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The Role of EEG Signals: Classification of Cognitive Load as a Support for UX Evaluation

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Abstract: Cognitive load is the mental effort that needs to be applied to working memory to process information received over a period of time. Cognitive load can be viewed as the level of mental energy required to process a given amount of information. In user experience design, cognitive load is considered as the mental processing power required to use a product. If the amount of information processed exceeds the user's ability to process it, the overall performance will be disrupted. An EEG device is needed that is used to record electrical activity that occurs in the brain by channelling brain electrical waves to cables and modulators that are sensitive to electrical waves. The object of this research is the EEG Beta signal with the attention wave type from UX testing activities on students aged 21-24 years with a frequency level of 13-30 Hz. The EEG tool records the activity of the respondent's wave signal by collecting data on the activity of working on a questionnaire about evaluating the WhatsApp application using the Google Form application. The classification of cognitive load studied is unencumbered and burdened. Unencumbered represents the ease that is felt when interacting with the application, while burdened represents the difficulty or confusion that is felt when interacting with the application. Testing is done with the Confusion matrix. The best accuracy results among the kernel types in the SVM method are linear kernel types with an accuracy result of 89%.

Keywords: COGNITIVE LOAD; UX; ELECTROENCEPHALOGRAM; SUPPORT VECTOR MACHINE

1. Introduction

User experience (UX) is related to the perceived benefits of users according to their respective perceptions. The level of user satisfaction with the application or system can be seen in terms of its usability. Usability testing is seen from the level of ease of an interface display when users can use the services of the system or application (Mariam Nosheen; et al., 2019) (Wardani et al., 2019).

In this study, the user experience testing process was carried out to determine the level of difficulty and ease of a person's use of the Google form application. The user experience testing process is carried out directly based on the questions given to the user. After that, an observation process is carried out to allow the results of the assessment data to be appropriate or not with the user's condition with a sense of difficulty or feeling the ease of using an application. So that real observation is needed with the help of a physiological measurement tool to determine the state of cognitive load of a user by looking at the level of brain signal waves. EEG is one of the technologies that has been developed to record electrical activity that occurs in the brain by channeling brain electrical waves to cables and modulators that are sensitive to electrical waves. This is usually done non-invasively by placing electrodes along the scalp that are connected to a device that records brain wave activity. From this wave activity recording device, recordings of brain activity can be seen, usually in the form of wave lines (Arjon Turnip, 2016).

The process of classifying cognitive load through brain waves uses the Support Vector Machine (SVM) method with the aim of getting the best accuracy results in testing the research. Support Vector Machine (SVM) is a supervised algorithm in the form of classification by dividing data into two classes using vector lines called hyperplanes (Bennett & Demiriz, 1998; Ghosh et al., 2019; Octaviani et al., 2014). In complex problems or problems with many parameters, this method is very good to use.

SVM has advantages including determining the distance using a support vector so that the computation process becomes fast. One of the advantages of the SVM method is the handling of errors in the training data set using Structural Risk Minimization (SRM). SRM is said to be better because it not only minimizes the errors that occur, but minimizes other factors. Basically the SVM method is a method that uses a hyperplane to be used as a linear separator between data, so to overcome data problems in the form of non-linear data, the Kernel trick technique can be used (Arya Perdana et al., 2018; Bogawar & Bhoyar, 2018).

This study discusses classifying a person's cognitive load to support user experience evaluation results through EEG signals with a stimulus using an application, where the assignment given to respondents is to make a questionnaire using the Google forms application for a duration of 7 minutes. During the testing process the respondent will be wearing an EEG device and recording his brain waves in a state of mind to find out how the cognitive load is felt, as well as the components observed during UX testing activities.

2. Study Literatures

Literature study is a type of research that is used for methods data collection of this research. Literature study method is a series of activities related to methods of collecting library data, reading and taking notes, and managing research materials. A literature study is carried out by exploring journals and articles that discuss the Support Vector Machine (SVM) Algorithm. Doing literature research to find out previous research activities. Browse journals and articles discussing SVM algorithms.

Support Vector Machine is an algorithm that functions to divide training data into two types in the input space, the algorithm actually determines the hyperplane with the largest margin according to the Kernel function used (Sofyan et al., 2019). The maximum margin limit is seen from the sum of the hyperplane distances to the closest point of each data in the two classes (Witten et al., 2017). In this algorithmic method, drawing data is taken as a point on an n-dimensional plane, where n is the number of features it has. Then classification is done by looking for a hyperplane that separates the two categories of data (Sofyan et al., 2019).

In general, the Support Vector Machine can only classify two classes because SVM belongs to the binary classifier (two types) (Barman & Choudhury, 2020; Cervantes et al., 2020; Tiwari & Melucci, 2018). Binary classification is a process or a classification task, by which a given data is being classified into two classes. It is basically a kind of prediction about which of the two groups the thing belongs to (Samie et al., 2019).

In a study of (Kumar et al., 2022) entitled A Comparative Study of Prototyping Methods for HCI Design Using Cognitive Load-Based Measures, the problem of this research is that ubiquitous computing involving complex interactive systems leads to increased cognitive load in daily activities. Apart from causing stress and mental fatigue, increased cognitive load tends to cause costly human error in the case of critical tasks. Although subjective measures of cognitive load are used in HCI, there is a need to explore non-invasive and non-intrusive physiological measures of cognitive load. The aim of this study is to determine the cognitive load caused by the complexity of tasks in the HCI system. The results of the study have yielded a significant difference between the average spectral power of the low and high auditory tasks. Although this was a small sample study to validate the framework, the difference between mental workload as represented by the power spectrum was significant between low and high difficulty multiplication tasks. Single-digit multiplication has shown a lower intrinsic cognitive load than three-digit multiplication problems as expected. The limitation of this study is that when calculating the strength of the alpha band in the prefrontal cortex independent components from non-brain sources are not excluded. The hypothesis is that the power spectrum contribution by the sources will be minimal and will be lost when comparing the signals from the two assignments.

In a study from (Feta & Ginanjar, 2019) entitled Comparison of the Kernel Function Support Vector Machine Method for Modeling Classification of Diseases of Soybean Plants. The research problem of this study is to detect symptoms of nutritional diseases and also to classify disease groups in soybean plants and to compare kernel function. The purpose of this study was to determine the function of the kernel according to the classification problem in soybean disease using two types of kernels, Radial Basis Function (RBF) and Linear. The results of this study are that it can be seen from the results of the accuracy of the test data that it is shown that the accuracy of the classification accuracy of the test data for the Linear and RBF kernel functions yields the same value of 94%. So, based on the classification accuracy of the training data and testing data, the RBF kernel function is more of an option than the Linear kernel function.

In a study by (Purnama Dewi & Djamal, 2015) with the title electroencephalogram signal classification for alertness using a Support Vector Machine. Research problems regarding alertness conditions that want to identify accuracy in testing by collecting data using EEG signals. The research objective was to find out the results of the identification and classification of alert conditions. This research has produced a classification system for alertness with two conditions, namely alert and non-alert conditions. Alert and non-alert conditions observe the frequency 5 Hz – 30 Hz, where at this frequency there are three waves, namely beta, alpha and theta. Testing the training data resulted in an accuracy of 49.13% for alert conditions, while not being alert resulted in an accuracy of 61.66%. Testing the test data resulted in an accuracy of 52.08% for alert conditions and 73.52% for non-alert conditions.

In research done by (Kusumaningrum et al., 2020) with the title Comparative Study of Mental Workload Classification Algorithms based on EEG signals. The problem of this research is that psychological and physical conditions can affect productivity levels, causing mental workload and a study is needed to determine which is the best algorithm in classification in terms of accuracy and memory usage. The purpose of this research is to find out the best comparative study of algorithms in classifying mental workloads in terms of accuracy, model creation time, and memory usage. The results of this study are the best algorithm in terms of accuracy is the KNN algorithm, the best algorithm in terms of test time and memory is the Random Forest algorithm.

In research by (Shantha Selva Kumari & Prabin Jose, 2011) entitled Seizure Detection In EEG Using Time Frequency Analysis and SVM. The problem of this study is that many brain disorders are diagnosed by analyzing EEG signals. The aim of his research to detect the presence of epileptic seizures in EEG signals is presented. The results of his research were that the EEG signal was first decomposed into delta, theta, alpha, beta, and gamma subbands. After decomposition of statistical features such as variance, energy, maximum sample value in PSD is calculated for each subband. Feature vectors are created based on statistical features. The linear Kernel function is used in the SVM classifier to classify or detect seizure EEG signals and normal EEG signals. The accuracy of the classification was calculated, and the accuracy of this project is much better than other results available in the literature. Autoregressive models and various time-frequency distributions can also be used to extract features to compare performance and accuracy for detecting Epileptic Seizures in EEG signals.

3. Methodology

3.1 Data Acquisition

The dataset used is taken in the form of signal recording sample results using the EEG Neurosky device which is tested on respondents who are working on the Google Forms app to replicate a set of questionnaire which was already prepared and designed with various model of questions. These respondents will be wearing the device during 7 minutes of work while their brainwaves are being recorded. Brainwaves are obtained in the form of a raw EEG signal and was exported to a data log file in the form of csv format.

In this study the brain waves used were beta waves which were related to the research objective of obtaining a cognitive response to the brain. The type of beta wave taken is the type of attention wave because the attention signal on the Neurosky Mobile Mindwave 2 tool already measures people's concentration directly on a scale of 0 – 100 in real time. Beta waves are characterized by a frequency of 13 to 30 cycles per second (cps) or the equivalent of 13 to 30 hertz (Hz). Beta Wave is designed to help people stay focused when doing activities that require concentration. Therefore, beta waves are often also called concentration waves (Azhari et al., 2015; Yudhana et al., 2019)(Dinesh Anton Raja et al., 2020; Koudelková & Strmiska, 2018).

Data acquisition was carried out by collecting data using an EEG device which was attached to the respondent who circled his head to capture the respondent's brain wave signal when working on the stimulus. The stimulus for completing the questionnaire was in the form of assessment questions about the whatsapp application using the Google form application where each question has a weight value with the difficulty level of each question, which is then taken as a result of working on the questionnaire from each respondent. Respondents as many as 30 data taken for this study. The EEG device records the activity of the respondent's wave signal by collecting data 1 time with a retrieval time frame of 7 minutes per respondent (Koelstra et al., 2012) where the results of the recorded data are in the form of brain wave signals. Recording of brain wave signals and processing of stimuli is done at the same time.

3.2 Research Variables

The variables used in this study were confirmed by the support of expert from psychologist with historical background towards human cognitive research. It consisted of five variables as inputs and one dichotomous variable as the target. Table 1 contains descriptions of the research variables.

3.3 Feature Extraction

After the data is acquired, the next process has entered into the preparation stage to enter the SVM classification process. The features on the EEG are extracted to separate the parts that are not needed. The stages of research work are modeled in Fig. 1.

Table 1. Research Variables

VAR. TYPE	VAR. NAME	CATEGORY	DESCRIPTION
Target	Label	1 : Burdened 2 : Not Burdened	Cognitive load (mental condition) burdened and not burdened. Not burdened (representing the ease that is felt when interacting with the application) and Burdened (representing the difficulty or confusion that is felt when interacting with the application).
Input	Avg	-	The average EEG value of the results of normalizing the min and max values of the respondents.
	Health problems	1 : No 2 : Yes	Does the condition of the respondent currently have health complaints?
	Work load scale	1 Very Low 2 : Low 3 : Neutral 4 : High 5 : Very High	The scale of workload that is being felt in the last 1 week.
	Rest intensity scale	1 : Very Low 2 : Low 3 : Neutral 4 : High 5 : Very High	Rest intensity scale in the last 1 week.
	Technology Proficiency Scale	1 : Very Unskilled 2 : Not Proficient 3 : Neutral 4 : Proficient 5 : Expert	Respondents' proficiency scale in using technology such as smartphones, browsing the internet and social media.

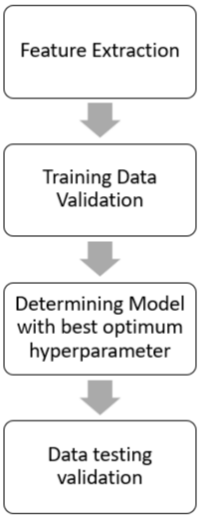

Fig 1. SVM methodology

This study performed feature extraction using the FFT method to analyze the amplitude value of human brain waves based on the stimulus received by the respondent. In the feature extraction process using the FFT method, the process of taking the peak signal is carried out as a more specific feature of the signal. The signal peak consists of two, maximum peak and minimum peak. From searching for the maximum value and minimum value of each input signal peak, signal normalization is then carried out and the search for the average value of each respondent's data is carried out.

From the processing of respondent data that has been recorded using the EEG tool. The data used is in the form of beta waves with attention wave types. Then the feature extraction process is carried out by taking the attention data column which is imported into Matlab to process the data.

After the attention data is imported, then the raw signal FFT process is carried out, namely feature extraction using the Fast Fourier Transform (FFT) where the process produces a raw signal output with X-axis time, Y-axis amplitude information and also an FFT spectrum signal process where the process makes changes original signal (raw signal) to the signal spectrum with information on the X-axis of frequency, Y-axis of amplitude. Figure 2 is the form of the raw signal and Figure 3 shows the form of the signal spectrum.

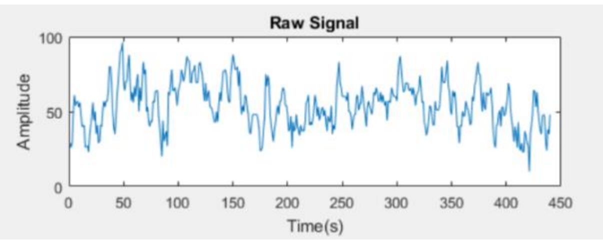

Fig 2. Raw Signal of EEG

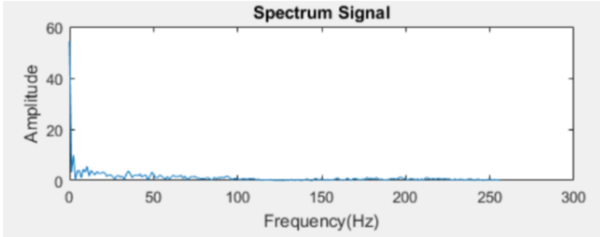

Fig 3. Spectrum Signal

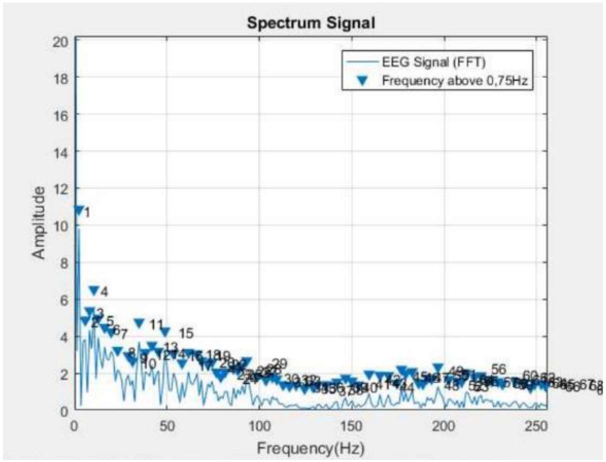

Fig 4. Peak signal of EEG output

After running the FFT raw signal and signal spectrum processes, proceed with the peak signal FFT process by taking the peak signal as a more specific characteristic of the signal. The signal peak consists of two, maximum peak and minimum peak (1 period consists of 1 hill and 1 valley). Figure 4 output of the peak signal process. From the process of taking the peak signal results from each respondent's data, then carrying out the process of normalizing the search for the average value of the maximum and minimum values that have been obtained from the feature extraction process in excel.

3.4 SVM Classification

Classification is a technique for grouping data based on data attachment to sample data (Oktanisa and Supianto, 2018). In the classification process this time the research was carried out using the method Support Vector Machine (SVM). EEG classification is usually done on one variable. Several studies on the classification of EEG signals for several variables, namely, classification using the Support Vector Machine (SVM) method with an accuracy rate of 81.03% (Duan et al., 2012). SVM projects features into another feature space using linear Kernel functions. In the SVM method itself there are 4 types of kernels including linear kernels, polynomial kernels, Gaussian kernels and sigmoid kernels. Then SVM iteratively approaches the optimal hyperplane which has the maximum margin (Duan et al., 2012). Table 2 shows an explanation of how each kernel is used in the SVM classification.

Table 2. Kernel types and definition (Bonthu, 2021; Dwi Saputro et al., 2019)

KERNEL TYPE	DEFINITION
Linear	used when the data being analyzed is linearly separated. In this analysis, parameter C or

	Cost is optimized. Parameter Cost is a hypermeter in SVM to control errors .
Polynomial	used when the data is not linearly separable. Kernel polynomials are well suited for problems where all training datasets are normalized. The parameters of the kernel polynomial function consist of C and degree *d* parameters.
RBF	used in analysis when the data is not linearly separable. The RBF kernel has two parameters, namely gamma and cost. Gamma is a hypermeter that is set prior to model training and is used to provide decision boundary curvature weights.
Sigmoid	similar to Neural Network with Sigmoid activation function. The parameter used in the Sigmoid kernel is the gamma parameter(Bonthu, 2021).

(Ekici, 2012) explains the basic concept of hyperplane in SVM linear function. With the following information:

- Hyperplane: a hyperplane or decision boundary /surface or dividing plane is an n dimensional euclidean space that clearly separates data points. Negative hyperplane (class 1 bounding plane) and positive hyperplane (class 2 bounding plane).
- Support Vectors : Individual data points that are close to the hyperplane.
- Margin : The width of the boundary that can be increased before reaching a data point or the distance between the hyperplane and the support vector.

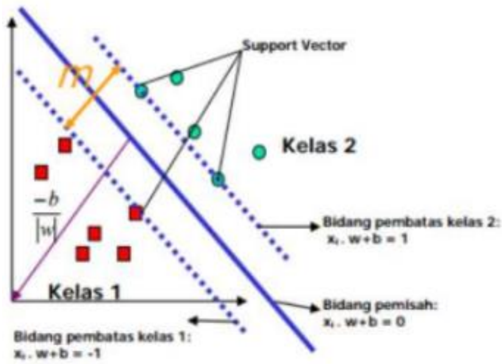

Fig 5. Basic concept of hyperplane in linear kernel SVM

(Al Amrani et al., 2018) explained there are 3 possibilities predictable hyperplane capable of classifying data points. Hyperplane one (H1) does not classify data points, hyperplane two (H2) classifies the data points but has the same marginal width small. Hyperplane three (H3) is said to be the best classification or optimal because it is able to classify data points properly and has the highest marginal width. Figure 5 shows how hyperplane in Linear Kernel works by separating data.

While the evaluation stage is carried out using a confusion matrix to test the system to find out the level of accuracy results. Table 3 shows a representation of the output results from the SVM classification which is then used to calculate Precision, Recall and accuracy as follow in Eq. (1, 2, and 3).

Table 3. Confusion matrix

		PREDICTED CONDITION	
		TRUE	*FALSE*
ACTUAL CONDITION	*TRUE*	TP (True Positive)	FN (False Negative)
	FALSE	FP (False Positive)	TN (True Negative)

$$\text{Precision} = \frac{TP}{TP+FP} \quad (1)$$

$$\text{Recall} = \frac{TP}{TP+FN} \quad (2)$$

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

4. Results and Discussions

4.1 Data Description and Labeling

The results of discussions with expert Mr. Muhammad Hidayat, S. Psi., as a psychologist lecturer at Ahmad Dahlan University, labeling the samples in the classification (Table 4) is based on the results of the task stimulus task questionnaire scores using the Google form application. Grouping as training data as many as 21 respondents with a total of 21 data to be tested by the system. Then proceed with the grouping process by conducting independent experiments.

The dataset that has been carried out by the feature extraction process is then divided into training and testing data using the split data train test technique. The classification process uses the SVM method to find the largest *y* distance from the equation $w.xi + b >= 1$ for $yi = +1$ and $w.xi + b <= -1$ for $yi = -1$.

Table 4. Raw dataset after labeling

RESPID	AVG EEG	HEALTH PROBLEMS	WORK LOAD SCALE	REST INTENSITY SCALE	TECHNOLOGY PROFICIENCY SCALE	LABEL
1	.1745	No	4	4	4	Not Burdened
2	.2698	No	3	3	4	Burdened
3	0.124	Yes	3	4	4	Burdened
…	…	…	…	…	…	…
30	.2794	No	1	4	4	Not Burdened

4.2 Parameter Tuning for Training Model

In testing the accuracy of the kernel type in the SVM method, two research experiments were carried out with the first test using the EEG feature and the second test without using the EEG feature. SVM classification for training is carried out to get the best parameters from each type of kernel in the SVM method. Table 5 and Table 6 are the results of testing the accuracy obtained from each type of kernel in the SVM method. In carrying out the analysis with this linear kernel function, optimization of the *c* or Cost parameters is carried out. This linear kernel function uses 4 parameter values c=0.001, c=0.01, c=0.1, c=1.

Table 5. Data training validation with various *c* parameters in linear kernels

LINEAR KERNEL		
C	*Incl. EEG val*	*Excl. EEG Val*
.001	.523	.666
.01	.523	.666
.1	.523	.714
1	.523	.809

Table 6. Data Training Validation with Various *C* Parameters in Polynomial Kernels

POLYNOMIAL KERNEL				
C/ degree	*Incl. EEG val*		*Excl. EEG Val*	
	d=1	*d=2*	*d=1*	*d=2*
.001	.523	.476	.523	.523
.01	.523	.666	.523	.523
.1	.666	.666	.523	.523
1	.666	.666	.619	.571

While on the RBF and Sigmoid kernels, parameter tuning is carried out with 4 values of the c parameter, and the value of γ = 1 to 5. All scenarios produce the same accuracy value: .523.

From the comparison of the results of the accuracy testing carried out above, it was found that the correlation of the effect of EEG on the value of the classification accuracy of this study was that the EEG features did not have a large influence on increasing accuracy in the classification study. Because in this case the EEG signal is needed to determine the signal wave level for each respondent who is being given a stimulus to work on the questionnaire. The results of the signal waves recorded by the respondent will be investigated by examining the level of focus of a person from the level of difficulty or ease felt by the respondent in testing UX from the Google Form application which is used as the object of UX testing in this study.

4.3 Data Testing Validation

Table 7. Accuracy value in data testing

TESTING DATASET		
C	*Incl. EEG val*	*Excl. EEG Val*
.001	.75	.777
.01	.75	.777
.1	.75	.777
1	.75	.888

From the results of tuning the parameters for each type of kernel in the SVM method above, it is concluded that the best parameters with the EEG feature are in the classification test on the linear kernel type with the optimization of the Cost parameter, c= 1 with an accuracy value in the experimental dataset training with the EEG feature. by 52% and in the trial dataset training without EEG features by 81%. Next, the best accuracy testing settings are carried out using data testing to find out the best accuracy results obtained. Table 7 shows results of the accuracy of determining the best parameters in the testing data.

The testing parameter for data testing with the EEG feature is reaching the most optimum when *c=1* with an accuracy value in the dataset testing experiment of 75% and without the EEG feature an accuracy value of 89% consisting of 1 data categorized as Not Burdened label and 8 labeled data as Burdened.

4.3 Author information

Brief biographies and either clear glossy photographs (25mm x 30mm) of the authors or TIF files of the figures should be submitted after the paper is accepted.

5. Conclusion

Based on research experiments that have been carried out on 30 data by testing the confusion matrix, the greatest accuracy value is obtained when using a linear Kernel type with an EEG feature of 75% and the highest accuracy value for a linear kernel type without an EEG feature is 89% which consists of 1 data categorized as a label unencumbered and 8 data labels burdened. The correlation of the effect of EEG features on the value of classification accuracy does not have a big effect on increasing accuracy because the EEG signal is needed to determine the level of signal waves in respondents who are being given a stimulus.

Conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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