Fatigue Detection of XYZ Driver based on Human Brain Wave EEG Signals

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***Abstract*— The cause of death due to traffic accidents is now increasingly common. One of the main factors causing this accident is driver fatigue. This can happen because the driver is not aware of his tired mental condition. Of course, mental fatigue can cause a lack of concentration while driving. Analyzing the brain waves through the EEG signal from the driver can be one of solution to detect the mental fatigue. This brain wave analysis can be done by various methods. In this study, the authors conducted a brain wave-based detection of mental fatigue using the Fourier transform and Support Vector Machine. The EEG signal data will be feature extracted using the Fourier Transform. Then, the results of this extraction will be used for the classification process with the Support Vector Machine method. Based on the experimental results, the average accuracy of mental fatigue obtained 85%.**

Keywords*— *Early detection of fatigue, EEG signals, Fourier Transform, SVM.

***Abstrak*— Penyebab kematian akibat kecelakaan lalu lintas kini semakin marak terjadi. Salah satu faktor utama penyebab kecelakaan ini adalah kelelahan pengemudi. Saat mengalami kelelahan, konsentrasi pengemudi menurun dan saat konsentrasi menurun, resiko kecelakaan lalu lintas akan semakin tinggi. Untuk mengantisipasi hal tersebut, diperlukan suatu sistem pendeteksi dini kelelahan pada pengemudi saaat berkendara dengan menganalisis gelombang otak melalui sinyal EEG. Pertama, sinyal EEG akan ditransformasi dalam bentuk *fourier* lalu dilakukan beberapa tahapan praproses untuk memperoleh sinyal EEG yang lebih bersih. Setelah itu, sinyal EEG akan diklasifikasi menggunakan metode klasifikasi Support Vector Machine untuk mengetahui apakah pengemudi tersebut terindikasi mengalami kelelahan atau tidak. Berdasarkan hasil percobaan, diperoleh rata-rata akurasi 85%.**

Keywords*— *Deteksi dini kelelahan, Sinyal EEG, Transformasi Fourier, SVM

INTRODUCTION

Today, the cause of death due to traffic accidents is very common. One of the main factors causing accidents is fatigue while driving a vehicle [1]. This can occur due to the driver's lack of awareness when they feel tired. Of course mental fatigue can cause a lack of concentration while driving.

The brain waves analysis through the EEG signal from the driver is used due to early detection of fatigue while driving. Brainwave analysis can be performed using a variety of methods. Abd. Rahman, et al proposed a real time eye blink removal using Adaptive Filtering [2], while Chai, R, et al approached classification of mental fatigue using principal componant analysis [3]. SVM and LDA are also proposed by Muhammad Afif Hendrawan to obtain the fatigue mental detection [4].

In this study, the authors conducted a brain wave-based detection of mental fatigue using the Fourier transform and a support vector machine. The features of the EEG signal data will be extracted using the Fourier Transform. Then, the extraction results will be used as input at the classification stage using the Support Vector Machine method. This research is expected to show the condition of the driver, whether the driver is tired or not. In addition, it will also be concluded what method is appropriate for conducting brain wave analysis to determine the mental state of the driver.

RESEARCH METHOD

In this study a system will be built to detect the mental fatigue based on EEG. First of all, the brain wave data is recorded first then the preprocessing and classification stages are carried out. The data capture stage is the first stage of this system where the recording of brain waves is done using the NeuroSky MindWave device. Furthermore, the preprocessing stage is carried out by noise in the missing signal and extracting the features of the wave so that the data to be classified can be classified optimally. The final stage is classification, to find out whether the driver is mentally exhausted or not. The overall system flow diagram is represented in Figure 1.

A. *Hardware*

The device used to record brain waves in this study is NeuroSky MindWave. The process of recording brain waves is carried out in the morning and at night in order to show significant differences in brain waves. NeuroSky MindWave has specifications as shown in Table 1 below.

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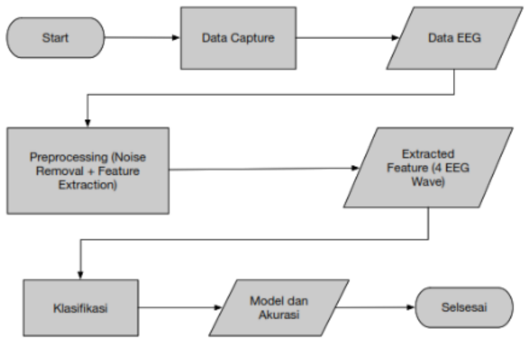

Figure 1. System Flowchart

TABEL I. NNEURO SKY MINDWAVE SPECIFICATION

Specification	Information
Sensor	Passive
Number of electrodes	2
Type of electrodes	Dry
Sampling Rate	512Hz
Other Specification	Wireless

The electrodes contained in NeuroSky MindWave consist of a receiver electrode and a grounding electrode. The form of NeuroSky MindWave is shown in Figure 2. This receiver electrode will come into contact with the scalp where its function is to receive signal waves from the brain. Because the nature of this electrode is a dry electrode, it does not need to be used with a saline solution. The grounding electrode is shaped like a clamp which will later be placed on the earlobe which functions as a reference for the baseline voltage of the human body. This electrode is very important so that the EEG is not disturbed by other electrical activity in the body.

Figure 2. NeuroSky MindWave

B. Fatigue Dataset

The mental fatigue dataset is obtained by recording an individual which is done repeatedly to avoid inconsistent results when done on different individuals. [5]. The subject recorded was a 21-year-old student who had lecture activities from noon to evening. The individual went to campus from home with a distance of about 21 km by motorbike for 45 minutes with busy protocol routes, especially in the afternoon. The subject's activity is continued by studying at night until entering bedtime. The results of the recording using this tool will be in the form of brain waves in the time domain with a sampling of 512Hz. The recording was carried out for a few minutes and then the waves were cut with a duration of 10 seconds each for 40 data with 20 data for each class. Cutting the wave is done by making visual observations and selecting the part of the wave to be used.

C. *Electroencephalography (EEG)*

The cortex layer of the brain consists of neurons that are connected to each other to form a network and receive input from other parts of the brain. Electrical activity in the form of nerve stimulation sent or received by cortical neurons always occurs even during sleep. Biologically, medically, and legally, the absence of activity indicates death.

The electrical activity to be measured reflects the intrinsic activity of the neurons in the cerebral cortex and the information transmitted from subcortical structures and nerve receptors. This whole activity is called the Electroencephalogram (EEG). An EEG electrode will only record activity from the area of the brain attached underneath. Even so, the electrodes receive activity from thousands of neurons. In fact, 1mm of cortex contains more than 100,000 neurons. If the input of a synchronized region with electrical activity occurs at the same time, it shows a simple periodic wave of EEG. The four simple rhythmic periods recorded in the EEG are alpha, beta, delta, theta waves [6]. These simple rhythmic period waves have different frequencies. These frequencies are shown in Table 2 [7].

TABEL II. EEEG FREQUENCY

Ritme	Frequency
Delta	0.5 – 4 Hz
Theta	4 – 8 Hz
Alpha	8 – 13 Hz
Beta	13 – 20 Hz

D. *Preprocessing*

The cortex layer of the brain consists of neurons that are connected to each other to form a network and receive input from other parts of the brain. Electrical activity in the form of nerve stimulation sent or received by cortical neurons always occurs even during sleep. Biologically, medically, and legally, the absence of activity indicates death.

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E. *Feature Extraction*

The next process aims to get the features of the signal. The features of brain waves consist of 4 wave forms namely alpha, beta, delta, and theta waves. The four waves have their respective frequencies which are described in Table 2. To carry out this stage, the signal magnitude is first removed and the power spectrum calculation of each wave is performed. This aims to change the wave in the form of a complex double to a double to make it easier to carry out power spectrum calculation operations.

One type of fourier transform is the Fast Fourier Transform (FFT). FFT is applied in a wide variety of fields from digital signal processing and solving partial differential equations to algorithms for multiplying large numbers of integers. The advantage of the Fast Fourier Transform is that the frequency content does not change easily with changes in time. This is very supportive of our data structure because the EEG frequency signal data is taken at different times. There are also basic classes of the FFT algorithm, namely decimation in time (DIT) and decimation in frequency (DIF). The outline of the word Fast is interpreted because the FFT formulation is much faster than the previous Fourier Transform algorithm calculation method. [10]. The FFT method requires about 10000 mathematical algorithm operations for data with 1000 observations, 100 times faster than the previous method. The invention of FFT and the development of personal computers, the FFT technique in the data analysis process has become popular, and is one of the standard methods in data analysis. One common form of transformation where F(ω) is the signal in the frequency domain and the time domain in the form of f(t) is used to convert the signal from the time domain to the frequency domain is the Fourier transform contained in Equation 1.

$$F(\omega) = \int_{-\infty}^{\infty} f(t)\, e^{-i\omega t} dt \qquad (1)$$

While equation 2 shows the inverse transform function, which returns the frequency domain to the time domain.

$$f(t) = \frac{1}{2\pi}\int_{-\infty}^{\infty} F(\omega)\, e^{i\omega t} d\omega \qquad (2)$$

F. Classification

At the beginning of this stage, the EEG signal data that has been extracted will be divided into 75% of the training data and the remaining 25% for testing data. The SVM technique is used to find the optimal classifier function that can separate two data sets from two different classes. The use of this machine learning technique, because of its convincing performance in predicting a new data class. Furthermore, the training process is carried out with 4 SVM kernels to obtain a classifier model which will later be used to classify the data testing in order to obtain classification results with optimal accuracy.

In real world, linearly separable cases or data cases which can be separated linearly rarely happening. Cases that occur are generally nonlinear. To solve SVM nonlinear problems modified by including kernel functions. The trick in working on SVM nonlinearity is transform the data from the initial coordinate space x into spaces.

The trick in working on SVM nonlinearity is transform the data from the initial coordinate space x into new spaces with functions Ø(x) so as to form a linear boundaries that can be used to separate the data which are desired. This is applied so that further can field boundary search method is carried out as in the process previous linear SVM.

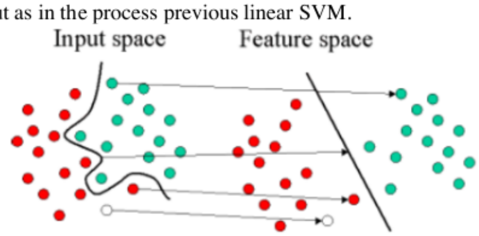

Figure 3. Hyperplane of Nonlinear SVM Illustration

K-fold cross validation is a step to divide the dataset into k subsets, and the holdout method is repeated k times. Every time is executed, one of the data k subsets is used as a test set and k – 1 other subset combined as training set. Then, average the output for all k trials is calculated. The advantages of this method is that it doesn't really matter how the data is divided. Every data will only be tested once, and become k – 1 times as training sets. An illustration of k-fold cross validation will be shown in Figure 2.4 where in the image it has a value of k of 10. The accuracy shown in the figure is only as an example. This test is done to test all data and avoid data testing that is repeated in stages testing and data sharing is not good.

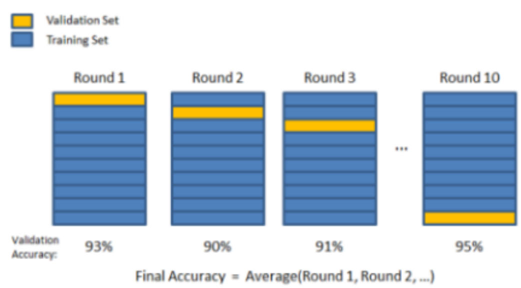

Figure 4. 10 fold Cross Validation Illustration

TESTING AND RESULT

A. EEG Data

The data to be tested is data recorded using NeuroSky MindWave according to the conditions previously described. Figure 5 is a representation of the visualization of the EEG recording results. This recording has a sampling frequency of 512 Hz, with a duration of 10 seconds, so one file contains ± 5000 values.

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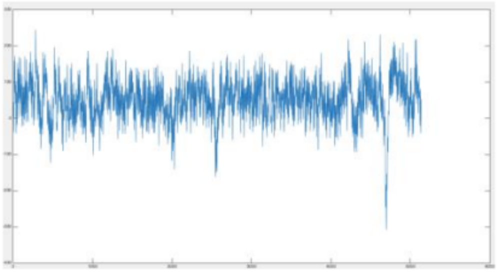

Figure 5. EEG recording example

B. Processing Data

All recorded data will be processed at the preprocessing stage, namely removing noise and obtaining its features from the EEG signal. The results of running the noise removal function are visualized using Matlab plotting function in Figure 6.

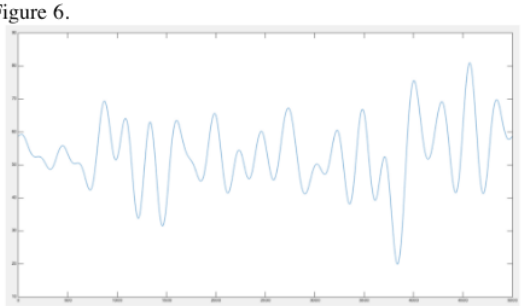

Figure 6. *Noise Removal Result*

Before the EEG wave can be selected for the signal frequency and taken for its power spectrum value, it is necessary to remove the magnitude. Figure 7 shows the resulting fourier transform wave that is ready for the signal selection process and power spectrum calculation.

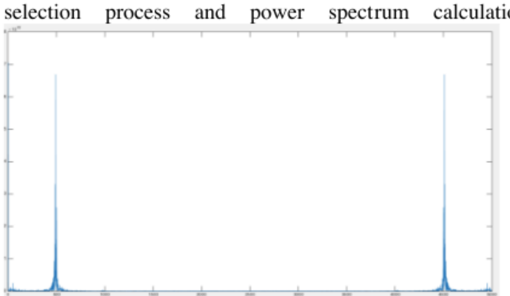

Figure 7. Magnitude removal result

While the result of these operations are shown in Tabel 3.

TABEL III. FEATURE SIGNAL EEG VALUE

Jenis Gelombang	Nilai
Delta	10489375298.4080
Theta	11411547001.8448
Alpha	5676671238.27336
Beta	5966074854.15926

C. Testing and Training Data

In this test, the classification stage uses a dataset of EEG signal features with a percentage split of 75% for training data and 25% for testing data. In addition to the percentage split, the accuracy calculation is also applied by cross validation with the fold value as a trial scenario [11][12]. There are two kind of testing scenario, the first scenario is testing the value of K parameter in cross validation stage and the second one is comparing SVM classifier with other classifier method such as LDA, PCA, etc.

1. Number of k-fold cross validation scenario

One of the test scenarios carried out is an accuracy computation test for k parameters on k-fold cross validation and SVM with linear kernels. This validation process is carried out to test each data existing data on the system by partitioning the data into subsets a number of k. Each subset is used only once testing. The k value tested is 5, 10, and 15.. Figure 8, 9, and 10 are represented of accuracy for every k value.

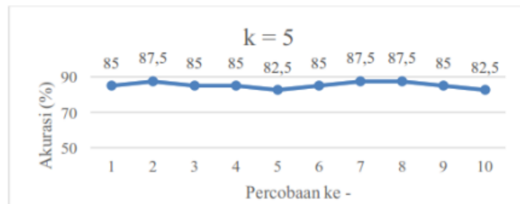

Figure 6. Accuracy of k=5

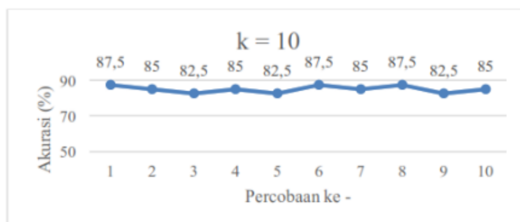

Figure 7. Accuracy of k=10

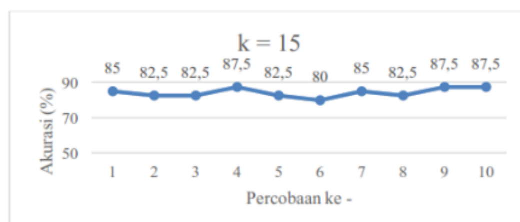

Figure 8. Accuracy of k=15

While Table IV is the average accuracy of k value in k-fold Cross Validation, respectively. The result shown that the highest accuracy is k=5 which is 85%

TABEL IV. AVERAGE ACCURACY OF K VALUE

K value	Accuracy (%)
5	**85**
10	84

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15	84

2. Comparing the accuracy value of SVM and other classifier

In order to make sure that SVM is the superlative solution for fatigue detection, the comparison among some classication methods are approached as represented in Table V. Based on the experimental result, SVM obtained the highest accuracy which is 85%.

TABEL V. COMPARISON OF CLASSIFIER

Classifier	Accuracy
SVM	**85%**
SVM-LDA	82%
PCA	80%

D. Results

The entire dataset with 40 instances is shown in Table 4. A class with a value of 1 indicates normal data, while 0 indicates fatigue data. From the test scenario results, the best classification results were obtained with an average accuracy of 85%. It showed an accuracy of 85% with a value of k = 5.

TABEL VI. DATASET OF EEG SIGNALS

delta	theta	alpha	beta	class
12203618983	6955171046	4252237268	2362493701	1
6861136625	6573293221	6041853826	6411416285	1
8482967199	6634503430	3276275656	1520138905	1
51394054600	37921953897	23798352314	9819334928	1
10330658097	7916013318	4537835851	2833928911	1
4716821477	4030418880	3328768161	2467382549	1
14893056650	7192625352	3389639825	2201298835	1
12154156505	11320710502	12121386615	7388475499	1
7606083521	20780075652	12590798580	14237051796	1
23065546125	32873310780	19045062943	10320215001	1
12883111235	14562303702	9364188370	2826096735	1
8126357423	6900505114	4381765012	1865086489	1
16346878992	56309495208	18768564230	10131845365	1
19812825319	16361611882	23821934055	7605661339	1
28913474048	27902838613	25656712630	22321677534	1
11895101757	9269442559	5245744451	3068392594	1
19261262302	14206914035	6189768711	3410134097	1
11626640795	12579325867	5108812293	2773001927	1
12209036419	12565895230	6341221440	3437535853	1
27826573702	21075947322	12403783831	9348841731	1
15209255432	15145559440	18524937244	26229940729	0
7024420089	5164797416	11904060204	7210779266	0
6154953823	5784531965	9874686709	7183688191	0
9152131287	9213156593	11425914585	8133859107	0
10883157244	4623412835	11552248548	2680756082	0
6514064542	6441781318	10391330325	1835223965	0
1282730086	983894688,4	3070817731	1235848830	0
1467265534	1675660439	12792485753	1699733633	0
1807273433	1853424072	12502188376	1342525286	0
6099069077	3150997845	2511038257	1411477298	0
4958199135	2807500565	11474602504	1523120797	0
1953101488	2829624424	9662423263	1341771436	0
1738711517	2903681429	8219873470	1154818420	0
1338128128	2261884375	9318037280	1258125478	0
1797525814	2203379922	12730221677	1101530333	0
1818196067	1848137952	10204225144	1147982272	0
3612994245	2478579508	14366549029	1371605348	0
2151836377	2473095778	9226762484	1680565640	0
2391016074	1675850800	13465338962	2001935963	0
10511057728	11398667599	5680675189	5952043492	0

CONCLUSIONS

Based on the results of trials that have been carried out on EEG signals to determine whether or not a person's mental state is tired, it can be concluded that the Fourier transform method or the one used hereis that the FFT has been able to parse the signal to obtain its features so that it can be classified properly. The Support Vector Machine method used in combination with the kernel is capable of classifying the provided datasets. Based on the test results, the best accuracy for dividing data is 3: 1 with an average value of 85% using a linear kernel. As for the test results using k-fold cross validation, the value of k = 5 is obtained with an accuracy of 85%.

REFERENCES

[1] H. Kececi and Y. Degirmenci, "Quantitative EEG and Cognitive Evoked Potentials in Anemia," Clinical Neurophysiology, pp. 137-143, April 2008.

[2] Abd Rahman, F. & Othman, M.., 2016. Real Time Eye Blink Artifacts Removal in Electroencephalogram Using Savitzky-Golay Referenced Adaptive Filtering. In IFMBE Proceedings. pp. 68–71.

[3] Chai, R. et al., 2016. Classification of EEG based-mental fatigue using principal component analysis and Bayesian neural network. 2016 38th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), pp.4654–4657.

[4] Hendrawan, M. A., Deteksi Kelelahan Mental dengan Menggunakan Sinyal EEG Satu Kanal. Jurnal Sistem Informasi dan Bisnis Cerdas (SIBC), vol 14, 2021.

[5] C. Cortes and V. Vapnik, "Support-vector networks," Machine Learning, vol. 20, no. 3, p. 273, 1995.

[6] James W. Cooley and John W. Tukey, "An algorithm for the machine calculation of complex Fourier series," Math. Comput., vol. 19, pp. 297-301, 1965.

[7] J. W., P. Lewis and P. Welch Cooley, "The Fast Fourier Transform and its Applications," IEEE Trans on Education, vol. 12, no. 1, pp. 28-34, 1969.

[8] Kai-Quan Shen, Xiao-Ping Li, Chong-Jin Ong, Shi-Yun Shao, and Einar P. V. Wilder-Smith, "EEG-based mental fatigue measurement using multi-class support vector machines with confidence estimate," International Federation of Clinical Neurophysiology, pp. 1524-1533, 2008.

DOI: https://doi.org/10/25047/jtit.v9i2.299

[9] N. Andharu F. P. et al., "Analyzing Brainwave Using Single Electroencephalographic Channel To Identify Manufacturing Supervisor Fatigue," in International Conference on Information, Communication Technology and System, Surabaya, 2014, pp. 87-92.

[10] Samuele M. Marcora, Walter Staiano, and Victoria Manning, "Mental fatigue impairs physical performance in humans,"Journal of Applied Physiology, vol. 106, no. 3, pp. 857-864, March 2009.

[11] Anto Satriyo Nugroho, Arief Budi Witarto, and Dwi Handoko, "Support Vector Machine - Teori dan Aplikasinya dalam Bioinformatika," Kuliah Umum IlmuKomputer.com, 2003.

[12] Christopher D. Manning, Prabhakar Raghavan, and Hinrich Schütze, Introduction to Information Retrieval, Online ed.Cambridge, England, United Kingdom: Cambridge University Press, 2009.

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