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ENSEMBLE-BASED MACHINE LEARNING MODELS FOR VEHICLE DRIVERS' FATIGUE STATE DETECTION UTILIZING EEG SIGNALS

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Abstract. *Currently, there is a great extent of academic research focused on evaluating fatigue among drivers due to its growing recognition as a major contributor to vehicle tragedies. Combining advanced features and machine learning techniques, signals from the electroencephalogram (EEG) can be analyzed to efficiently detect fatigue in the shortest possible time. This study presents an innovative approach to detect driver fatigue states utilizing ensemble-based machine learning techniques from EEG signals. Two ensemble models (Ensemble-based RUSBoosted Decision Trees and Ensemble-based Random Subspace Discriminant) were applied and compared. The study utilized an online EEG dataset of 12 individuals, with data collected during normal and fatigued driving conditions and Fast Fourier Transform was applied for feature extraction. The Ensemble-based RUSBoosted Decision Trees model achieved superior performance with 98.53% classification accuracy, compared to 83.13% for the Random Subspace Discriminant model. Multiple performance metrics were used for evaluation model performance. Finally, the proposed Ensemble-based RUSBoosted Decision Trees model outperformed Ensemble-based Random Subspace Discriminant model and existing conventional methods for fatigue state detection. This research contributes to the development of more accurate and reliable fatigue detection systems, which could potentially improve road safety by identifying fatigued drivers in real-time.*

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Key words: *Fatigue state detection, EEG signal, Ensemble based classifier, RUSBoosted Decision Tree, Random Subspace Discriminant*

1. INTRODUCTION

The excessive frequency of highways catastrophes has led to socioeconomic problems that endanger both human beings and their belongings. The WHO mentions that road accidents cause more than 1,300,000 deaths worldwide each year, and millions additional individuals are injured or left permanently disabled [1]. Furthermore, there has been a noticeable rise in the frequency of vehicle crashes lately, which has prompted communities and governments to give this problem a lot of emphasis [2]. Road accidents are so prevalent that it is critical to focus resources on international projects that try mitigating them. Studies previously conducted indicate that between twenty percent and thirty percent of vehicular crashes are caused by fatigued driving. Consequently, this emphasizes how important it is that tired driving be considered a preliminary aspect in highway mishaps [2]. Fatigued drivers are more likely to make careless mistakes, have trouble focusing, and have slower reaction times, all of which raise the risk of a collision between two vehicles [3]. However, due to adrenaline ability to conceal fatigue after an occurrence, people who were involved in accidents involving fatigue circumstances might not be aware of their pre-accident emotions or the momentary loss of awareness [4].

It is currently being worked on using three main methods to create a strong and effective fatigue recognition system. Specifically, the operations in question can be broken down into three main categories: physical strategies, behavioral strategies, and vehicle strategies [5]. Figure 1 offers a detailed summary of main elements used in the three principal approaches of fatigue systems for identification.

Initially, physical-based solutions involve utilizing external equipment connected to the driver's head, hands, chest, and fingers to gather numerous physiological data. The driver's situation can be assessed by examining different information, such as electrical neural activity, blood pressure, variation in heart rate, inhalation rates, body temperatures, pulmonary rates, and total heartbeats [6]. Behavioral-based solutions utilize visual processing and automated vision methods to analyze pictures and videoclips monitored from the driver of the vehicle. This method involves analyzing key indicators displayed by the driver to determine their degree of alertness, tiredness, or drowsiness. Extracting crucial insights depends on observing multiple factors such as absence of eyesight, napping via mouth motions, pupil closures, facial features, and head movement [7]. In final analysis, vehicle-based techniques are utilized to construct a built-in system for the goal of evaluating drivers' weariness. These methodologies make use of mechanisms and indications that are integrated within the vehicle's wheels of an automobile. The research employs computerized technology to assess driver behavior through the continuous monitoring of various factors including steering wheel angle, speed, hand activity, lane deviation, and position of the steering [8].

Researchers have recently started using electroencephalography (EEG) to detect driving fatigue. The EEG has specific features that make it potentially useful for detecting driving fatigue. These factors consist of its ability to move, accuracy in timing, and exceptional sensitivity to the state of the nervous system. EEG is used as a diagnostic method for evaluating neuronal activities on the surface of the scalp to examine if the person is feeling fatigued [9]. However, using multiple-electrode methods to collect EEG data can be affected by external factors. Therefore, it is essential to extricate relevant information from mixed brain data to accurately detect weariness while operating a vehicle [10]. Recordings from multiple EEG channels provide thorough information of neural events. Particular channel may comprise extraneous and irrelevant information [11]. Choosing the relevant channels is challenging to optimize the effectuality of models that depend on electroencephalography (EEG) [11]. Developing a high-quality single classifier might be crucial as a consequence of the unpredictable nature of brain data and limited size of the training dataset. As a result, each classifier may show less than ideal performance or lack reliability.

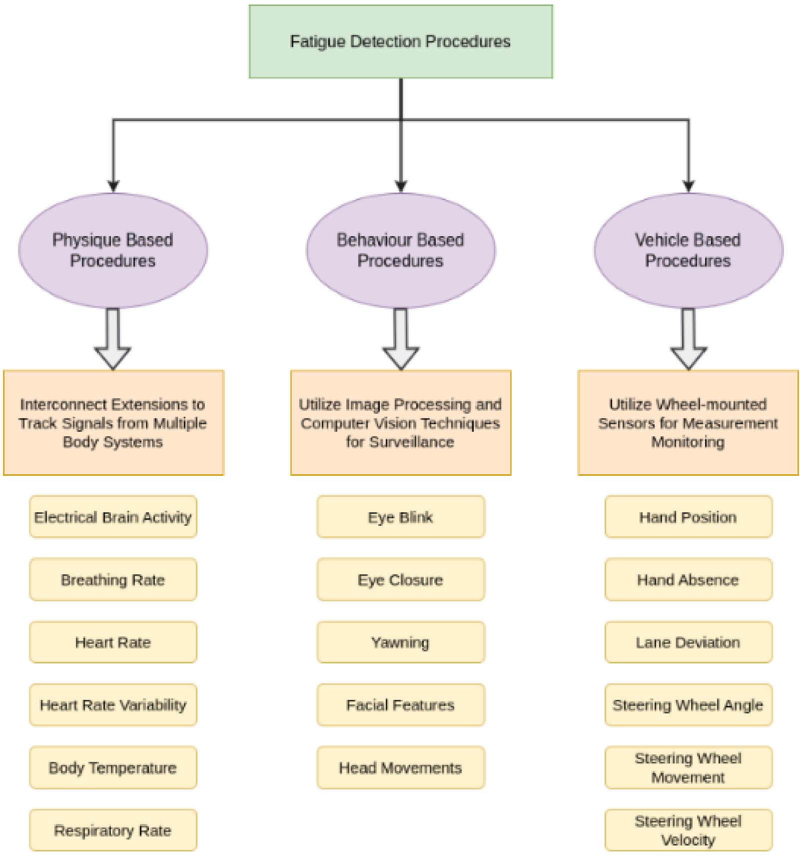

Fig. 1 Preliminary ways of fatigue detection

This is why, this research study introduces a method of categorization for identifying driver fatigue in an EEG-based system, using ensemble learning methods. This initiative primarily aims to enhance the performance of identifying driver fatigue states while simultaneously decreasing computational intricacies. This study has investigated two ensemble-based machine learning models and proposed the best model in terms of detecting fatigue states utilizing EEG signals.

The remainder of the article is organized as follows: A comprehensive literature review is provided in section 2. Complete methodology of this study is explained in section 3, which includes data description, Fast Fourier Transformation, ensemble-based machine learning techniques and assessment of performance. A comprehensive experimental result is explained in section 4. This section 5 discusses the proposed model's comparison with related studies and the significant advantages of our proposed approach over the earlier studies. Section 6 concludes the outcome of the presented study.

2. LITERATURE REVIEW

Diversified approaches have been put forth to determine the underlying mechanisms of fatigue via EEG data. In [12], a straightforward and efficient method for identifying drivers' fatigue in real-time environments is presented. The suggested approach results in a 1.8-second latency and an identification rate of 92.7%. An advanced technique was created to detect fatigue among drivers by analyzing EEG data in [13]. The framework includes a characteristic synthesizing network which combines textural attributes and a combination of features selecting mechanism to enhance the identification efficiency. The suggested approach identified fatigue with 97.29% exactness using EEG data. Zhao et al. [14] classified fatigue conditions in driving circumstances using a Support Vector Machine (SVM) using KPCA, achieving a success rate of 81.64%. Another experiment that was conducted with 43 good-health people and utilized Bayesian Neural Networks as the classification model and autoregressive modeling as the technique for extracting features in order to identify fatigue, achieved an accuracy rate of 88.2% [15]. Two studies that analyzed a model based on CNN and EEG recordings to find signs of exhaustion were 85.42% and 75.87% accurate, respectively [16 – 17]. A recent study utilized a single classifier Decision Tree to detect fatigue states from EEG signals, which gave an accuracy of 88.6% [18]. In the context of the real world, the main problem with these models is that they are not accurate to a great extent.

A study assessed the effectiveness of numerous linear as well as nonlinear single classification methods, such as Decision Tree, Fisher Discriminant, Support Vector Machine, k-Nearest Neighbors, Neural Network, and Hidden Markov Model, in the detection of driver fatigue via electroencephalography signal [19]. Fu et al. presented tiredness detection approach based on Hidden Markov Model (HMM) [20]. Some research has shown that ensemble-based classifiers outperform single classifiers [21 - 23]; minimal research has been done on using ensemble-based algorithms that utilize electroencephalogram (EEG) signals to detect weariness in vehicle drivers. Hassan and Bhuiyan [21] developed a technique that utilizes Entire Ensemble Experimental Mode Decomposition in conjunction with Adjustable Noise and Bootstrap Combining (Bagging) to structure sleep patterns from EEG signals. The study's results showed that the suggested methodology had more accuracy than current state-of-the-art procedures. Moreover, an investigation was carried out in [22], presented an innovative approach for identifying seizures using linear programming Boosting. Their research results showed that this method functioned better than earlier attempts. Chatterjee et al. [24] produced a method to classify myocardial infarct data by integrating Support Vector Machines, Naive Bayes, and k-Nearest Neighbors algorithms. Various collective learning models like loggitboost, AdaBoost, and bagging were used.

However, the use of ensemble-based categorization for identifying fatigue stages through EEG signals is a relatively recent idea.

3. METHODOLOGY

This study introduces an innovative automated fatigue detection technique, highlighting the significance of roadway security and saving lives of those on the road. Previous research studies have used different approaches to identify driver fatigue states. This study compared two ensemble-based classifiers, Ensemble-based RUSBoosted Decision Trees and Ensemble-based Random Subspace Discriminant, for identifying fatigue conditions. During the course of our evaluation, we compared the performance of these models to that of other works that were already in existence. We found that the models that we suggested achieved a higher level of accuracy when it came to identifying fatigue states in drivers. The models can employ several tactics to achieve optimum efficiency in a short amount of time with minimal complexities. The study procedure is illustrated in Figure 2.

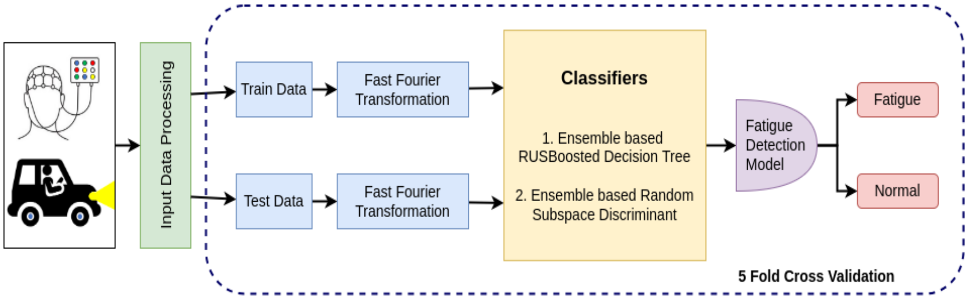

Fig. 2 Methodological representation of the current study

Technical computing and data analysis in the study were conducted using MATLAB R2021a, which was selected due to its outstanding effectiveness and reliability. The present study was conducted utilizing a PC equipped with an Intel(R) Core(TM) i7-8650U processor, 16 GB RAM, and Windows 11 OS.

3.1. Data Description

We used an online electroencephalogram (EEG) dataset with 12 individuals for our study [25], which is widely used for fatigue state detection studies. The dataset description is available in reference [26]. This data set was gathered in two separate stages. Initially, in 1200 seconds driven event, the final 300 seconds of EEG signals were collected and identified as normal. Furthermore, when participants drove continuously for 2400 to 6000 seconds, a questionnaire was used to evaluate their level of fatigue while driving. In addition, two measuring scales were also used [27 – 28]. The final 300 seconds of EEG waves were collected and recognized as representing levels of weariness. The data were fine-tuned relative to A1 and A2 mastoids that were electrically associated. The data was captured at 1000Hz sampling rate using a 32-channels electrode device. The device contained activate of 30 channels and 2 channels as reference.

After the EEG readings were gathered, Neuroscan Scan- 4.3 version software was employed to prepare the data [29]. The raw signals were filtered with a 50Hz notch filter and a 0.15Hz to 45Hz bandpass filter that worked to get rid of noise. After that, the electroencephalogram (EEG) data that was collected from 32 electrodes for a period of five minutes was divided into epoch of each second, eventually a total of around 300 epochs. In a study with twelve individuals, the normal states produced 3600 datapoints, while exhausted states produced the same number of points.

3.2. Fast Fourier Transformation

The Fast Fourier Transform (FFT) is a computationally efficient algorithm used to compute the Discrete Fourier Transform (DFT). The algorithm decomposes the Fourier transform of an order of n points into smaller complications, resulting in a decrease in computing difficulty. Equation 1 demonstrates the computation of the Discrete Fourier Transform (DFT), where X_k represents the Fourier transform of a given discrete sequences x_n with a length of n.

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{i2\pi kn}{N}} \tag{1}$$

3.3. Ensemble-based Classification Techniques

Presently, ensemble methods and hybrid systems constitute a significant area of investigation within the domain of Artificial Intelligence. Ensemble methods utilize many learning algorithms to improve performance [30]. Furthermore, there have been proposals to use Model Trees that are regressive models structured in trees format. These methods link the leaves with different linear regression functions, allowing for the calculation of numerical values [31].

Ensemble-based classification methods make it easier to combine the forecasting power of several different classifiers, like decision tree or ANN. Because they are unstable and can be computed quickly, decision trees are great for groups [32]. It is because decision trees are particularly change-sensitive in the input data that they become unstable. This can cause them to make completely different trees. Using these things as a group helps to solve this problem. In ensemble learning, many classifiers are used. Each one is given a weight, and then they are all put together to make a classifier that is better than the sum of its parts. The method is like the idea of wisdom of the crowd [33] because it takes into account which people are more likely to look for or think about different points of view before making big decisions.

Three methods are usually used to make ensemble-based decision trees: random subspace, boosting, and bagging, as explained within comparative inspection in [34]. A lot of people agree that boosting is the best way to choose model-guided cases. Boosting is a common method for making a bad learner, like a decision tree, work better by changing the weights given to training cases repeatedly. The method involves running a weak learner on a lot of different types of scattered datasets for training. After that, one strong classifying framework was created to combine the classification models of the learners that weren't doing so well, making the system more accurate than any single tree could be. The AdaBoost algorithm, which is also called Adaptive Boosting, was first suggested in [35]. In order to improve the efficiency of the basic boosting method, it is a popular ensemble method for classifying binary data. This advancement can be achieved by a repetition technique that emphasizes identifying complex patterns.

3.3.1. Ensemble-based RUSBoosted Decision Tree

This method tries to get more accurate by using more than one model, which is more accurate than any one model alone. An ensemble inducer may include different conventional classification methods, and with various forms of conventional models. The study utilized decision trees as the basic learner and RUSBoost as the ensemble methodology. The current method utilizes the RUSBoosted technique along with decision trees to create a system called the Ensemble-based RUSBoosted Decision Trees. The maximum quantity of clusters allowed in this applied system is 20. There are 30 learners with a learning rate of 0.1. RUSBoost is a kind of hybrid algorithm which merges Boosting technique and under sampling. Following the method outlined in [36], N subsets of the dataset are created, and the preliminary weight of the overall weight is divided by N at random to determine every subset. Regularization is applied to update the weights after training the sub-dataset. An iterative process applies a classification for training which meets specified limitation on the subset of data. The optimal method is eventually chosen.

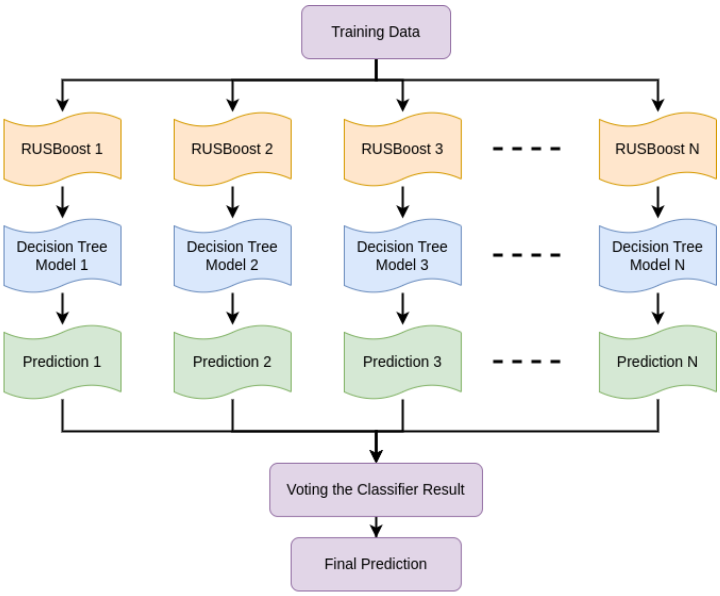

Fig. 3 Architecture of Ensemble-based RUSBoosted Decision Tree

Figure 3 illustrates the entire method. Within the Decision Tree model, an initial design is chosen as the testing samples, and considering the pertinent characteristics is employed as inputs. The technique of Ensemble-based RUSBoosted Decision Tree comprises routing every information set into the designated RUSBoost model. When RUSBoost technique is selected, a brand-new Ensemble-based Decision Tree model is generated. The trees determined by RUSBoost are aggregated, and the class membership of testing samples are concluded utilizing majority vote. The identical training sample is again introduced into this ensemble while it is limited to many chosen RUSBoost inside the center area of adjoining Decision Tree.

3.3.2. Ensemble-based Random Subspace Discriminant Analysis

The subspace methods are crucial, especially in the linear discriminant analysis (LDA) framework, used to find a discriminant subspace with lower dimensions [37 – 39]. Several studies have investigated how different sub-spacing, weighting, and resampling methods affect the classification performance in ensemble technique [40 – 42]. The random subspace approach to apply random subspace features configurations is utilized in [43]. Each learner was built by randomly sampling features to decrease mistake rates [44]. One limitation of the random subspace technique is the random preference of qualities within subspace, that may result in insufficient discriminating ability in some cases. In this case, the overall group decision shows less than optimal performance. To address this constraint of the random subspace method, the majority voting (MV) methodology is utilized. Typically, single classifier method in an ensemble uses solely a small attainable features subset in the features space. Additionally, it is important to highlight that every classifier has the potential to categorize any newly acquired or unfamiliar example. The MV method utilizes distinct classifications for providing particular projections with relation to the class of a novel or unusual situation. The finalized classification of the instance is evaluated through a majority-vote relying on the prediction.

The creation techniques of the ensemble-based random subspace technique entail utilizing an altered feature space to generate groups of learners. This sets them apart from the ensemble-based techniques of bagging and boosting [45]. Typically, creating individual classifiers entails using a certain set of attributes. The classification models' output is combined utilizing the MV strategy in the proposed method. Sorting unlabeled cases is done using the MV method. This method depends on an ensemble of classification model to identify classes that receive most votes for every occurrence. Equations 2 and 3 depict the mathematical description of the MV.

$$\mathrm{Class(a)} = \underset{ci \in dom(y)}{\arg\max} \left(\sum_{\mathrm{v}} \mathrm{h}(\mathrm{y_v(a)}, \mathrm{c_i}) \right) \tag{2}$$

Where $h(y_v(a), c_i)$ denotes an indication expression, and $y_v(a)$ classifies the classifier "v," using the preceding equation of h:

$$\mathrm{h}(\mathrm{y_v(a)}, \mathrm{c_i}) = \begin{cases} 1 & \mathrm{y=c} \\ 0 & \mathrm{y \neq c} \end{cases} \tag{3}$$

3.4. Assessment of Performance

Several indicators, including model accuracy, sensitivity, specificity, precision, F1-score, recall, and AUC, MCC are utilized in order to evaluate the results for both models. The stats are listed as follows:

$$Accuracy = \frac{TP + TN}{TP + FN + TN + FP} \times 100\% \tag{4}$$

$$Sensitivity = \frac{TP}{TP + FN} \times 100\% \tag{5}$$

$$Specificity = \frac{TN}{TN + FP} \times 100\% \tag{6}$$

$$Precision = \frac{TP}{TP + FP} \times 100\% \tag{7}$$

By providing a comprehensible measurement of the classification model's capacity to significantly categorize the whole samples, the precision metric ensures that positive examples are correctly identified as positives and negative instances are correctly identified as negatives.

$$Recall = \frac{TP}{TP + FN} \tag{8}$$

One way to evaluate the importance of recall is to consider the proportion of positive samples that are properly identified.

$$F1 - score = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{9}$$

The F1-score is an indicator which integrates precision and recall into one value, with a perfect score being one and the worst score being 0.

The MCC being a statistic is frequently used in machine-learning to assess effectiveness of binary categorization activities [46]. The MCC is a quantitative measure which quantifies the strength and directions of the relationship between two variables. It runs from -1 to +1, indicating the degree of correlation within the elements [47].

$$MCC = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}} \tag{10}$$

Where "TP", "TN", "FP", and "FN" express the abbreviations for true positive, true negative, false positive, and false negative, correspondingly.

A statistical measure called Cohen's kappa is used to assess how reliable or cooperative raters are while handling category items. When calculating the degree of agreement between two raters, Cohen's kappa statistic accounts for the agreement that would result from pure chance. The level of assessment as determined by Cohen's Kappa is shown in Table 1.

Table 1 Evaluation Criterion of Cohen's Kappa

Cohen's Kappa value	Level of agreement
≤0	No agreement
0.01 – 0.20	None to slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost perfect agreement

4. EXPERIMENTAL RESULT

The initial method used was to combine testing from all individuals to examine the effectiveness of the classification models. This study utilized two distinct neural conditions of the car drivers: fatigue and normal. Mathematical numbers of 0 and 1 were assigned to indicate the normal states and fatigue states in the labelling procedure. The classifier's performance was determined using the k-folds cross-validation method. The parameter k is set to 5 in the k-fold cross-validation process in this experiment. The Ensemble-based RUSBoosted Decision Trees has 98.53% classification accuracy, whereas the Ensemble-based Random Subspace Discriminant has 83.13% accuracy.

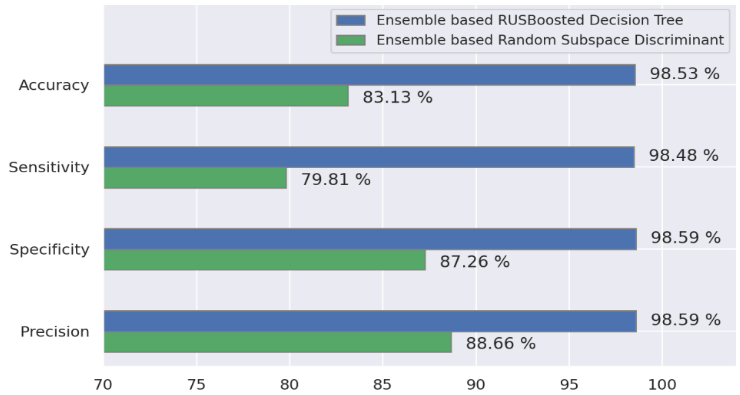

Fig. 4 Comparisons between two classification models accuracy, sensitivity, specificity, and precision

We evaluated the classifier's performance using various performance parameters in addition to analyzing its accuracy in classification. The study utilizes multiple performance evaluation metrics including accuracy, sensitivity, specificity, precision, recall, F1-score, MCC, and Cohen's Kappa. Both classifiers' performing comparisons are depicted in Figures 4 and 5, using different evaluation measures.

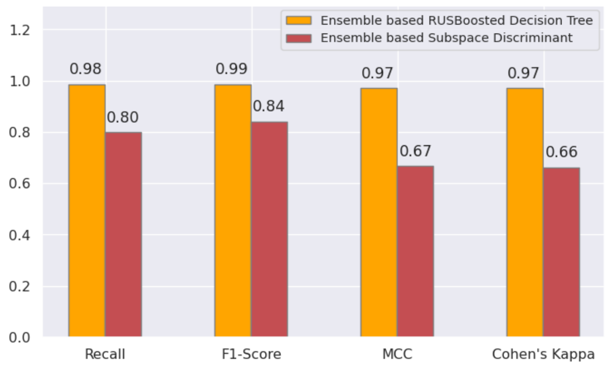

Fig. 5 Comparisons between two classification models Recall, F1-Score, MCC, Cohen’s Kappa

Meantime, scatter plots and parallel coordinate plots were utilized in order to assess the two models respective levels of performance. Figures 6 and 7 are scatter plots that visually represent the identification of datapoints for both strategies. There are unique markers on the scatter plots that indicate scenarios of inaccurate detection of fatigue and normal states. Scatter plots exhibit the detection datapoints. A very high level of accuracy may be inferred from the detection rates of both systems. In contrast, the identification efficacy of Ensemble-based RUSBoosted Decision Trees demonstrates a considerable increase when compared with performance of the other model.

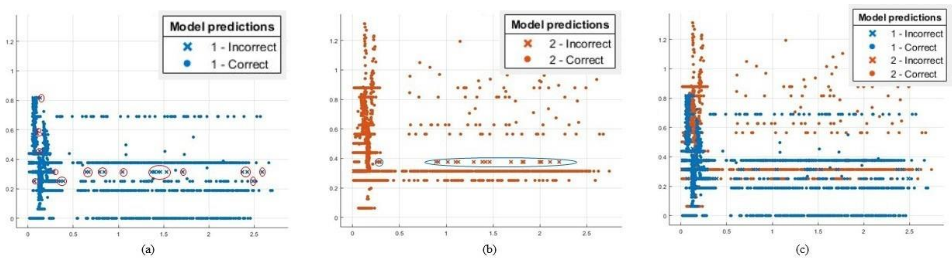

Fig. 6 Scatter plots for Ensemble-based RUSBoosted Decision Trees (a) normal, (b) fatigue, (c) both

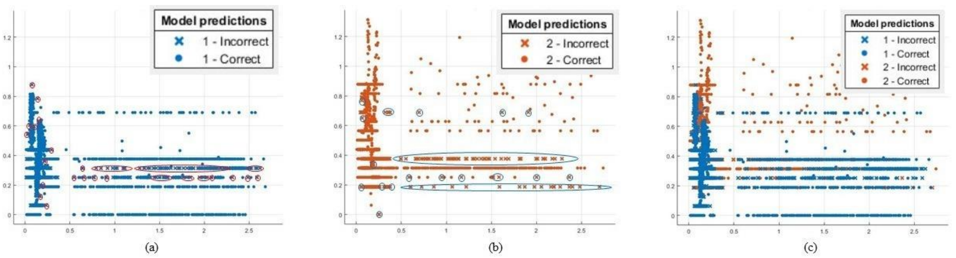

Fig. 7 Scatter plots for Ensemble-based Random Subspace Discriminant (a) normal, (b) fatigue, (c) both

It is possible to observe two-dimensional patterns for both models by using parallel coordination plots that are illustrated in Figure 8. This plot delivers as technique to graphically portray multi-dimensional data in a single plot. Having this visual representation makes it easier to appreciate the linkages that exist between the various factors, and it also makes it easier to identify valuable predictors that can effectively differentiate between the various classes.

Training data and misclassified locations can both be shown in the parallel coordinates display. In the context of classification, dashed lines are used to depict points that were misclassified. There are more dashed lines in Figure 8(b) than in Figure 8(a).

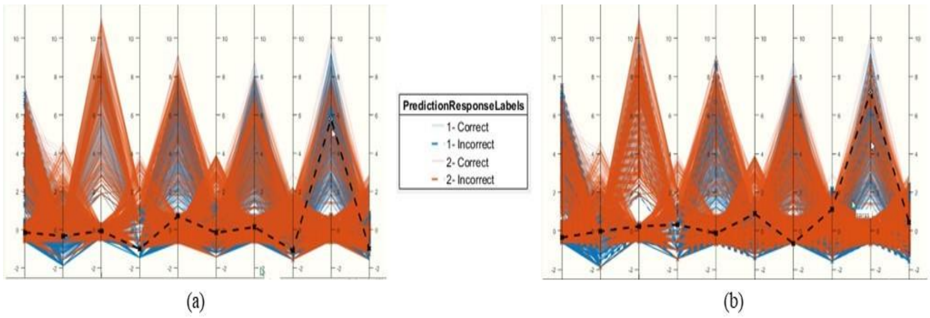

Fig. 8 Parallel-Coordination plots (a) Ensemble-based RUSBoosted Decision Trees, (b) Ensemble-based Random Subspace Discriminant

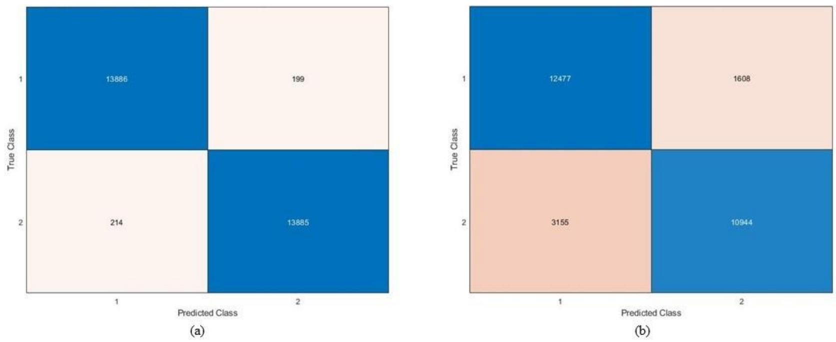

Fig. 9 Confusion matrix (a) Ensemble-based RUSBoosted Decision Trees, (b) Ensemble-based Random Subspace Discriminant models

When it came to forecasting fatigue states, Ensemble-based RUSBoosted Decision Trees model outperformed another model. Figure 9 represents the confusion matrix for both the applied models. There has been a small amount of trial misclassification in both instances.

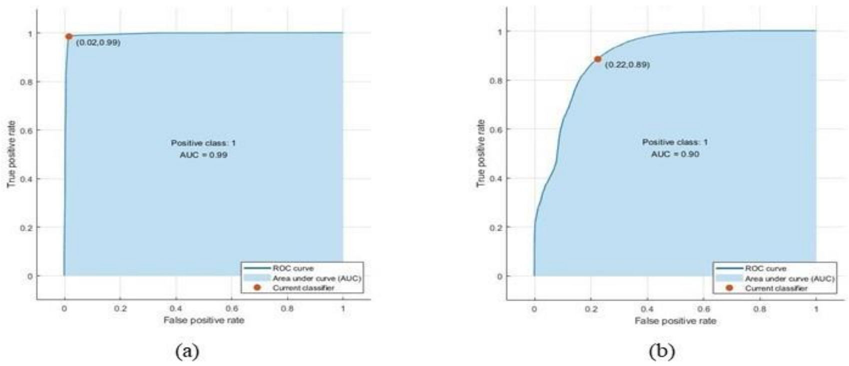

Fig. 10 ROC curve (a) Ensemble-based RUSBoosted Decision Trees, (b) Ensemble-based Random Subspace Discriminant

The ROC curves, or Receiver Operating Characteristics is illustrated in Figure 10, for two different ensemble-based decision-making models. The ROC is one of the useful visual tools for showing the relationship between true-positive rate and false-positive rate at distinct classifying standards. This link is shown with sweeping variables that include various threshold ratios. A false-positive rate is the percentage of the negative occurrences which categorized wrongly as the positive, whereas true-positive rate is the percentage of positive occurrences which recognized accurately. When comparing the ROC curves of both models, the latter is more closely aligned with the top-left corner. An evaluation statistic that measures the classifier's effectiveness in differentiating between positive and negative examples is AUC. A classification model having an AUC of 1 achieves perfect discrimination, whereas another having an AUC of 0.5 shows performance at the chance level and makes random predictions. We get an AUC of 0.99 for the Ensemble-based RUSBoosted Decision Trees, and 0.90 for the Ensemble-based Random Subspace Discriminant. According to the results, when comparing the two methods, the Ensemble based RUSBoosted Decision Tree appears to be more capable of accurately distinguishing between positive and negative scenarios. Overall, the evaluations show that when it comes to detecting fatigue states from EEG signals, Ensemble-based RUSBoosted Decision Trees can work better than the Ensemble-based Random Subspace Discriminant.

5. Discussion

The point of this study is to show how two new ensemble models can be used to find states of driver fatigue. In order to successfully achieve a classification accuracy of 98.53%, the Ensemble-based RUSBoosted Decision Trees model is recommended to use related EEG studies. Additionally, this research proposes one model, in comparison to other studies conducted in this area. Using an electroencephalogram (EEG) signal, the proposed framework consists of the potentiality to offer a unique method for evaluating the degrees of normal or fatigue among the vehicle drivers. This might be accomplished through the utilization of the system.

The effectiveness of the proposed model is examined in contrast to earlier research on the detection of fatigue, sleepiness, and tiredness. As shown in Table 2, a number of research pieces have been conducted in order to determine the levels of fatigue experienced by drivers through the utilization of EEG data. In conclusion, it is readily apparent that the framework that we have proposed demonstrates a greater level of

Table 2 Comparison of relevant studies concentrated on identifying fatigue states

References	Class	Features	Classification Model	Accuracy
[48]	2	EN	KNN	88.74%
[49]	2	EN	SVM	86%
[50]	2	CN	SVM	94.40%
[51]	2	FD	NN	88.20%
[52]	3	FD	SVM	81.60%
[53]	2	EN	SVM	97%
[54]	2	FD and EN	NN	98.30%
[55]	2	FD	SDBN	90.60%
Our Proposed Method	2	*FD (Fast Fourier Transformation)*	*Ensemble-based RUSBoosted Decision Tree*	*98.53%*

classification efficiency in comparison to currently existing conventional methods for identifying stages of fatigue among vehicle drivers.

6. CONCLUSION

As a result of the fact that driver's fatigue is a crucial issue in crash prevention due to its significant contribution to a high number of accidents and fatalities each year. In addition to a wide variety of subjective and objective detection methods, it has been determined that the use of driver physiological measures, more especially electroencephalography (EEG), is a reliable method for determining the levels of alertness or weariness that drivers are experiencing. This study indicates that it is possible to discern between states of weariness and alertness by analyzing EEG signal whilst engaging throughout a virtual driving exercise. Following the execution of two ensemble-based classifiers, the feature collection procedure included the use of Fast Fourier Transform (FFT). An improved level of classification accuracy, precisely 98.53%, is shown by the final suggested method. The findings from experiments indicate that Ensemble-based RUSBoosted Decision Trees possess the ability to significantly enhance the identification of driver fatigue states using EEG signals. For our upcoming research, we plan to develop a real-time feedback system by utilizing ensemble based machine learning technique.

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