

EEG Analysis of Sleepy Drivers: Identifying Key Brainwave Indicators of Fatigue

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Abstract— Driver fatigue is widely recognized as a major cause of traffic accidents, resulting in millions of injuries and numerous fatalities each year. Existing driver fatigue detection systems primarily rely on facial cues and vehicle behavior. However, such approaches often fail to identify early signs of drowsiness. This study investigates the effectiveness of electroencephalogram (EEG) signals for early driver drowsiness detection using machine learning techniques. An open-access EEG dataset collected under controlled driving conditions using the NeuroSky MindWave headset was utilized. EEG features from multiple brainwave bands were analyzed to distinguish between alert and fatigued states. Power spectral density and band power analysis were employed for feature extraction, followed by feature importance evaluation and independent t-test to identify the most significant indicators. Three classification models—Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN)—were implemented and evaluated. Experimental results show that the RF model trained on a combined set of original and engineered band power features achieved the highest classification accuracy of 78.9%, outperforming CNN (74.0%) and SVM (72.8%). Future work will focus on validating the proposed approach using multi-channel EEG systems in real-world driving environments to enhance its practical applicability.

Keywords—Driver Fatigue Detection, Electroencephalogram (EEG), Machine Learning, Deep Learning

I. INTRODUCTION

Fatigue is one of the reasons why the driver is unable to focus on the drive, which leads to road accidents with injuries and deaths numbering in the millions every year [1]. According to the World Health Organization [2], fatigue-related incidents account for about 100,000 road crashes worldwide. Modern detection systems rely mainly on external indicators. These can be divided into two main types: driver-centered systems that measure factors such as yawning and eye movements, and vehicle-centered systems that measure factors such as steering patterns and lane changes. While these approaches are unobtrusive and convenient, they have significant limitations; their effectiveness can be subject to environmental influences, such as illumination and road conditions, and the various forms of fatigue presented by individual drivers [3].

To overcome these challenges, Electroencephalogram (EEG) has emerged as a preferred method for cognitive state analysis because it provides immediate data on brain activity. EEG signals offer high temporal resolution, transmitting brain activity at a millisecond scale. Due to the ability to directly reflect brain dynamics during cognitive processes, EEG

signals are widely employed in applications such as neurological disorder detection [4]–[6] and driver fatigue monitoring [7]–[9]. As the most direct physiological-based methods, EEG testing can achieve high detection accuracy, with some controlled studies reporting rates above 90% [10]. The brain electrical activity measurement through EEG reveals different frequency bands that indicate brain alertness levels. Research indicates that fatigue detection occurs through theta activity increases and beta activity decreases [9]. The detection of fatigue onset through EEG occurs before behavioral methods because EEG detects neural changes in the brain.

Machine learning approach is frequently used in EEG data analysis to identify fatigue-related brainwave patterns [4]. Traditional methods such as Support Vector Machine (SVM) and Random Forest (RF) have shown effectiveness and robustness on the classification performance. However, they often depends on extensive manual feature engineering to achieve optimal performance. In contrast, the deep learning methods such as Convolutional Neural Network (CNN) has its ability to extract relevant features from raw data automatically. This end-to-end learning capability often improved the classification performance with minimal preprocessing [11]. The recent technological developments create opportunities to build precise real-time driver fatigue detection systems, which could decrease accidents from drowsy driving.

The main purpose of this research is to investigate whether EEG signals can detect driver fatigue through machine learning models. The specific objective is to implement machine learning algorithms to classify EEG data into alert or fatigued states, to identify the most relevant EEG features indicative of fatigue. RF, SVM and CNN are employed to evaluate the classification performance.

The rest of the paper is organized as follows: Section II presents the background of study. Section III describes the materials and methods, which includes dataset description, data preprocessing and feature engineering, classification and performance measurements. Section IV depicts the results and discussions while Section V draws the conclusion and the direction of future works.

II. THE BACKGROUND STUDY

Driver fatigue is considered one of the major reasons for road accidents around the world [12]. On this basis, growing awareness of the problem has stimulated serious research efforts toward the development of reliable and accurate driver fatigue detection methods to help drivers before it goes out of control.

Current driver fatigue detection systems can be classified into three main categories: driver behavioural-based systems, vehicle-based systems, and driver physiological-based systems [12]. Behavioural-based systems are non-intrusive and relatively easy to implement, making them attractive to real-world applications. These systems detect the signs of fatigue through facial expressions, yawning frequency, head position and movement, eye movements, and blinking behaviour. However, they face significant challenges and one of the main issues is their dependence on the lighting conditions, particularly if there is too little light or shine [3]. Additionally, individual differences play a crucial role, as everyone shows various kinds of fatigue, which can give rise to fallacies. Behavioural-based systems also have limited capability in detecting early-stage fatigue, as behavioural changes during the initial incubation period are often subtle and difficult to identify.

In contrast, vehicle-based systems monitor driving-related parameters such as steering wheel movements, lane shift or departure patterns, speed variation and braking patterns. Although these systems provide indirect indicators of driver fatigue, their performance is influenced by multiple external factors. Road conditions can significantly affect steering and lane deviation patterns, as variations in road type or roadwork may lead to different driving behaviours. Weather conditions such as rain or fog, may also result in erratic driving not caused by fatigue, further complicating the detection process. Moreover, the type of vehicle for example, size and suspension elements may reflect the differences in how fatigue manifests in driving behaviours and thus can lead to possible false alarms or missed detection.

Driver physiological-based systems that utilize EEG signals provide the most direct method for measuring driver fatigue due to their physiological basis. These systems monitor the brain activity directly and able to detect fatigue at the early stage. EEG-based approaches are highly sensitive in distinguishing between alert versus fatigued state and enable continuous monitoring of cognitive states. Recent research showed that detection accuracies as high as 90% and above were achievable with EEG-based systems in controlled environments [13]. Despite their advantages, current EEG-based systems also face challenges, including signal noise and artifacts, optimal electrode placement, user comfort and acceptance, and identifying key brainwave indicators of fatigue.

Machine learning has improved the analysis of EEG signals in identifying driver fatigue. Traditional machine learning methods and deep learning architectures are the two major categories of this technique, both of which have different strengths that can be used in different parts of the clinical EEG system development and implementation. Traditional machine-learning approaches have demonstrated significant success in EEG-based fatigue detection through various algorithms. Decision Tree (DT) are another common choice for EEG-based fatigue detection due to their interpretability and low computational complexity. Decision tree identify key features with the most contribution to classification. Therefore, they are ideal for lightweight and real-time systems. But their susceptibility to overfitting is a big limitation unless combined with ensemble methods like Random Forest or Gradient Boosting [10]. Naïve Bayes classifiers are very common, especially in the case of smaller datasets, since they are straightforward and efficient. Though

they assume independence of features, which may not be a good representation of the complex relationships that might exist in EEG signals, they provide a good baseline model to compare against [14]. The application of SVM and Random Forests has also been quite useful in the detection of fatigue, which is generated using EEG. These methods usually require strict feature extraction and selection before the classification. SVM-based systems can reach a level of up to 96.42% if frequency-domain features that have been extracted diligently are applied. By contrast, Random Forests, powered by very smart programming, are good at detecting and catching the behaviour of EEG signals that have been proven to be false. They scored around 98.12% in those studies, which were very controlled and solidified [14].

Deep learning architectures revolutionized EEG-based fatigue detection, largely due to their capabilities for automatic extraction and learning of features from raw EEG data, hence eliminating feature engineering. CNN works very well in capturing both spatial and temporal patterns of EEG signals [15]. Among its main benefits, we can distinguish the possibilities to automatically learn hierarchical features directly from raw information, which reduces the need to perform significant amounts of manual feature engineering [11].

III. MATERIALS AND METHODS

A. Dataset Description

The dataset used in this study was “Sleepy Driver EEG Brainwave Data”, which can be downloaded from Kaggle dataset repository [15]. EEG signals were recorded using the NeuroSky MindWave headset, a non-invasive EEG monitoring device. Multiple recording sessions were carried out with different subjects to ensure a representative and varied sampling of brainwave patterns across persons and situations. The dataset’s diversity makes it possible to create drowsiness detection models that are more broadly applicable. The dataset consists of 3735 instances with 10 features, including brainwave frequencies (Delta, Theta, Low Alpha, High Alpha, Low Beta, High Beta, Low Gamma, High Gamma), Attention, Meditation, and a binary classification label indicating alert (0) or fatigued (1) states.

B. Data Preprocessing and Feature Importance

A methodical data preprocessing pipeline was created to make the dataset ready for machine learning analysis. Following the Exploratory Data Analysis (EDA), the signal cleaning process removes artifacts and noise from the raw EEG signals, which is crucial for accurate analysis [16]. Artifacts may come from muscle movements, eye blinks, or external electrical interference, usually at 50 or 60 Hz, which can contaminate the recordings. The EDA confirmed that the dataset was of high quality, with no missing values or duplicate rows, which simplified the preprocessing requirements.

However, the descriptive statistics indicated a large variation in the brainwave measurements. Therefore, the normalization is required to set a standard for the analysis of EEG recordings consistently [16]. This includes the standardization of the amplitude of EEG signals throughout recording sessions so that any variation in signal strength due to equipment or recording conditions does not affect the analysis. Recordings are then temporally aligned to make sure all segments are well synchronized and can be compared.

Normalization at its last step involves the filtering processes of band-pass, each for different frequency ranges; this enables the segregation of specific EEG frequency bands required for fatigue detection.

To further identify the most important EEG features relevant to driver fatigue identification, feature importance analysis and independent t-test validation were conducted. The top 10 most important features by the Random Forest and t-test results are shown in Fig. 1 and Fig. 2, respectively.

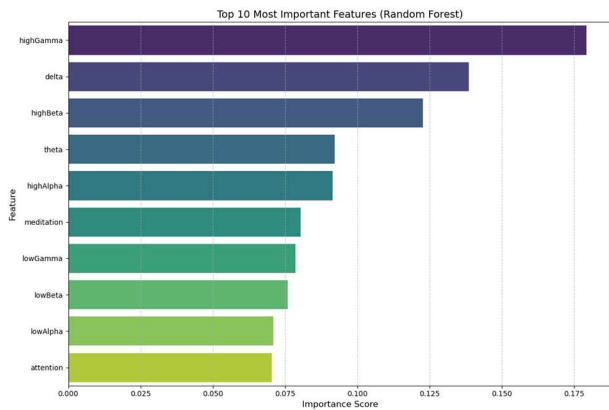


Fig. 1. Top 10 Most Important Features (Random Forest) Bar Plot

Fig. 1 shows the clear order of fatigue predictors. The two most important features in the model are highGamma and delta, with importance scores of 0.179 and 0.138 respectively. The two features together account for more than 31% of the model's predictive power, indicating that high-frequency cognitive activity and low-frequency sleep associated waves are the most important biomarkers in this dataset.

	Feature	p-value	Significant
12	Alpha_power	2.377946e-46	True
2	delta	5.323666e-46	True
10	Delta_power	5.323666e-46	True
7	highBeta	8.789203e-40	True
3	theta	6.217612e-37	True
11	Theta_power	6.217612e-37	True
5	highAlpha	5.382010e-32	True
13	Beta_power	1.507946e-30	True
4	lowAlpha	5.240018e-27	True
9	highGamma	2.018506e-10	True

Fig. 2. Independent T-Test Results for Key EEG Features

In order to statistically prove these results, independent t-tests were conducted to compare the mean value of each feature between the alert and fatigued classes, as shown in Fig. 2. This test shows whether the differences obtained are significant. The results were highly consistent with the model-driven importance ranking, which strongly aligns with the statistical significance tests. The features with the highest importance scores, including delta, highBeta, theta, and highAlpha, were the same features found to have extremely low p -values (< 0.001), confirming a statistically significant difference between the alert and fatigued states. The highGamma and delta being ranked as the best features repeatedly by the Random Forest model and the statistical tests, in particular, give a solid reason to believe in their significance. This alignment between fatigue importance scores and statistical tests reinforces the relevance of delta, theta, and gamma-related brainwaves as discriminators of fatigue.

In addition to the original features, feature engineering was performed to create a more concise representation of brain activity. Power Spectral Density (PSD) analysis was performed on the EEG signals using the Welch method in order to study the frequency components of the signals. The method is used to estimate the power of a signal at various frequencies, allowing one to understand which frequency bands are the most active. The data was bandpass filtered to isolate the standard EEG band: Delta (0.5-4 Hz), Theta (4-8 Hz), Alpha (8-13 Hz) and Beta (13-30 Hz). That enabled the specific analysis of the power of each significant frequency range relating to the cognitive states.

C. Classification

The pre-processed EEG data is used for the classification of fatigue states by using Random Forest (RF), Support Vector Machine (SVM) and Convolutional Neural Network (CNN). The RF and SVM classifiers were trained using engineered feature representations derived from the EEG signals, while the CNN model was trained directly on the normalized raw features to leverage its automatic feature learning capability. The dataset was partitioned into 70% for training and 30% for testing to ensure an unbiased evaluation of classification performance across all models.

1) Random Forest (RF)

Random Forest is an ensemble learning algorithm that constructs multiple decision trees during the training phase and outputs the average prediction of individual trees [17]. Random Forest generates forests with a random number of trees. The aggregation of multiple decision trees can reduce the chances of overfitting, and therefore helps to improve the performance. The strength of this benefit stems from the natural complexity and heterogeneity contained in the EEG data from the participants. The RF model used in this study was configured with 100 decision trees ($n_estimators=100$) and a fixed random state ($random_state=42$) for reproducibility, and it was trained on the scaled training dataset.

2) Support Vector Machine (SVM)

Support Vector Machine (SVM) is frequently used in EEG signals classification. It aims to find the maximum margin hyperplane in multi-dimensional space that distinctly classifies the feature vectors. Hyperplane is the decision boundary that helps to classify the feature vectors. It is obtained by training the initial dataset, which entirely separates these data and is defined by a small set of support vectors. When the feature vectors fall on either side of the hyperplane, there can be assigned to different classes. Support vectors are the subset of the feature vector that close to the hyperplane. It influences the orientation and position of the hyperplane. The main idea of the support vectors is to maximize the margin of the classifier. The position of the hyperplane will change whenever the support vectors are changed.

In this study, the SVM is trained with Radial Basis Function (RBF) kernel, which is very practical in dealing with the non-linearity of decision boundaries common in complex biological signals such as EEG signals. The default hyperparameters were chosen ($C=1.0$, $gamma='scale'$), and the probability estimation feature was set to True in order to be able to analyze the ROC curves.

3) Convolutional Neural Network (CNN)

A Convolutional Neural Network (CNN) is a specialized type of feed-forward neural network originally developed for computer vision tasks, but it has also been widely applied in EEG signals classification. Unlike conventional neural networks, CNN has the capability to identify relevant features without the need for manual feature engineering. A typical CNN architecture consists of several distinct layers such as convolutional layers, pooling layers and fully connected layers, each serving a specific role in feature extraction, dimensionality reduction, and classification. As for the data input, CNN utilizes data tensors in a 3D array (samples, timesteps, features). The CNN model was constructed in sequential architecture as follows:

TABLE I. CNN ARCHITECTURE USED FOR FATIGUE CLASSIFICATION

Component	Architecture/ Specification
Input Layer	Input shape configured for the 3D array of EEG features (samples, timesteps, features)
Convolutional Layers	Layer 1: - Conv1D (64 filters, activation='relu') - MaxPooling1D () - Dropout (0.3) Layer 2: - Conv1D (32 filters, activation = 'relu')
Pooling Layer	GlobalAveragePooling1D ()
Fully Connected Layer	Dense (32 units, activation = 'relu')
Output Layer	Dense (1 unit, activation = 'sigmoid')
Compilation	- Optimizer: Adam - Loss Function: binary_crossentropy
Training Parameters	- Epochs: 20 - Batch Size: 32

The model is summarized with the Adam optimizer and the loss function of binary_crossentropy. It was trained for 20 epochs with a batch size of 32. Training and validation accuracy and loss curves help to see that the model was learned successfully, as the validation accuracy is growing steadily, and the validation loss is decreasing throughout the epochs, which is not a significant indication of overfitting.

D. Performance Measurement

To quantitatively assess the effectiveness of the classifiers, a suite of standard performance metrics was used to ensure a reliable evaluation of fatigue state classification. The evaluation included accuracy, which measures the proportion of correctly classified samples. However, accuracy may not be an appropriate measure of performance concerning the reliability of the models in the case of class imbalance; the analysis was supplemented with precision, recall (sensitivity), and the F1-score. Precision captures how many actual cases among those that have been predicted as fatigued really had this class. Sensitivity measures how well a model captures real cases among those identified with this target feature. The F1-score is also applied for this kind of imbalanced dataset classification task and captures both measures, precision and recall, into a single value. These different metrics show specific model behavior regarding performance on a single number when classes are not perfectly balanced [16].

In addition to these metrics, a confusion matrix [18] is also provided as an output, showing the performance of the model in terms of true positives, true negatives, false positives, and

false negatives. This gives a clear picture of the strengths and weaknesses of the model with respect to classification.

IV. RESULTS AND DISCUSSIONS

This section presents and discusses the classification performance of Random Forest (RF) and Support Vector Machine (SVM) models using feature-engineered data, and CNN model using the original scaled features. The models are evaluated based on accuracy, area under ROC curve (AUC), precision, recall and F1 score. The data was split into 70% for training and 30% for testing. Table II summarizes the performance of different machine learning models and feature configurations for EEG-based driver fatigue classification.

TABLE II. COMPARISON OF CLASSIFICATION PERFORMANCE BETWEEN DIFFERENT FEATURE SETS

Model	Accuracy	AUC	Precision	Recall	F1-Score
Random Forest (RF)	78.60	0.871	0.784	0.693	0.736
SVM	72.80	0.797	0.664	0.743	0.701
CNN	73.60	0.804	0.697	0.683	0.690
RF (Band Power)	67.40	0.722	0.638	0.560	0.597
RF (Combined)	78.90	0.854	0.786	0.699	0.740
RF (Delta + HighGamma)	69.50	0.771	0.657	0.608	0.631

Among the baseline classifiers, the Random Forest (RF) model achieved the best overall performance, recording the highest accuracy (78.60%), AUC (0.871), and F1-score (0.736). These results indicate that RF possesses strong discriminative capability and robustness in distinguishing between alert and fatigued mental states.

The SVM model demonstrated competitive recall (0.743), suggesting its effectiveness in identifying fatigued instances. However, this was accompanied by lower precision, implying a higher false-positive rate. The CNN model showed relatively balanced performance across all evaluation metrics but underperformed compared to RF. This may be attributed to the limited dataset size, consisting of 3,735 instances with 10 features, and the use of single-channel EEG data, which can constrain the model's ability to learn complex feature representations. This can limit the effectiveness of deep learning models, which typically require larger datasets to achieve optimal performance [19].

Given the superior performance of the RF model, further experiments were conducted using RF with different feature sets. When using band power features alone, the RF model exhibited a notable decline in performance, with accuracy dropping to 67.40% and F1-score to 0.597, respectively. This indicates that the band power features alone are insufficient to represent fatigue-related EEG patterns comprehensively. Similarly, the RF model trained using only the two most important features (Delta and High-Gamma), as identified through the feature importance analysis, achieved moderate performance. This result showed that predictive relevance of these features while also highlighting the limitations associated with relying on a reduced feature subset.

The best overall performance was achieved by the RF model trained on the combined feature set, yielding the highest accuracy (78.90%), precision (0.786), and F1-score (0.740). This demonstrates that integrating raw and engineered features enhances discriminative capability and improves classification robustness.

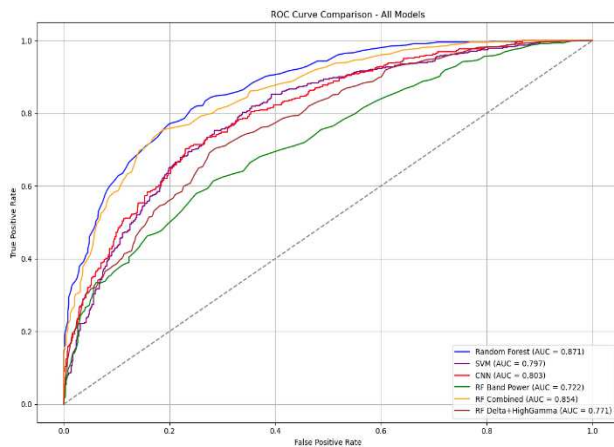


Fig. 3. Comparison of ROC Curves between the Classification Models

The Receiver Operating Characteristics (ROC) curve analysis presented in Fig. 3 helps to visualize model performance comparison. The ROC curves demonstrate that Random Forest models possess the best discriminative capabilities. The baseline RF model achieved the highest AUC value of 0.871, which demonstrates its excellent classification ability. The RF model with combined features displayed the best overall performance through its AUC value of 0.854 while achieving the best balance across all metrics, which makes it a suitable choice for real-world implementation.

The result of this study demonstrates that the engineering process of features directly influences the classification results. The model accuracy decreased when using band power features alone, yet the combination of original features with engineered features led to better classification results. The engineered features contain extra information that enhances the existing predictive capabilities of the raw data. The model that combined different features produced the highest results among all others because it merged detailed raw signal information with meaningful biological summaries.

Research results demonstrate that EEG-based driver fatigue detection systems can be developed in real-time with cost-effectiveness. The combination of basic hardware and components with machine learning algorithms offers a practical method for monitoring driver fatigue in vehicles. The model requires validation with multi-channel EEG systems and real driving scenarios to boost its generalization capabilities and operational stability.

V. CONCLUSION

This research explored the detection of driver fatigue using EEG signals and machine learning models, namely Random Forest (RF), Support Vector Machine (SVM), and Convolutional Neural Network (CNN). Among the three models, the RF model achieved the best classification performance, recording an accuracy rate of 78.9% when

trained on a combination of raw and engineered features. The HighGamma and Delta bands were identified as the most discriminative indicators of fatigue. Furthermore, the combination of raw and engineered features led to increased model accuracy, elucidating the key role of feature representation in EEG signals classification. These findings form a solid base for the creation of functional detection systems to enhance driving safety. Future work should focus on validating the proposed approach using multi-channel EEG systems in real-world driving environments to further advance the applicability of this technology.

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