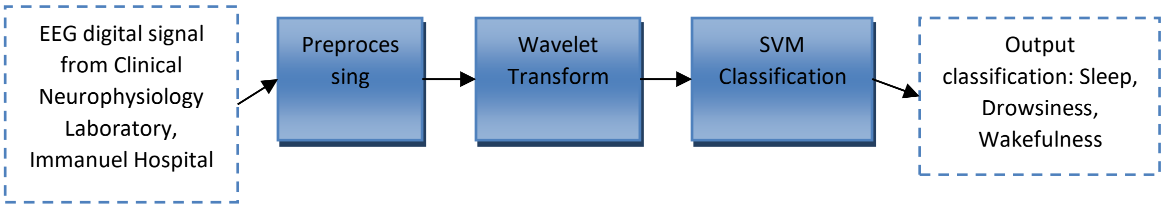

Fig 5. System Block Diagram

B. Data Retrieval

The data in this study will be in the form of an EEG signal which is recorded using a digital EEG tool in the clinical neurophysiology laboratory at Immanuel Hospital in the .eeg (dot eeg) format. The data used will be obtained from the EEG Clinic at Immanuel Hospital, Bandung. The data used is anonymous so that the identity of the patient whose EEG is recorded will be unknown. In this study, the data are collected only from young adult patients of 26 to 35 years. The data collection was carried out during the day so that the sleep conditions that can be obtained are wakefulness, stage 1 sleep (drowsiness), and stage 2 sleep (light sleep). The number of data received is 39 data, consisting of 13 data on wakefulness conditions, 13 data on sleeping conditions, and 13 data on drowsiness conditions. The data having artifacts, for example artifacts of eyeball movement, movement, etc., will be ignored by not selecting the time when converting the data from raw signal to .csv (dot csv) format so that the data used is only those having no artifacts or with minimum artifacts; therefore, it will not have a big effect on the original signal.

C. Data Preparation

In this study, the focus will be on wakefulness conditions, stage 1 (drowsiness) and also stage 2 (light sleep). For wakefulness conditions, an EEG signal containing alpha waves will be taken. Moreover, for stage 1 or drowsiness, an EEG signal containing theta waves will be taken, and for stage 2 or sleep, an EEG signal containing vertex waves and sleep spindles will be taken. Figure 6 shows an example of an EEG signal representing sleep in the Nihon Kohden EEG application.

Fig. 6 EEG Signal from a digital EEG device in Clinical Neurophysiology Laboratory at Immanuel Hospital

In Figure 6, the X axis represents the time of the EEG recording, while the Y axis represents each feature. The numbers on the Y axis (1 to 19) represent the feature numbers, while letters like "Fp1-F7", "F7-T3", etc. state the features to be used and this has followed the rules of the 10-20 electrode system. First, the EEG signal will be given a band-pass filter with a lower cut-off frequency of 0.27 Hz and with a higher cut-off frequency of 50 Hz in the Portaview EEG application. This filter aims to reduce noise due to a reference potential which has a frequency above 50 Hz. The EEG signal will be sampled with a sampling frequency of 500 Hz and each data will last 2 seconds. The signal will then be converted into .csv (dot csv) format so that it can be processed using the Python programming language. The feature number 19 in Fig. 6 will be used because this feature has information about the ECG; thus, the data will have 18 features. There will be 39 data, each of which has a duration of two seconds and 18 features. The 39 data consist of 13 wakefulness data, 13 sleep data, and 13 drowsiness data.

The EEG data that will be used will have 18 features and 39,000 data lines. The number of rows is obtained from 1,000 rows per data and there are 39 data. There are 13,000 data lines for each of these wakefulness, sleep, and drowsiness conditions.

E. Feature Extraction

At this stage, the data that has gone through the pre-processing stage will be feature extracted in the form of a 1-D discrete wavelet transform (DWT) with decomposition levels 1, 2, 3, and 4. The type of wavelet that will be used is Daubechies db4. In this process, two new coefficients will be obtained for each feature, namely the approximation coefficient (A) and detailed coefficient (D) so that the previous number of features, which is 18, will become 36 features.

In a DWT with decomposition level 1, there will be a one-time downsample so that the number of data which was originally 1,000 data lines will become 503 data lines. The coefficients to be used as features are cA1 (Level-1 approximation coefficient) and cD1 (Level-1 detail coefficient).

In DWT with decomposition level 2, there will be two downsamples so that the number of data which was originally 1,000 data lines will become 255 data lines. The coefficients to be used as features are cA2 (Level-2 approximation coefficient) and cD2 (Level-2 detail coefficient).

F. Data Splitting

In this study, a data splitting process will be carried out, which can divide the data into two, namely train data and test data with a ratio of 80% for train data and 20% for test data.

G. Classification

In this study, a support vector machine (SVM) algorithm will be used to classify wakefulness, sleep, and drowsiness conditions. "Linear", "rbf", "poly", and "sigmoid" kernels will be used to find out whether the data obtained can be separated linearly or not. The features that will be used are the extracted features at each decomposition level.

H. Tuning Hyperparameter

In the parameter tuning process, the pipeline process will be carried out. In the pipeline process, various functions can be included in it, but these functions must have the same data type. In this research, numeric data types will be used for the pipeline process, so that other types of data cannot be used for the same pipeline. The pipeline that will be given in this study is a feature scaling process and also the SVM algorithm. The scaling process will use the MinMaxScaler function.

To simplify the tuning process, the GridSearchCV function will be used. This function already includes the K-Fold cross validation function and the parameters can also be set in the SVM algorithm, such as 'C', 'gamma', and also 'kernel' values. Parameter 'C' which will be used has the value of 0.1, 1, and 10. The 'gamma'parameter used are 1, 0.1, 0.01, and 0.001, while the 'kernel' parameter which will be used are 'linear', 'rbf', ' poly', and 'sigmoid'. The GridSearchCV function will first carry out the process following the sequence in the pipeline that has been made, namely the scaling process and the SVM algorithm. After that, GridSearchCV will perform a K-Fold cross validation with a total of 5 folds for each SVM parameter that has been input. Then, GridSearchCV can sort the accuracy results from highest to lowest.

IV. Results and Analysis

In this part the result metrics (before tuning and after tuning) of each level will be shown.

A. Results Before Tuning

Based on the testing with test data at all levels of decomposition, the results are shown in Table 1. Based on the two levels that have been tested (Level-1, Level-2), the rbf kernel has the highest accuracy for all these levels. However, the value of the accuracy will slowly decrease when the level of decomposition is increased, 78% for Level-1 to 74% for Level-2. The sigmoid kernel is the worst kernel for the dataset used. The accuracy obtained is only 34% for Level-1, and 35% for Level-2.

Table 1 Results Before Tuning.

Level	Kernel	Akurasi	Presisi	Recall	F-1 Score
1	Linear	47%	47%	47%	47%
	Rbf	78%	79%	78%	78%
	Poly	62%	69%	62%	62%
	Sigmoid	34%	38%	34%	30%
2	Linear	46%	46%	46%	46%
	Rbf	74%	75%	74%	74%
	Poly	55%	64%	56%	54%
	Sigmoid	35%	39%	34%	30%

B. Results After Tuning

In this section, tuning will be carried out by scaling the data using MinMaxScaler, and changing the value of the hyperparameter. The hyperparameters whose values will be changed are C with the values of 0.1, 1, and 10; gamma with the values of 1, 0.1, 0.01, and 0.001; and kernels in the forms of linear, rbf, poly, and sigmoid. This process will be carried out using GridSearchCV. Based on the specified hyperparameter value, there will be 48 combinations. The displayed accuracy results are the results of the average accuracy after cross validation using 5-fold. In Table 2, five models with the highest average accuracy values as well as one model with the lowest values for each level of decomposition will be shown.

Table 2 Results After Tuning.

Level	C	Gamma	Kernel	Akurasi Rata-rata
1	10	1	Poly	78,77%
	1	1	Poly	75,67%
	10	1	Rbf	75,65%
	0.1	1	Poly	69,95%
	1	1	Rbf	68,85%
	10	0.1	Sigmoid	28,92%
2	10	1	Poly	76,6%
	1	1	Poly	73,93%
	10	1	Rbf	73,71
	0.1	1	Poly	66,24%
	1	1	Rbf	64,83%
	10	0.1	Sigmoid	30,38%

Based on trials that have been carried out at Level-1, Level-2, it can be concluded that the model using poly kernels and with C 10 and gamma 1 values is the best model as this model has the third highest accuracy value. Nevertheless, at Level-4, the accuracy obtained by that model is not much different from the highest accuracy value. The model's accuracy value decreases when the decomposition level is increased, from 78.77% for Level-1 to 76.6% for Level-2. Based on the experiments that have been carried out, the second best model based on its accuracy value is the model with C 1, gamma 1, and with poly kernels. This model obtains the accuracy of 75.67% for Level-1, 73.93% for Level-2. The model also experiences a decrease in accuracy if the decomposition level is increased. At the two decomposition levels tested, the lowest accuracy value is found in the model using the sigmoid kernel with an average accuracy of around 30%.

V. Conclusion and Suggestions

The Support Vector Machine (SVM) algorithm has succeeded in classifying the desired conditions, namely the wakefulness, sleeping, and drowsiness conditions from EEG data obtained from Immanuel Hospital, Bandung. The best accuracy value (after tuning) is 78.8% for Level-1 decomposition, 76.6% for Level-2 decomposition. This accuracy is obtained by using the GridSearchCV function which applies the pipeline function and 5-fold cross validation. The pipeline function includes scaling with the MinMaxScaler method. Based on the test results, the best model is the model with the parameter values of C 10, gamma 1, and with poly kernels for Level-1 and Level-2. Based on the results of GridSearchCV, it can be concluded that the best kernels for the data used are poly and rbf kernels, while the worst kernel is the sigmoid kernel. The sigmoid kernel always gets the lowest accuracy value even though the value of the parameter has been changed.

To improve the performance of the model, another algorithm as a classifier can be used; besides, the number of data can also be increased. This research can be developed by classifying the conditions of the next sleep stage, namely stage 3 and stage 4 so that the sleep quality of the patient can be determined. In addition, the data can also be differentiated based on gender.

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