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Research Article

DETECTION OF DRIVER DROWSINESS FROM EEG SIGNALS USING WEARABLE BRAIN SENSING HEADBAND

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ABSTRACT:
Driver drowsiness detection plays an important role in the field of road safety and advanced driver assistance system. Electroencephalogram (EEG) signals are one of the most accurate and reliable indicators of fatigue and drowsiness but in the case of detecting drowsiness, its medical graded measuring system can be intrusive to the driver. The purpose of this research is to test the feasibility and usability of the consumer graded EEG sensor to use in a driver drowsiness detection system. The experiment was carried out by using MUSE S brain sensing headband. Fast Fourier Transform (FFT) method was used to extract features from EEG signals. The extracted feature data are then used to build two classification model, the Support Vector Machine (SVM) and Artificial Neural Network (ANN). The detection of drowsiness is the binary classification task which is to classify between drowsy epochs and alert epochs. In the case of detecting only drowsy epochs, the SVM model detected 82.7% of the drowsy epochs which was better than the ANN model which can only detect 81.25% of the drowsy epochs. But in the detection of both drowsy and alert epochs, the ANN model performed better than that of SVM. The SVM model was tested with different kernel function and Fine Gaussian SVM model showed the highest accuracy of 87.8%. The ANN model performed slightly higher than the SVM model with an accuracy of 87.9%. The ability of consumer graded EEG sensor to use in drowsiness detection system was validated in this research.

Keywords: *Driver drowsiness detection, Electroencephalography (EEG), Brain-Computer Interface (BCI), Support Vector Machine (SVM), Artificial Neural Network (ANN)*

1. INTRODUCTION

Road accidents caused by driver's false have increased year after year and a lot of innocent lives were lost in vain. According to the United States National Sleep Foundation (NSF), drowsy driving is responsible for more than 6,400 U.S. deaths annually. Approximately 1.35 million lives are cut short because of road accidents every year according to the Global Status Report on Road Safety [1]. Among many other causes like alcohol consumption and multitasking such as using smartphones while driving, drowsy driving is one of the main reasons for the road accident. Drowsiness which can also be defined as sleepiness is the state between fully awake and sleep. The reason behind getting drowsy or sleepy can commonly be assumed as the loss in sleep or sleep restriction and sleep fragmentation [2]. The cause of drowsy driving could be more than that reason. For example, the monotony of the road environment which mostly

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occurred during driving on a highway can lead to drowsy driving [3]. To prevent the driver from losing focus and consciousness while driving in other words protecting from a road accident, drowsiness detection systems were developed based on different methods.

Driver drowsiness detection systems are developed based on three different sources of information. They are – (1) the vehicle position measurements such as steering wheel position and lane deviation, (2) the physiological signals from the driver such as Electrocardiogram (ECG), Electroencephalogram (EEG), and Electrooculogram (EOG), and (3) the behavioural/facial measures such as PERCLOS (PERcentage of eyelid CLOSure over the pupil over time), head position and yawing [2]. Another method is the fusion of the three methods. Since drowsiness is a biological process of human metabolism, there is a higher chance that the drowsiness detection model based on physiological signals could be outperformed than the other methods and among other physiological signals, EEG signals seem useful and have a higher chance to give better accuracy in the detection of drowsiness [4-6]. The drawback of EEG based drowsiness detection system is that the sensor and equipment to measure brain signals are usually not portable and intrusive. However, the development of wearable brain-sensing headbands like MUSE, Neurosky, and Open BCI makes it possible for the EEG based driver monitoring system to use in the commercial sector.

The hypothesis of our study is that the drowsiness can be detected with a portable consumer graded EEG sensor which has a reduced number of electrodes. The feasibility of a portable brain sensing headband was analyzed in our research.

2. METHODOLOGY

The application of Brain-Computer Interface (BCI) is the main idea behind this research. The overall workflow of a typical BCI application can be seen in Fig. 1. The proposed method in this research is nearly the same as traditional BCI workflow. First, raw EEG data were collected and preprocessed by filtering noises such as powerline frequency interference. And then features were extracted by frequency analysis of EEG time series data, in other words, that is calculating the power spectral density of each EEG frequency band (delta, theta, alpha, etc.). The significant features of alert and drowsy EEG signals were selected based on the power contents of different frequency bands. The selected features were fed to the inputs of the classification algorithm, in this research the Support Vector Machine (SVM) and Artificial Neural Network (ANN).

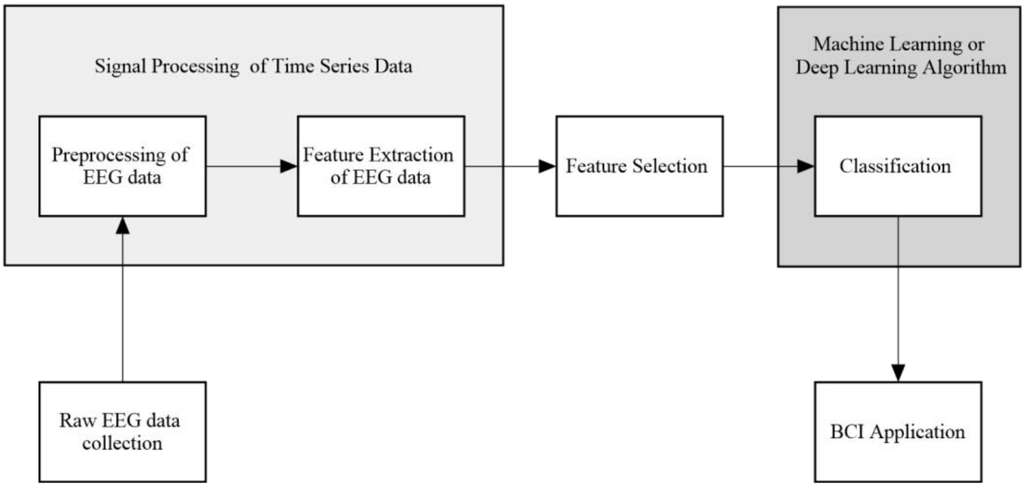
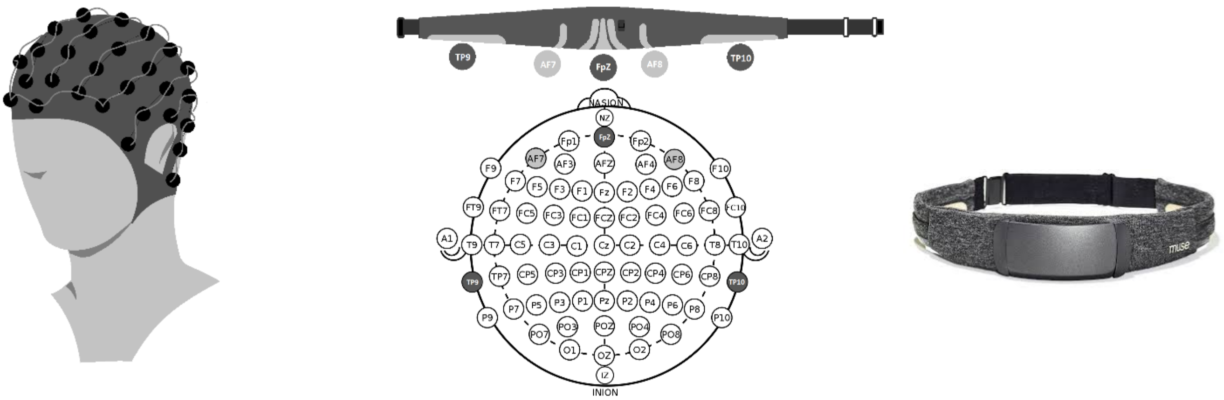


Fig. 1. The overall workflow of a typical Brain-Computer Interface (BCI) Application.

2.1 Experiment Implementation

In previous works done by other researchers [6, 7], the pre-built datasets like CAP Sleep Database and MIT-BIH Polysomnographic dataset were used to develop drowsiness detection models from EEG data. Since the EEG brain sensing headband which we use in this research is not a medical-grade system and the electrode positions in those datasets are not compatible with the headband's electrodes' position, it was impossible to use the pre-built dataset in this research. Therefore, experiments for the collection of EEG data were carried out with human drivers with an aid of a driving simulator. There were 8 participants, four females and four males, with an average age of 24.5 years old who took part in the experiment. They were asked to avoid drinking coffee before the experiment. It was permitted to terminate the experiment immediately if any of the participants felt any kind of simulator sickness or motion sickness. The diving time was one hour and most of the participants did not show any signs of drowsiness until the last 20 minutes. To induce drowsiness, the room was air-conditioned to 25 degrees Celsius and all the lights were dimmed. Each participant drove for at least one hour with a brain-sensing headband on their head and raw data were collected while driving. A web camera was mounted in front of the drivers and the whole experiment was video recorded to use for the ground truth determination of drowsiness.

The driving simulator was used instead of a real car for the safety of participants. The simulator is made up of an i9 Intel Core Processor with NVIDIA RTX 2080 graphic, 49” curved-screen monitor, and Thrustmaster T300 RS GT Racing Wheel. The simulation software used in the experiment was Euro Truck Simulator 2. For the raw EEG data collection, MUSE S brain sensing headband which is designed for guided meditation. The developments of portable EEG systems like MUSE give another option to overcome the problem of being unable to use physiological signal-based drowsiness detection systems in the commercial field. The number of electrodes in the portable MUSE headband was reduced to four, namely TP9, AF7, AF8, and TP10, not including the reference electrode. The medical-grade EEG measuring systems are designed accordingly with the international 10-20 system [8] which consists of many electrodes up to 256 while the MUSE headband only contains four electrodes and one reference. The medical-grade systems use multiple electrodes connected to each wire to detect the electrical activities of the brain as can be seen in Fig. 2(a) and the electrodes are placed accordingly with the 10-20 system. As can be seen in Fig. 2(b), in the 10-20 system, the electrodes above the eyes are AF7 and AF8, and the electrodes close to the ears are TP9 and TP10. The MUSE EEG sensor is designed to fit around the head and electrodes are embedded in its fabric headband and positioned near the eyes and ears. Therefore, MUSE’s electrode positions can be assumed as the equivalent of AF7, AF8, TP9 and TP10 in the 10-20 system. The middle electrode in MUSE which has a similar position as the FpZ in 10-20 system serves as the reference electrode. The visual forms of two systems and a comparison of the placement of electrodes of MUSE headband to the international 10-20 system can be seen in Fig. 2. The data sampling rate of the MUSE S headband is 256 samples per second, and it uses BLE low energy technology to transmit data to a smartphone [9]. An application named Mind Monitor was used to collect data from MUSE headband. Raw EEG data were collected every 10 minutes while the participant was driving.



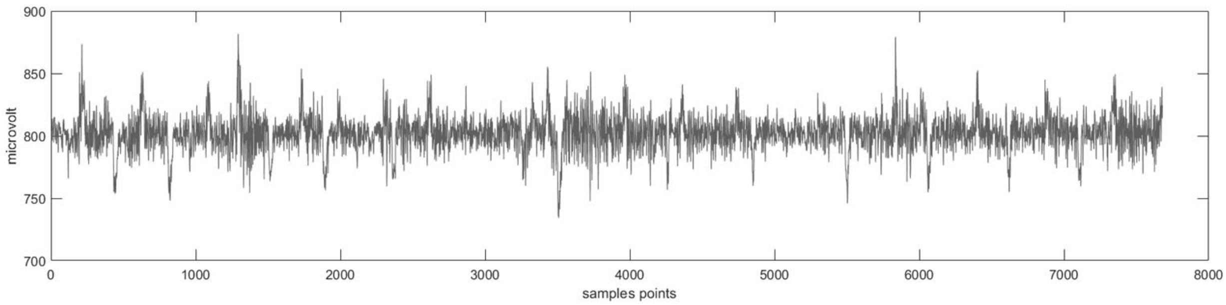
(a) (b) (c)

Fig. 2. Comparison of electrode placement between MUSE and the international 10-20 system: (a) Medical grade multi-channel EEG sensing system, (b) Rear view of MUSE headband and top view of medical-grade multi-channel EEG sensing system which follow the 10-20 system (c) MUSE S brain sensing headband

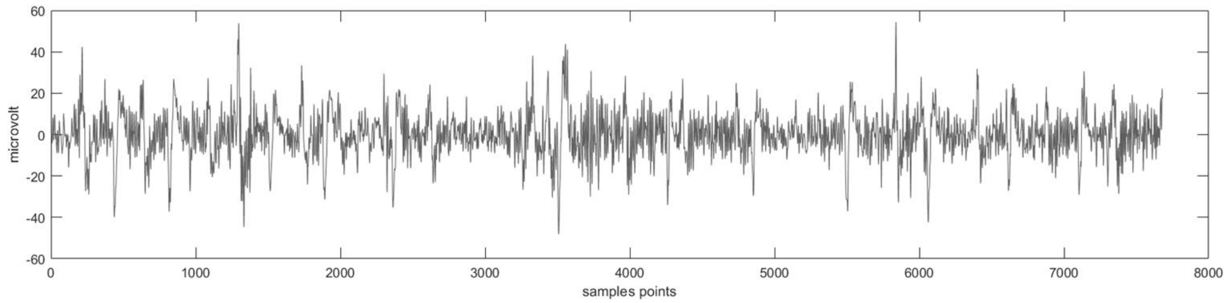
During the experiment, participants were asked to answer the questionnaire for the ground truth determination of drowsiness. Karolinska Sleepiness Scale (KSS) [5], a 9-grade scale with different levels of alertness and sleepiness, is used in this research and written permission was granted from the Karolinska Institute. Since the KSS has 9 levels of scale, level 7 was set as a threshold for drowsiness which means levels 7,8 and 9 were drowsy and others to be assumed as an alert. The ground truth determination of drowsiness in this research was assessed with two systems for better accuracy since the drowsy state is still a confusing matter to clearly define. First, the KSS scales were checked and after that, the video records were checked to determine the alertness and drowsiness level of participants which is also known as the Observer Rating of Drowsiness (ORD). A participant was assumed to be drowsy if and only if it matched both KSS and ORD system.

2.2 EEG Data Pre-processing

We only use two electrodes, AF7 and AF8, in our research to reduce the number of electrodes and test if it is possible to detect drowsiness with the lesser number of electrodes. The collected raw EEG data were mixed with different sources of noise such as power line frequency and muscle and eye movements. The pre-processing of EEG data was implemented in MATLAB 2020a. MUSE S headband records EEG signals with a large DC offset, so the raw EEG data from MUSE S headband were de-meaned by subtracting the average value of four channels which is around 800 [10]. The powerline frequency of 50 Hz was removed with a second-order IIR notch filter. Then, the signal was processed with a Butterworth band-pass filter of 1Hz to 45Hz because the delta frequency range starts from 1Hz and the gamma sub-band ends at 44Hz as described by the MUSE [9]. The comparison between the raw EEG signal and processed EEG signal can be seen in Fig. 3. As it can be seen in Fig. 3, the processed signal still has some noises and artifacts. Typically, artifacts from EEG signals such as muscle and eye movements were removed by Independent Component Analysis (ICA) and some manual techniques. In this research, we decided to retain the noises which are unable to avoid in real-life and to preserve some important information that is mixed with noises. Another fact is that manual artifact removal is impossible to implement for real-time applications.



(a)



(b)

Fig. 3. Comparison of thirty seconds of EEG signals before and after the data pre-processing step: (a) Raw EEG signals, (b) Processed EEG signals

2.3 EEG Feature Extraction

The next step is the process of feature extraction which will give numbers of feature vector inputs to the classification model. Feature extraction of EEG is a wide area of study which comprises different techniques and methods. Raw EEG signals were obtained as time-series data that means they were in time-domain. Since EEG signals are non-stationary, it is difficult to analyze the changes in time-domain. Therefore, frequency analysis of EEG signals is required to extract some useful information. The classical frequency analysis method of Fourier transform was used to compute the power content in five different frequency bands of EEG. The frequency band definitions of EEG in the general standard [11] and MUSE [9] has some differences. The comparison of frequency band definitions is shown in Table 1. In our work, we compute the power contents in each frequency band accordingly with the MUSE definitions.

Table 1: EEG frequency bands definitions of General Standard System and MUSE

	Delta	Theta	Alpha	Beta	Gamma
General Standard	<4Hz	4-8 Hz	8-13 Hz	13-30 Hz	>30 Hz
MUSE	1-4 Hz	5-8Hz	9-13 Hz	13-30 Hz	30-44 Hz

The calculation of Fast Fourier Transform (FFT) and power spectral density estimation was implemented with MATLAB 2020a. The calculation procedure was inspired by previous research [12] but some modification was made, that was applying hamming window on each epoch of EEG data. First, the times series EEG data were segmented into one-second epochs which is 256 data points, and after that, the one-second segment of the EEG signal was multiplied with a hamming window of 256. Then, the FFT of the windowed signal was calculated. Since the number of FFT points is 256 and the data sampling rate is 256, the frequency resolution results in 1Hz bins. The power spectral density (PSD) was calculated by using the periodogram method. The periodogram of a discrete-time EEG signal can be expressed by the equation (1), where *x[n]* is the discrete-time EEG signal (*n=1, 2, 3,..., N*), *N* is the total number of EEG sample data points, *Fs* is the sampling frequency and *w[n]* is the window function [8].

$$\boldsymbol{P(f) = \frac{1}{Fs.N}\left|\sum_{n=1}^{N} x\,[n]w[n]e^{-j2\Pi fn/Fs}\right|^{2}} \tag{1}$$

The average power of each frequency band was calculated by summing the PSD values within that frequency range and divided by the number of frequency bins. For example, the average power of delta can be calculated by summing all the PSD values of 1Hz,2Hz,3Hz, and 4Hz and divided by 4. The average power values of five frequency bands were later used to select significant features to segregate the drowsy EEG signal from fresh EEG signals.

2.4 EEG Feature Selection

According to previous literature studies [13], there is a correlation between EEG frequency bands and a certain type of activities. As an example, the beta frequency band associated with focusing and alertness, delta, and theta frequency bands are correlated to sleep and drowsiness [13]. In this study, we selected the features based on the changes in delta and theta, together with the other five bands. We calculated the changes in theta and delta with respect to the total power in the rest of the three bands. After that, we computed the changes in theta and delta with respect to the power contents of the other three frequency bands. One important feature we integrate is the ratio of the average delta power to the average gamma power. During deep sleep, delta power is the highest amplitude and gamma amplitude is the lowest [14]. Therefore, we assume that the ratio of the delta to gamma could be one of the significant features to detect drowsiness and alertness. The features we calculated can be seen in Table 2.

Table 2: List of selected features

No.	Features	No.	Features
1	delta	8	delta/alpha
2	theta	9	delta/beta
3	alpha	10	delta/gamma
4	beta	11	theta/alpha
5	gamma	12	theta /beta
6	delta/(alpha+beta+gamma)	13	theta /gamma
7	theta/(alpha+beta+gamma)	14	delta/theta

2.5 Dataset Preparation

A total of 8 participants took part in this experiment and each driver drove the simulator for an hour. The ground truth of drowsiness was defined as mentioned previously with two systems, KSS and ORD. There was a large gap between the number of alert epoch and the drowsy epoch, and it could lead to a bias in training a model. Therefore, it was decided to prepare the data with a nearly equal amount of drowsy and alert epochs. Among eight participants, some of the participants did not experience any kind of drowsiness and that causes the number of drowsy epochs to lower value. However, we successfully collected and prepared 2141 epoch of alert epoch and 1846 epoch of drowsy, in a total of 3987 epoch.

3. Classification Results

Two classification models, Support Vector Machine (SVM) and Artificial Neural Network (ANN) were trained with MATLAB 2020a Classification Learner and Deep Learning Toolbox, respectively.

3.1 Support Vector Machine (SVM)

A supervised machine learning algorithm Support Vector Machine (SVM) is one of the popular classification algorithms which is mostly used for binary classification but not limited to multi-class problems. This machine learning technique constructs a hyperplane or sometimes multiple hyperplanes in multi-dimensional space to gain the highest separation between the classes. If the data are not linearly separable, a kernel trick can be applied to the SVM to develop a non-linear classifier. The kernel function maps the data points to a higher dimension space to become linearly separable. The kernel function plays an important role in SVM which means it can alter the result of the classification model. In our work, we use different kernel functions to test which one can give the best accuracy. To avoid overfitting the training data, we choose the 10-fold cross-validation method. For simplicity, we assumed the alert state as ‘0’ and the drowsy state as ‘1’.

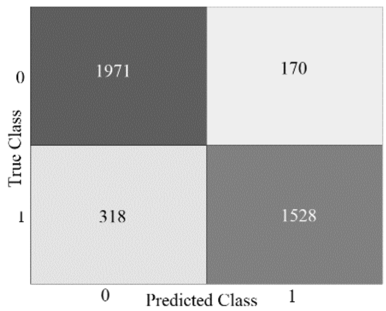


Fig. 4. Confusion Matrix of SVM Model.

The accuracy of the SVM model with different kernel functions is shown in Table 3. The Fine Gaussian kernel predicts the classes with the highest accuracy of 87.8%. The confusion matrix of the SVM model with Fine Gaussian kernel is shown in Fig. 4. The performance of the classifier was evaluated from the confusion matrix. From this matrix, we got the true positive value of 1971, a false-positive value of 318 and a true negative value of 1528, and a false negative value of 170, respectively. The accuracy was calculated by using equation (2) [15].

$$\boldsymbol{Accuracy} = \frac{\boldsymbol{True\ Positive} + \boldsymbol{True\ Negative}}{\boldsymbol{True\ Positive} + \boldsymbol{True\ Negative} + \boldsymbol{False\ Positive} + \boldsymbol{False\ Negative}} \qquad (2)$$

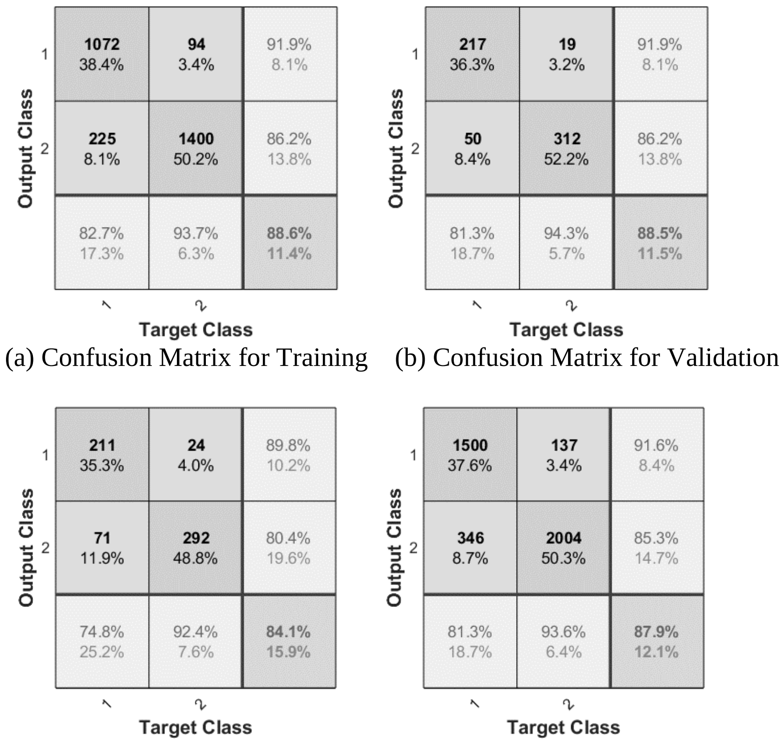
Table 3: Comparison of accuracy of SVM models with different kernel functions

Kernel Function	**Linear**	**Quadratic**	**Cubic**	**Coarse Gaussian**	**Medium Gaussian**	**Fine Gaussian**
Model Accuracy	76.2%	86.9%	62.0%	77.8%	87.3%	87.8%

3.2 Artificial Neural Networks (ANN)

The design of artificial neural network was inspired by the way the human brain works to process information through neurons. It is an adaptive system that learns by using interconnected nodes or neurons in a layered structure that resembles a human brain [16]. A neural network can learn from data. Therefore, it can be trained to recognize patterns, classify data, and forecast future events [16]. In this study, we use MATLAB’s built-in pattern recognition app which is a part of deep leaning toolbox. The neural network is a two-layer feed-forward network, with sigmoid hidden and softmax output neurons which can classify vectors arbitrarily. We then separate the data set into three parts, 70% for training, 15% for validation, and 15% for testing.

For simplicity, we set the drowsy target class as ‘class 1’ and the alert target class as ‘class 2’. The fully connected neural network model was trained with 14 hidden neurons, the same size as the number of feature inputs. This network configuration consists of 14 inputs, 14 hidden neurons, and 2 outputs. With this architecture, we achieved an accuracy of 87.9%. The accuracy can be calculated by using equation (2) [15]. The confusion matrices of the training, test, validation, and overall sets can be seen in Fig. 5.



(a) Confusion Matrix for Training (b) Confusion Matrix for Validation

(c) Confusion Matrix for Test (d) Overall Confusion Matrix

Fig. 5. Confusion Matrixes of training, testing, and validation of the ANN model

4. RESULTS AND DISCUSSION

In the detection of the drowsy epoch, the SVM detected 82.7% of the drowsy epochs, that is 1528 epoch from 1846 drowsy epoch. While ANN model detected 81.25% of the drowsy epoch, which is 1500 epoch out of 1846 drowsy epoch. However, in the detection of both drowsiness and alertness, the performance accuracy of the ANN model is slightly higher than that of SVM.

In the SVM model, the kernel with the highest accuracy is Fine Gaussian but the Quadratic and Medium Gaussian also hit over 85%. The Neural Network model performs quite well, which is 87.9% accuracy, but an improvement can be done by using recurrent neural networks such as Long-Short-Term-Memory (LSTM) network which is mainly used in natural language processing and Convolutional Neural Network (CNN)which is widely used in image processing and computer vision. The performance of neural network model can also be improved by collecting more data because the deep learning models, in general, require a large dataset to perform a better accuracy while regular machine algorithms like SVM and K-Nearest Neighbour (KNN) can carry out the task with small amount of data.

The nature of EEG waves changes accordingly with the ages of persons [6]. Since the experiment was carried out with young people at the average age of 24.5, the models we trained may or may not perform well enough when it comes to people of different ages.

5. Conclusion

In this research, we have proved the usability and feasibility of wearable brain sensing headband in the detection of drowsiness. The complex calculation methods were avoided since the scope of research is to test the feasibility of headband that means if it is possible to use in the detection of drowsiness. Both classifiers which we used in this research, SVM and ANN, were the most basic types of classifiers in their respective field regular machine learning algorithms and deep learning algorithms. Therefore, it can be stated that the EEG signal processing procedure and feature extraction method we developed in this study were reasonable and powerful enough to support the portable headband to carry out the task. The detection of drowsiness from physiological signals such as EEG is theoretically the most accurate way, but the barrier is EEG signal sensors are still not comfortable enough to use in the automotive manufacturing industry. The use of this wearable brain sensing headband could lead to another alternative change in the field of driver drowsiness detection system and other brain-computer interfaces (BCI) applications such as prosthetic arms and legs.

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