International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Comparison of Machine Learning Algorithms for Recognizing Drowsiness in Drivers using Electroencephalogram (EEG) Signals

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Submitted: 19/11/2021 Accepted : 13/01/2022

Abstract: Drowsiness is one of the major reasons that causes traffic accidents. Thus, its early detection can help preventing accidents by warning the drivers before the unfortunate events. This study focuses on the detection of drowsiness using classification of alpha waves from EEG signals with 25 different machine learning algorithms. The results were evaluated in terms of classification accuracy and classification time. Accordingly, the Bagged Trees and Subspace k-Nearest Neighbor models gave better results in terms of classification accuracy compared to the Tree algorithm methodology, although the classification times are relatively high. Tree Algorithms approach displays optimal features as it serves as both a considerably satisfactory classification accuracy in much shorter times. The requirements in terms of accuracy and time for the recognition of drowsiness should determine the method to be applied.

Keywords: *Alpha band, Drowsiness, Electroencephalogram, Machine learning*

1. Introduction

The widespread application of artificial intelligence have brought radical changes and innovations in the automotive industry. Among the recent technologies employed, studies on ensuring safe-drive quality have been a focus of interest. Drowsiness, which can be described as feeling abnormally sleepy during the day is undoubtedly one of the most important factors that causes traffic accidents [1]. Several reasons can yield to drowsiness including fatigue, sleep disorders, long-term concentration, and monotonous work. Therefore, recognition of the drowsiness of drivers using sensors and information technology is an important topic for advanced driver-assistance systems [2]. Detection and prevention of drowsiness using wearable sensors, signal and image processing technologies emerge as a handy tool to reduce risks of traffic accidents.

The emergence of intelligent systems and the rapid development of internet of things and wearable sensor technology provide opportunities for detecting driver drowsiness. Numerous methods in this regard have been proposed in recent years [3–7]. One approach considers the collection of vehicles driving parameters, such as speed, acceleration, lane tracking errors and turning indicator usage by sensors and their evaluation [8,10]. However, external factors such as the effects of other drivers, vehicle dynamics and weather conditions also have a significant impact on determination of driver drowsiness. Another method focuses on measuring driver behaviour characteristics, such as blink rates, yawning frequency and facial expressions, using cameras and image processing techniques [11, 12]. In this method, low accuracy values can be encountered depending on the driver's personal characteristics and the amount of light in the environment. Therefore, drowsiness detection systems, in which physiological parameters such as electrocardiogram (ECG), electrooculogram (EOG), electromyogram (EMG), electroencephalogram (EEG) and photoplethysmogram (PPG) are evaluated, give more objective and accurate results [13,14]. Among them, EEG, which analyses the electrical activity of the brain, is the most common strategy as it is demonstrated to due to its high efficiency in identification of driver drowsiness [15-19].

There are many studies in the literature using EEG signals and artificial intelligence methods for drowsiness detection. Chaabene et al. [20] developed a new EEG-based drowsiness detection system based on a convolutional neural networks (CNN) model. The average classification accuracy of the system using 14 channels of EEG signals received on the Emotiv EPOC+ was found to be 90.14%. Ren et al. [21] established a two-level learning hierarchy radial basis function neural network for EEG-based driving fatigue detection to optimize the classification performance. The average accuracy value of the system in which the fatigue and alert states are determined as 92.71%. Rundo et al. [22] proposed a CNN-based drowsiness detection system, which is consisted of seven layers and was trained on EEG spectrogram images. Results with 62 volunteers showed that the system reached 100% accuracy in drowsy/wakeful discrimination.

The contribution of this study to the literature is the comparison of the most widely used machine learning algorithms to determine whether a vehicle driver is in a state of drowsiness or not with EEG signals. By using the 16 channel EEG signals in the EEG dataset published by Cattan et al. [23], the classification of drowsiness state was made with 26 different types of 8 different machine learning algorithms. These algorithms are Decision Trees, Discriminant, Regression, Naïve Bayes, Support Vector Machines (SVM), k-Nearest Neighbor (KNN), AI-based classification and

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community classification. The performance evaluation of these methods and their comparison were made based on classification accuracy and training time.

2. Material and Method

2.1. EEG Signal Analysis

EEG signals have five different frequency bands: alpha, beta, gamma, theta, and delta. These frequencies and stages are shown in Table 1. The onset of drowsiness and relaxed wakefulness are determined by alpha waves. Attenuation of alpha waves has been reported as the most valid electro-physiological marker of sleep onset period (SOP) in many sleep studies [24-26].

Table 1. EEG frequency bands and stages

Band	Frequency (Hz)	Stage
Delta	0.5 - 4	Deep sleep
Theta	4 - 8	Light sleep
Alpha	8 - 12	Eyes closed, quiet wakefulness
Beta	12 - 30	Wakeful, active

In this study, the EEG Alpha Waves dataset published by Cattan et al. [23] was used. The dataset contains EEG recordings of 20 subjects (7 female, 13 male) with a mean age of 25,8 in a simple resting-state eyes open/closed experimental protocol. EEG signals were acquired using a research grade amplifier (g.USBamp) and the EC20 cap equipped with 16 wet electrodes (EasyCap), placed according to the 10-20 international system. The locations of the electrodes were FP1, FP2, FC5, FC6, FZ, T7, CZ, T8, P7, P3, PZ, P4, P8, O1, Oz, and O2. Figure 1 shows the locations of the electrodes on the head. The reference electrode was placed on the right earlobe and the ground at the AFZ scalp location. Data collected via OpenVibe [27-29] software. No digital filter was used during data collection and sampling frequency was 512 Hz. The processing of the EEG signals is carried out in three stages: preprocessing, feature extraction/dimensionality reduction and feature classification. Preprocessing is done to prepare the raw data before classification. There are many preprocessing techniques, but the commonly used methods are Common Spatial Patterns (CSP) and Independent Component Analysis (ICA). Feature extraction is used to reduce the data count of a large dataset. It is the process of identifying a set of features or image characteristics that will most efficiently and most meaningfully represent information important for analysis and classification [30]. In Figure 3, the preparatory steps of the raw EEG data taken before the classification is shown. The raw EEG signal is preprocessed in the time domain (TD), frequency domain (FD) and time-frequency domains (TFD) using Butterworth filter, Fourier Transform and wavelet transform. Then, Delta, Theta, Alpha, Beta waves, which are defined with different frequency ranges in each area, are used to extract the relevant features. However, in this study, raw data was used to evaluate the ability of each algorithm to extract features from unfiltered data. Although this is extremely meaningful since it does not require extra software and hardware elements, it is one of the remarkable aspects of this study.

2.2. Detection and Classification of Sleepiness with EEG Data

EEG signals are evaluated by machine learning algorithms and classified. It is desired to make two separate classifications of the signals given as input to machine learning algorithms as sleep transition phase and wakefulness state. The phase of transition to sleep state is determined according to the frequency ranges of the

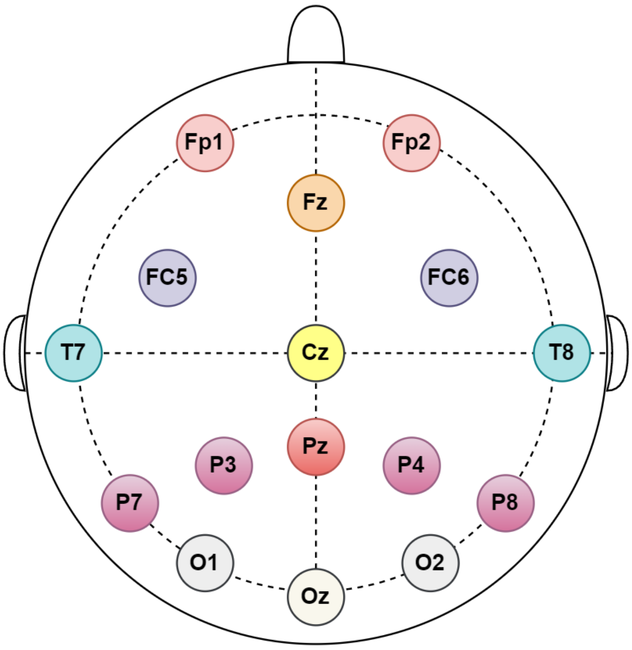

Fig. 1. EEG electrode positions placed on the scalp.

signals. The signals were classified as 1 in the transition to sleep state, that is, when alpha waves are active (8-12 Hz), and 0 in the active state of mind (12-30 Hz) without sleep state. This classification is shown in Table 2. The block diagram of the classification algorithm is shown in Figure 2. The EEG data were classified and tested with 25 different algorithms under 8 different machine learning methods. The performance of each algorithm according to classification accuracy and training time criteria under 3 different validation methods (cross validation 5, cross validation 10 and no validation) has been demonstrated. Here, cross validation (5) is a validation system and cross validation is done by dividing the data into 5 parts. Likewise, in cross validation (10), cross validation is performed by dividing the data into 10 parts. In the No Validation method, the data is not separated as test and training data, but all data is included in the training and tested.

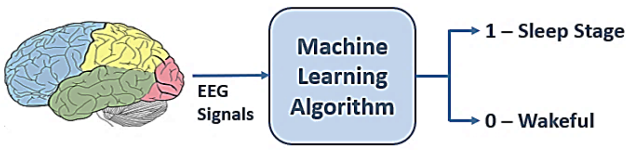

Fig. 2. Block diagram of the classification process

Table 2. EEG signal classification according to sleep stages

Classification Range	Output value	Stage
8 – 12 Hz	1	Sleep stage
12 – 30 Hz	0	Wakeful

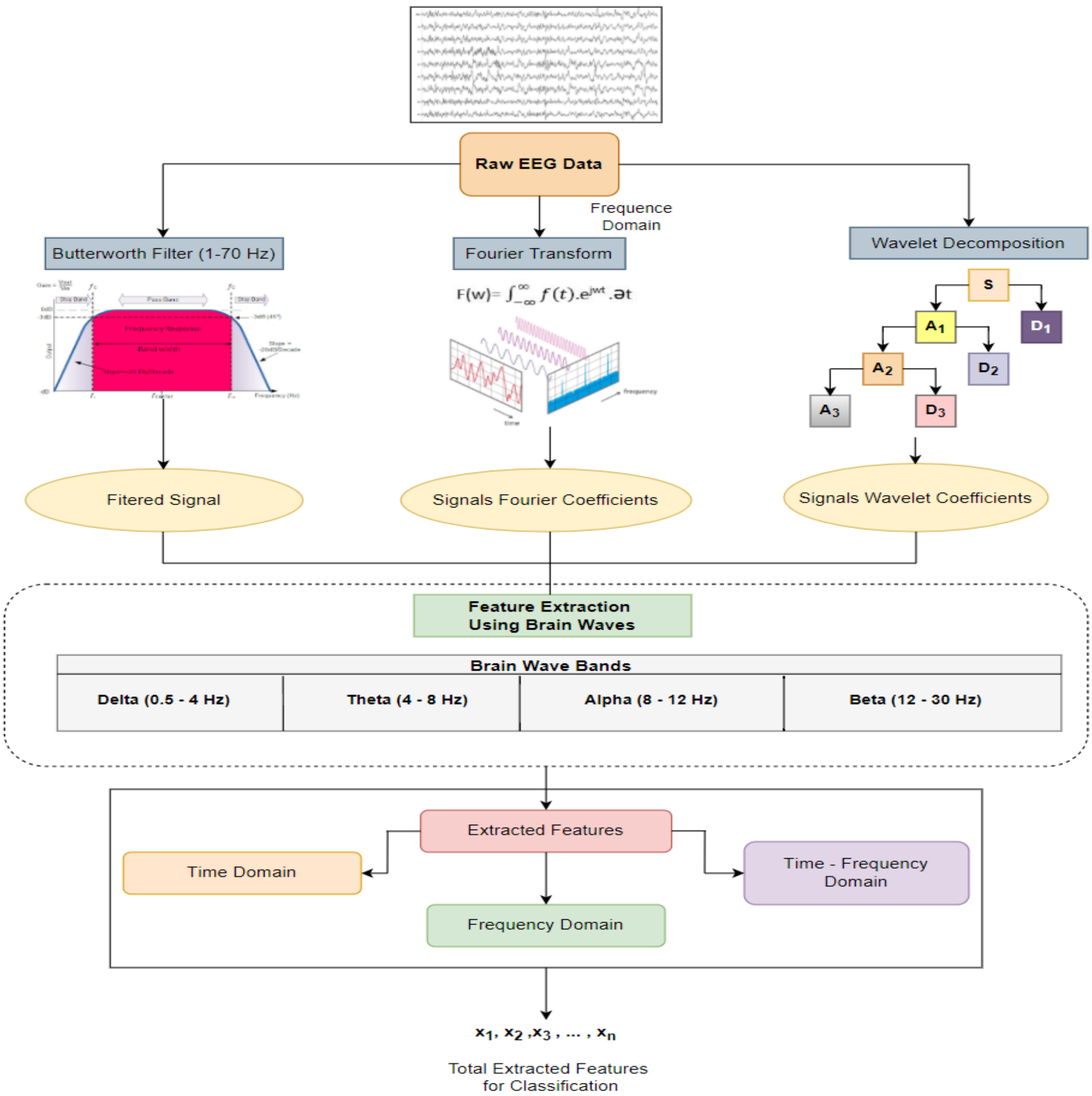

Fig. 3. Feature extraction architecture

3. Results and Discussion

The classification accuracies and training times of 25 different machine learning models are given in Table 3, and the training, validation and testing rates of the artificial intelligence classification method and the classification accuracy are given in Table 4. Different training methods were used for the machine learning models in Table 3. In the machine learning model in Table 5, 65% of the data was reserved for training, 20% for validation and 15% for testing, and an accuracy rate of 98.1% was obtained. In this study, no validation and cross validation were used as classification techniques. In the no validation technique, the data does not separate as training and test data, it learns all of them and then classifies them by testing them all again. In some classifications made using no validation in the study, a high accuracy rate of 100% was obtained. In this case, excessive learning may have occurred because the data in the system is not separated as training and testing. For this reason, the results obtained using cross validation are given in the table and compared. Cross validation is an important factor preventing excessive learning. It's also a smart technique that helps us make better use of data. In this method, the data is randomly selected and divided into k subsets. A subset is used to validate the model trained using the remaining subsets. This process is repeated k times, with each subset used exactly once for each subset validation. This method is one of the most popular techniques, but it can take a long time to execute because the model has to be trained repeatedly. The accuracy rates obtained by choosing the k value as 5 and 10 in cross validation are given in Table 4. A low accuracy rate was obtained in the Logistic Regression model cross validation (5) and (10) validation types included in the Regression algorithm in Table 4.

Coarse KNN, which is included in the KNN algorithm, and Boosted Trees, RUSBoosted Trees models, which are included in the Ensemble algorithm, gave low accuracy in all three training types, the training times were also long. Therefore, it is not appropriate to use these machine learning algorithms for drowsiness detection with EEG signals. In the Fine Tree, Medium Tree and Coarse Tree models included in the Tree Algorithm, the same accuracy rate has emerged for each verification type. These classification accuracy rates are 96.2%, 98.1% and 100%, respectively. The training times of these classification models are also shorter compared to other models. In addition, it is seen that the artificial neural network-based classification model has a classification accuracy rate of 98.1%.

Table 3. Machine learning algorithms examined in this study

Decision Trees	***Discriminant***	***Regression***	***Naïve Bayes***	***SVM***	***KNN***	***Ensemble***	***AI***
Fine Tree	Quadratic Discriminant	Logistic Regression	Gaussian Naïve Bayes	Linear SVM	Fine KNN	Boosted Trees	AI Classification
Medium Tree			Kernel Naïve Bayes	Quadratic SVM	Medium KNN	Bagged Trees	
Coarse Tree				Cubic SVM	Coarse KNN	Subspace KNN	
				Fine Gaussian SVM	Cosine KNN	Subspace Discriminant	
				Medium Gaussian SVM	Cubic KNN	RUS Boosted Trees	
				Coarse Gaussian SVM	Weighted KNN		

Table 4. Classification accuracy and training time according to machine learning algorithms

Algorithm	***Model Type***	***Cross Validation (5)***		***Cross Validation (10)***		***No Validation***	
		Classification Accuracy (%)	***Training Time (sec)***	***Classification Accuracy (%)***	***Training Time (sec)***	***Classification Accuracy (%)***	***Training Time (sec)***
Tree	**Fine Tree**	96,2	64.913	98,1	113.92	100	15.418
	Medium Tree	96,2	224.18	98,1	119.73	100	17.407
	Coarse Tree	96,2	61.115	98,1	122.59	100	17.121
Discriminant	**Linear Discriminant**	80,8	79.372	78,8	134.55	100	25.184
	Quadratic Discriminant	-	-	-	-	-	-
Regression	**Logistic Regression**	57,7	433.67	44,2	719.73	100	91.802
Naïve Bayes	**Gaussian Naïve Bayes**	98,1	194.58	96,2	330.53	96,2	48.13
	Kernel Naïve Bayes	98,1	584.48	96,2	991.9	96,2	114.19
SVM	**Linear SVM**	96,2	123.97	96,2	241.81	96,2	31.539
	Quadratic SVM	96,2	139.1	96,2	233.56	96,2	32.302
	Cubic SVM	98,1	183.3	96,2	254.22	96,2	33.972
	Fine Gaussian SVM	96,2	193.98	98,1	349.88	98,1	44.21
	Medium Gauss SVM	96,2	239.13	96,2	352.58	96,2	45.461
	Coarse Gauss SVM	86,5	251.99	84,6	365.77	86,5	47.225
KNN	**Fine KNN**	98,1	251.4	100	448.42	100	57.429
	Medium KNN	98,1	426	96,2	456.56	96,2	58.614
	Coarse KNN	59,6	298.78	59,6	469.75	59,6	57.897
	Cosine KNN	96,2	316.39	96,2	484.86	96,2	58.924
	Cubic KNN	98,1	309.43	96,2	562.46	96,2	71.169
	Weighted KNN	96,2	354.38	98,1	572.02	100	69.92
Ensemble	**Boosted Trees**	59,6	359.54	59,6	560.22	59,6	67.058
	Bagged Trees	98,1	366.94	100	584.64	100	69.18
	Subspace Discriminant	82,7	414.19	80,8	656.12	98,1	78.844
	Subspace KNN	98,1	414.26	100	652.28	100	79.787
	RUS Boosted Trees	59,6	417.53	59,6	649.23	59,6	75.734

The training, validation, testing, and the total confusion matrices are shown in Figure 4. Here, 97.1%, 100%, 100% and 98.1% classification accuracy rates were obtained, respectively. Here, 12 of the data allocated for training represent the wakefulness phase, and 12 data of them were predicted correctly. The remaining 22 data represent the transition to the sleep stage. Of these 22 data, 21 data were predicted correctly and 1 was predicted incorrectly. Of the data allocated for the validation confusion matrix, 3 represent the wakefulness stage and 3 were correctly predicted. The remaining 7 data represents the transition to the sleep stage. All of these data have been estimated correctly. In addition, 5 of the data allocated for the Test represent the waking stage and all were correctly estimated. The remaining 3 data represent the transition to the sleep stage. All of these data have been estimated correctly. And finally, all the data, namely 52 data; 20 of them represent the wakefulness stage and all have been predicted correctly. The remaining 32 data represent the transition to the sleep stage. In these data, 31 of them were predicted correctly and 1 of them was predicted incorrectly. Figure 5 shows the error histogram. This figure represents the error between actual output and predicted output of the processing data. The ideal line for minimum errors during the training, validation, and testing stages displays the efficiency of the ANN model and Figure 6 shows the best validation performance graph. Here, the best validation performance was realized in 74 iterations and the best validation value was found to be 0.06223. In Figure 7, the Receiver operating characteristic (ROC) curve is shown separately as training, validation and test. Here it is seen that the curves are linear. According to these results, the classification appears to be good, but these data are not sufficient to prove that the classification is good.

Table 5. ANN classification accuracy

Training (%)	**Validation (%)**	**Testing (%)**	**Accuracy (%)**
65	20	15	98,1

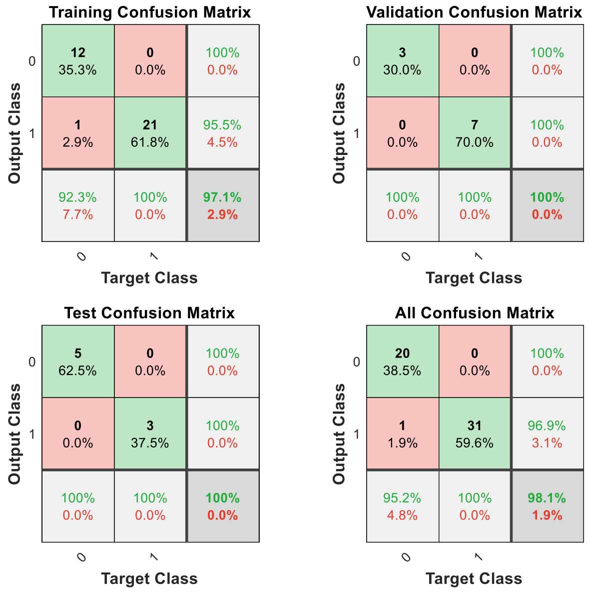

Fig. 4. ANN confusion matrices

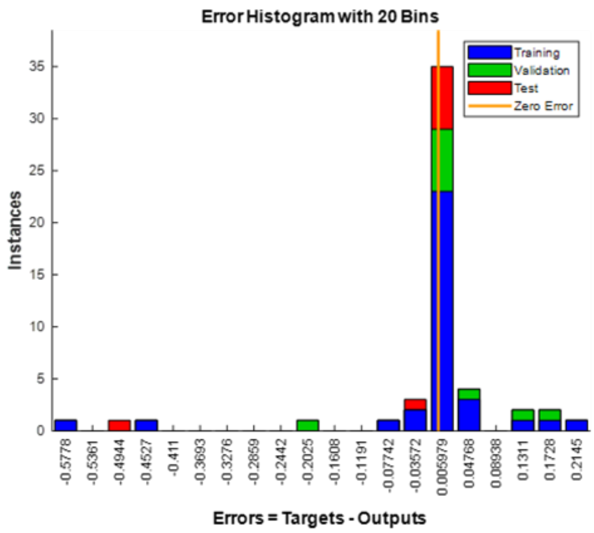

Fig. 5. Error histogram graph

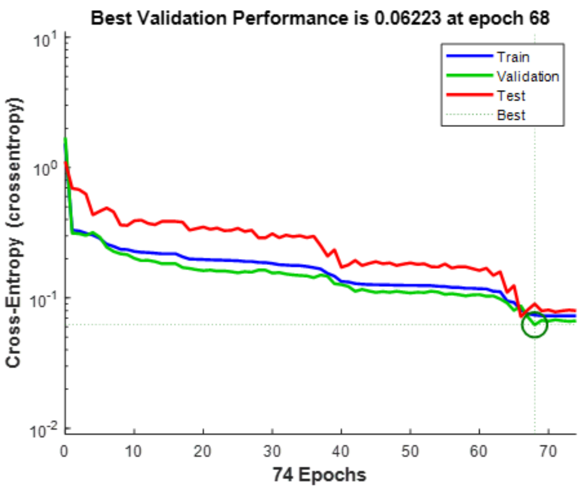

Fig. 6. Best validation performance

Apart from these results, the efficiency of the performance of machine learning is also determined by using data such as true positive rate, false positive rate, true negative rate and false negative rate. These data are used for sensitivity and specificity, to describe the clinical diagnostic test, and to estimate how well the test is. The terms TP, TN, FP and FN are used for accuracy, sensitivity and specificity. These can be defined as; TP, number of people predicted as positive and actually positive. TN, the number of people who were negatively predicted and actually negative. FP, number of people predicted positive and actually negative. FN, number of people predicted negatively and actually positive [31,32]. In Figure 8, the terms TP, TN, FP and FN are shown on the confusion matrices. In addition, in Figure 9, the terms TP, TN, FP and FN are visualized for better understanding. Here, the stars in the TN cluster are negatively predicted and actually negative data. Stars within the FP cluster are data that are predicted positively but actually negative. The circles inside the FN cluster are data that are predicted negatively but are actually positive. The circles inside the TP set are positively predicted and actually positive data.

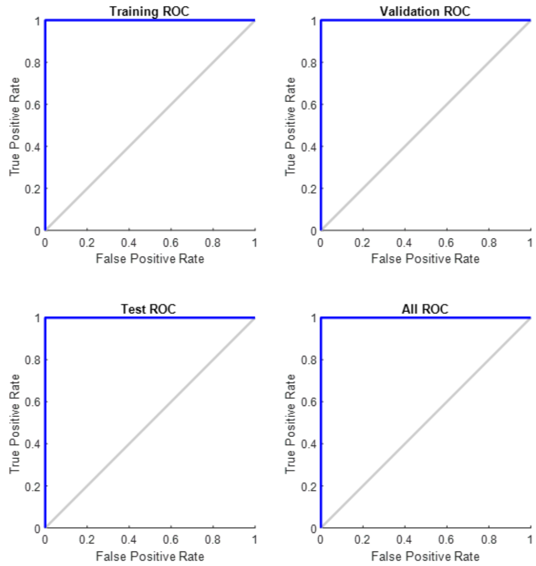

Fig. 7. ROC curves

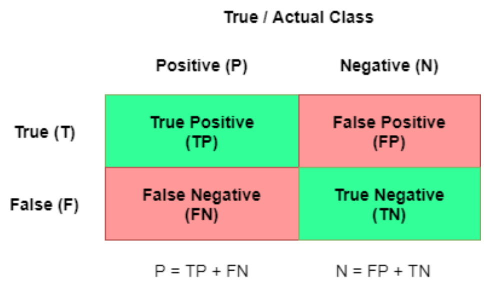

Fig. 8. Confusion matrices

In classification, prediction accuracy is the ratio of correctly classified data to all data in the cluster, as seen in Eq. (1).

$$Accuracy = \frac{\mathrm{TP+TN}}{\mathrm{P+N}} = \frac{\mathrm{TP+TN}}{\mathrm{TP+TN+FP+FN}} \quad (1)$$

Classification recall and sensitivity, on the other hand, calculates the probability that the positive data will also be positive in the prediction, and it is as seen in Eq. (2).

$$Recall, Sensitivity = \frac{\mathrm{TP}}{\mathrm{P}} = \frac{\mathrm{TP}}{\mathrm{TP+FN}} \quad (2)$$

Specificity in classification is the ratio of predicted negative data to actually negative data, as seen in Eq. (3).

$$Specificity = \frac{TN}{N} = \frac{TN}{TN+FP} \tag{3}$$

Precision in classification gives the ratio of positively predicted data to the total number of positively data and is as shown in Eq. (4).

$$Precision = \frac{TP}{TP+FP} \tag{4}$$

F1 in classification is the Harmonic mean of recall and precision, as seen in Eq. (5).

$$F1 = \frac{2TP}{2TP+FP+FN} \tag{5}$$

Accuracy, Recall, Sensitivity, Specificity, Precision, F1 values are calculated according to each of the machine learning algorithms method in Table 4 and shown in Table 6. Considering the data obtained in Table 6, although the specificity value of the Logistic regression, Coarse KNN, Boosted Trees and RUS boosted algorithms is 100%, the values of accuracy, recall/sensitivity, precision, F1 were found to be 59%, 0%, 0%, respectively. The data here is obtained for Cross Validation (5). In cross validation (10), only the accuracy, recall/sensitivity, specificity, precision and F1 values of the logistic regression method were different from cross validation (5). In the No validation method, the accuracy, recall/sensitivity, specificity, precision and F1 values of the Logistic regression method were 100%, which is quite good. However, good results in no validation do not mean that this method is suitable for this study because cross validation (5) and (10) give poor results. As in cross validation (5) and (10) of Course KNN, Boosted Trees and RUS boosted algorithms, accuracy, recall/sensitivity, specificity, precision and F1 values were found to be 59%, 0%, 100%, 0%, 0%, respectively. It has also been confirmed by these data that it is not possible to use these algorithms. The same accuracy, recall/sensitivity, specificity, precision and F1 values were obtained for each verification type in the Thin Tree, Medium Tree and Coarse Tree models in the Tree Algorithm. These are 96%, 100%, 93%, 90% and 95%, respectively, in the cross validation (5). In cross validation (10), it is 98%, 100%, 96%, 95% and 97% respectively. In the no validation, all values were obtained as 100% and according to these values, it is proven that the tree algorithms are suitable for this study.

As seen in the results, Table 4 and Table 6 confirm each other. In the ANN Classification method, accuracy, recall/sensitivity, specificity, precision and F1 values were calculated as 98%, 95%, 100%, 100%, 97%, respectively. These results show that the performance of the classification is high. In addition, these values are shown in Table 7. As a result, the most appropriate method should be chosen by the developers considering the minimum accuracy rate and the maximum time required for classification that must be met in the system to be designed for drowsiness detection.

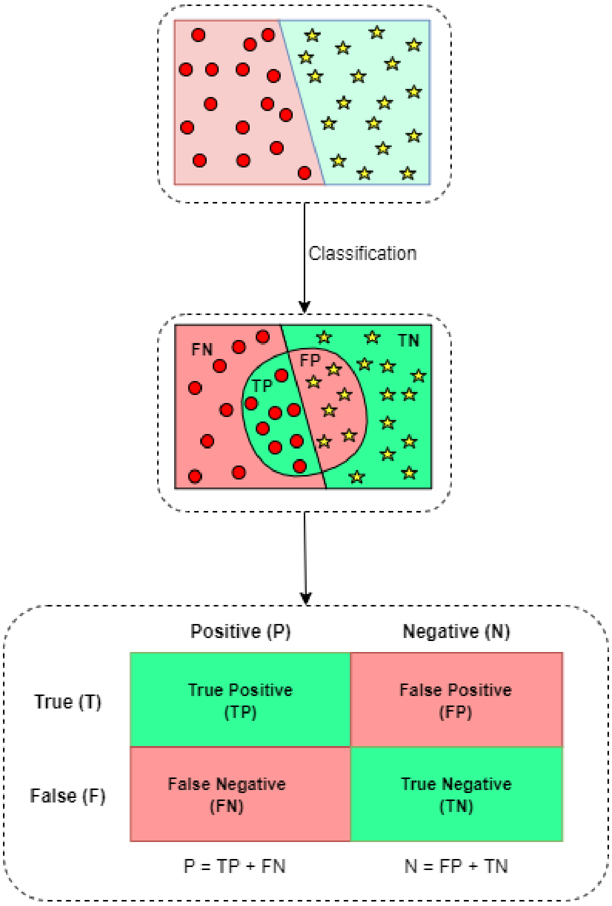

Fig. 9. The process of forming the confusion matrix

Table 6. Change of accuracy, recall/sensitivity, specificity, precision and F1 values according to classification algorithms

Algorithm	*Model Type*	*Cross Validation (k=5)*					*Cross Validation (k=10)*					*No Validation*				
		Accuracy	*Sensitivity*	*Specificity*	*Precision*	*F1*	*Accuracy*	*Sensitivity*	*Specificity*	*Precision*	*F1*	*Accuracy*	*Sensitivity*	*Specificity*	*Precision*	*F1*
Tree	**Fine Tree**	0.96	1	0.93	0.90	0.95	0.98	1	0.96	0.95	0.97	1	1	1	1	1
	Medium Tree	0.96	1	0.93	0.90	0.95	0.98	1	0.96	0.95	0.97	1	1	1	1	1
	Coarse Tree	0.96	1	0.93	0.90	0.95	0.98	1	0.96	0.95	0.97	1	1	1	1	1
Discriminant	**Linear Discriminant**	0.80	0.76	0.83	0.76	0.76	0.78	0.77	0.61	0.66	0.71	1	1	1	1	1
	Quadratic Discriminant	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
Regression	**Logistic Regression**	0.59	0	1	0	0	0.44	0.34	0.53	0.71	0.50	1	1	1	1	1

Naïve Bayes	**Gaussian Naïve Bayes**	0.98	1	0.96	0.95	0.97	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95
	Kernel Naïve Bayes	0.98	1	0.96	0.95	0.97	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95
SVM	**Linear SVM**	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95
	Quadratic SVM	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95
	Cubic SVM	0.98	1	0.96	0.95	0.97	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95
	Fine Gaussian SVM	0.96	1	0.93	0.90	0.95	0.98	1	0.96	0.95	0.97	0.98	1	0.96	0.95	0.97
	Medium Gauss SVM	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.97	0.96	1	0.93	0.90	0.95
	Coarse Gauss SVM	0.86	1	0.81	0.66	0.80	0.84	0.88	0.82	0.71	0.73	0.86	1	0.81	0.66	0.80
KNN	**Fine KNN**	0.98	1	0.96	0.95	0.97	1	1	1	1	1	1	1	1	1	1
	Medium KNN	0.98	1	0.96	0.95	0.97	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95
	Coarse KNN	0.59	0	1	0	0	0.59	0	1	0	0	0.59	0	1	0	0
	Cosine KNN	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95
	Cubic KNN	0.98	1	0.96	0.95	0.97	0.96	1	0.93	0.90	0.95	0.96	1	0.93	0.90	0.95
	Weighted KNN	0.96	1	0.93	0.90	0.95	0.98	1	0.96	0.95	0.97	1	1	1	1	1
Ensemble	**Boosted Trees**	0.59	0	1	0	0	0.59	0	1	0	0	0.59	0	1	0	0
	Bagged Trees	0.98	1	0.96	0.95	0.97	1	1	1	1	1	1	1	1	1	1
	Subspace Discriminant	0.82	1	0.77	0.57	0.72	0.80	0.76	0.83	0.76	0.76	0.98	1	0.96	0.95	0.97
	Subspace KNN	0.98	1	0.96	0.95	0.97	1	1	1	1	1	1	1	1	1	1
	RUS Boosted Trees	0.59	0	1	0	0	0.59	0	1	0	0	0.59	0	1	0	0

Table 7. Variation of accuracy, recall/sensitivity, specificity, precision and F1 values according to ANN classification algorithm

Algorithm	***Accuracy***	***Sensitivity***	***Specificity***	***Precision***	***F1***
ANN Classification	0.98	0.95	1	1	0.97

4. Conclusion

In conclusion, performance analysis on 25 models of 8 different machine learning algorithms using EEG signals in a data set collected from 20 different subjects was studied for the detection of drowsiness. Thus-obtained performance data were compared by means of classification accuracy and classification time. Accordingly, the Tree Algorithm showed the optimal display in terms of both accuracy and classification time in 3 different validation types. The reasons for the good performance of tree algorithms can be attributed to its simple classification logic, rapidity, less data cleaning required after created, no necessity of data preprocessing. In addition, since the missing values in the data will not significantly affect the formation of the decision tree unlike other classification algorithms, the methodology serves high performance. It should also be noted that the Bagged Trees and Subspace KNN models, which are included in the Ensemble algorithm, gave better results in terms of classification accuracy compared to the Tree Algorithms despite their long classification time. Therefore, the priorities in determining the most appropriate technique should be selected according to the expectations and the area of practice.

Performance tests run by creating a hybrid structure that includes other measurements (driving parameters, facial expressions, other physiological signals etc.) used in the detection of drowsiness is also an interesting topic to increase the efficiency of the artificial intelligence in safety driving. Studies in this line are now in progress.

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