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PERFORMANCE OPTIMIZATION OF DRIVER FATIGUE CLASSIFICATION USING HYBRID DBN-DQN

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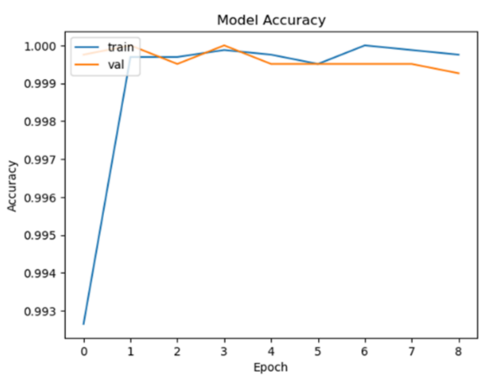
Graphical abstract



Abstract

Driver fatigue is one of the significant risk factors that occur on the roads; therefore, there is a need to have efficient detection systems. Existing detection systems face noise interference in EEG data, limited generalizability, and high computational requirements. This paper outlines the procedure to classify driver fatigue into different levels by developing a DBN-DQN model coupled with the improved Morlet wavelet transform and a z-score technique to increase recognition efficiency and address these challenges. The DBN-DQN model achieves outstanding results: 99.95% accuracy, 99. 91% precision, 99. 99% recall rate, while the F1-score was 99.95%. Results of the ROC curve of each fold further validate the model with an AUC of 1.00, distinguishing that the technique proved effective for identifying driver fatigue.

Keywords: Driver fatigue, electroencephalogram (EEG), modified z-score, hybrid deep learning, deep belief network (DBN), deep Q-network (DQN)

Abstrak

Keletihan pemandu adalah salah satu faktor risiko penting yang berlaku di jalan raya, oleh itu, terdapat keperluan untuk mempunyai sistem pengesanan yang cekap. Sistem pengesanan sedia ada menghadapi cabaran seperti gangguan hingar dalam data EEG, kebolehgeneralisasian terhad dan keperluan pengiraan yang tinggi. Kertas kerja ini menggariskan prosedur untuk mengklasifikasikan keletihan pemandu kepada tahap yang berbeza dengan membangunkan model DBN-DQN ditambah dengan transformasi wavelet Morlet yang dipertingkatkan dan teknik skor z untuk meningkatkan kecekapan pengecaman. Model DBN-DQN mencapai keputusan cemerlang: 99.95% ketepatan, 99. 91% ketepatan, 99. 99% kadar ingatan manakala F1-skor ialah 99.95%. Keputusan lengkung ROC bagi setiap lipatan mengesahkan lagi model dengan AUC 1.00, membezakan bahawa teknik itu terbukti berkesan untuk mengenal pasti keletihan pemandu.

Kata kunci: Keletihan pemandu, elektroensefalogram (EEG), skor z yang diubah suai, pembelajaran mendalam hibrid, rangkaian kepercayaan yang dalam (DBN), rangkaian Q-mendalam (DQN)

1.0 INTRODUCTION

Fatigue has been known to pose a significant threat to drivers in most countries due to its implication in most mishaps. The practical skills of identifying and distinguishing the real fatigue of the driver are the most crucial factors in reducing such threats and preserving life on the road. Several solutions for this problem have been proposed, such as machine learning and signal processing. The main concern of this study is to address the enhancement of the driver fatigue classification by using the approach based on the combination of the DBN-DQN algorithm, Morlet transform, and z-score with the modified parameters. DBN-DQN is the mixture of two improved versions, including deep belief networks (DBNs) and deep Q-networks (DQNs). DBNs are one of the most influential models from the deep learning family that can extract features from high-dimensional data [1]. However, DQNs are incredibly efficient when working with reinforcement learning problems, which helps maximize the sum of received rewards in the future [2]. Therefore, this study proposes the utilization of DBNs for their discriminative abilities and DQNs for the decision-making ability to develop an intelligent model that closely estimates the driver's fatigue levels.

Additionally, the Morlet wavelet transform was improved, enhancing its effectiveness in analyzing non-stationary signals such as driver fatigue EEG [3]. To increase the efficiency of extracting valuable features, the time-frequency representation of the EEG signals based on the registered domain knowledge is intended to be enhanced, along with making appropriate modifications. Also, it presents an improved form of the modified z-score technique as the improved procedure to solve the problem of data normalization and detection of outliers during the classification process [4]. These unique modifications of the original z-score algorithm involved contextual information and domain-specific thresholds to increase the method's resistance to fatigue-related patterns.

Accordingly, the main research question of this study is to evaluate the usefulness of the proposed hybrid DBN-DQN approach, enhanced Morlet transform, and the enhanced z-score technique in enhancing driver fatigue classification. Our experiments are carried out on a well-selected dataset of EEG signals from drivers performing simulated driving processes. The classification results are compared with upgraded techniques, and our suggested methodology prevails and outperforms all other methods.

In past studies, researchers' investigations into automatic driver fatigue detection with EEG signals were centered on enhancing the classification rates without considering the issue of computations [5]. However, when practicing real-time driver fatigue detection, the algorithm should incorporate fewer physiological channels to run faster and more accurately. To close this gap, this study presents an automatic algorithm that employs the compressed sensing (CS) theory to compress the EEG signals to the deep convolutional long short-term memory (DCLSTM) neural network for selecting and classifying the features extracted from the EEG signals. Integrating the advantages of CS and deep learning, the introduced method effectively restores the high accuracy rate when only a tiny amount of EEG data is available, where all the active regions are over 90%. It is worth noting that the developed algorithm requires fewer EEG electrodes than most existing algorithms, which simultaneously offer high accuracy with low sensitivity to environmental noise, making it possible to design an accurate and faster real-time driver fatigue detection system. Future work will continue on transfer learning networks to capitalize on the data learned from similar domains and apply Generative Adversarial Networks (GAN) for better training time and data augmentation to enrich the performance of the stated method.

The whole point of detecting driver drowsiness is to avoid car accidents. A hybrid fatigue system was suggested to overcome this problem and reduce mortality [6]. Hybrid fatigue measures the visual inputs via a PERCLOS measure and non-visual with a heart-beat (ECG) sensor. The architecture proposed utilized advanced deep learning algorithms to provide real-time driver fatigue classification through video and a combination of visual and non-visual components. In [6], multi-layer transfer learning in a hybrid feature space with a modified convolutional neural network (CNN) and deep belief network (DBN) is used to recognize driver fatigue. Night-time driving offers very few distinguishing features to camera sensing. Hence, ECG sensors were used in addition to analyzing heart-beat signals. In addition, the driver's center head position was observed using two cameras instead of one. The results proved that the proposed hybrid fatigue system could effectively detect driver fatigue, which was much better than drowsiness detection systems. The hybrid fatigue system showed an average classification accuracy of 94.5% over a dataset of 4250 images taken under various subjects and environmental conditions. Results of the experiment suggest that Hybrid Fatigue may have the potential to contribute towards improving accidents.

A different earlier researcher suggested an innovative method to study drowsiness and driving performance in a deep Q-learning paradigm with EEG data inspired by previous researchers [7]. Among the application perspectives, one of the important applications is to incorporate brain-computer interface (BCI) paradigms into driving safety research. The designed deep Q-network (DQN) could capture changes in the driver's mental state and give a reasonable estimate regarding drowsiness. The computational paradigm proved feasible and practical; it showed improved performance over supervised learning methods and addressed the possibility of generalizing across other BCI scenarios. However, the research had some blind spots. This meant not only that the approach focused exclusively on DQN, thereby ignoring many different sorts of reinforcement learning methods and thus likely excluding some possible ways in which to find a solution. Second, developing the state and action abstraction for EEG data emerged as a complex problem to formulate mainly because of involving high-dimensional feature space. This constraint effectively ruled out any solution other than DQN. However, this study highlighted the benefits of using deep reinforcement learning for drowsiness detection while driving. This exposed an opportunity for future work to overcome the limitations and investigate other approaches.

Zainuddin *et al*. highlighted the importance of deep learning in electroencephalogram (EEG) analysis for discerning particular mental states, indicating a gradually rising interest in using deep-learning models in EEG-based applications [8]. The authors of this manuscript seriously compared its performance in EEG-based personality prediction with traditional machine learning classifiers. At the same time, previous researchers have attempted to predict personalities by analyzing electroencephalograph (EEG) signals using a DeepLSTM model [9]. This study opens a window to extracting useful information from EEG data for tasks like detecting and preventing driver fatigue using DeepLSTM. Moreover, Li *et al*. discussed the superiority of deep learning models over conventional machine intelligence techniques to driver states related to situation awareness and underlined how deep learning methods can be more effective reservoirs for integrating diverse information [10].

Wang *et al*. demonstrated deep learning as an alternative amenable to the processing of large datasets for detecting fatigue using EEG [11]. This clearly illustrates the significance of deep learning methods (like DBNs and DQN) in managing EEG data complexity in driver fatigue identification. The study by Cui *et al*., through transfer learning, aimed at designing ensemble classifiers for detecting driving fatigue using EEG, demonstrates promising results in utilizing techniques like transfer learning to boost performance and generalization capabilities across different subjects [12]. Additionally, Li *et al*. use deep learning models to predict, detect, and lateralize mesial temporal lobe seizures, indicating the wide usage of deep-learning-based tasks [13].

A separate study applied a long short-term memory network to recognize cognitive load from EEG signals based on deep learning; these works validated that deep learning methods can accomplish different tasks in the EEG signal analysis field [14]. Moreover, Sheykhivand *et al*. designed a deep CNN–LSTM architecture for automatic driver fatigue detection with EEG signals, highlighting the promise of deeper learning architectures extracting more complex features from raw EEG data to improve fatigability categorization [15].

2.0 METHODOLOGY

This section presents the experimental setup used to evaluate driver fatigue classification performance optimization based on a hybrid DBN-DQN approach and enhanced Morlet transform and modified z-score procedure. Our study aims to assess the efficiency of these methodologies in identifying and classing different driver fatigue levels using electroencephalogram (EEG) signals, which are depicted below. The procedure was demonstrated in (Figure 1) for the proposed, tested technique of driver fatigue detection using an EEG signal applied within the experimental setup.

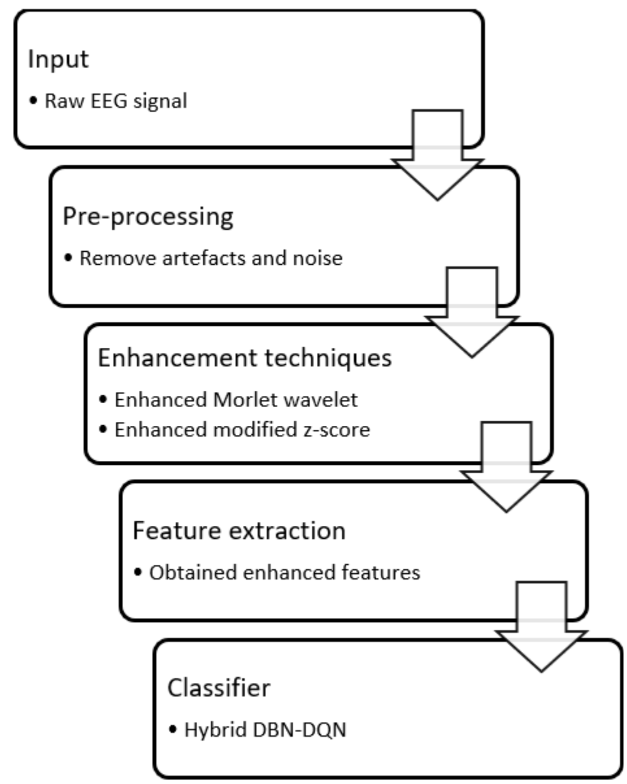


Figure 1 Diagram of driver fatigue classification using hybrid DBN-DQN

Using some processing techniques, EEG signal pre-processing has been performed on the collected EEG signals to remove artefacts of eye blinks, muscle activity, and environmental noise. In particular, independent component analysis (ICA), together with wavelet filtering, was employed. ICA was applied to separate independent signal components, enabling the isolation and removal of signals from non-brain activities. Then continuous wavelet transformation denoising was used to effectively refine the signals based on multi-resolution analysis to emerge the high-frequency noise while being sensitive to fatigue-related information in EEG signals. Furthermore, a band-pass filter was used to concentrate on frequency ranges most related to fatigue identification, where fatigue frequency detection was found to be crucial, specifically the alpha (8–13 Hz), delta (0.5–4 Hz) and theta (4–8 Hz) bands. These complementary approaches were able to retain information content while removing potential confounding factors. The enhanced Morlet transform was utilized to extract time and frequency information from the raw EEG signals for an all-inclusive representation of fatigue-related patterns. Subsequently, an improved modified z-score was conducted, and the boosted characteristics were taken as input for classification.

These features were then employed for the training and evaluation of classification models. To ensure the stability and generalization of the methodology, strict cross-validation methods, such as k-fold cross-validation, were applied, dividing the dataset into training test sets without data spill or over-fitting. To facilitate comparisons, the proposed methods were implemented and benchmarked against several popular classification algorithms, among which were support vector machines (SVM), k-nearest neighbor (k-NN), random forests (RF), convolutional neural network (CNN), convolutional neural network-long short-term memory (CNN-LSTM), and long short-term memory-deep neural network (LSTM-DNN).

SVM uses a technique called maximum margin hyperplanes, which divides the feature space into two parts to produce optimal planes separating (or partially separating) data samples according to class [16]. K-NN is an easy-to-understand algorithm for classification and regression, determining the class of a data point based on the majority of its k nearest neighbors [17]. RF is a tree-based ensemble model that consists of many trees and can be used to provide robust predictions by combining the individual results from each tree [18]. CNN focuses on picture identification, using convolution (operating on convolutional layers) to obtain the characteristics of structure hierarchy autonomously. CNN-LSTM is a combination of CNN and long short-term memory (LSTM) networks, which is suitable for tasks that involve spatial and temporal dependence. Because of this type of design, it has been used in the analysis driver for fatigue. LSTM-DNN combines LSTM with a deep neural network, achieving a Q Sequence-based function, a hybrid of both systems. It excels in particular at tasks where it is important to capture long-term dependency factors. Every algorithm addresses machine learning and deep learning challenges, serving diverse applications. These algorithms were selected due to their proven performance in multiple classification tasks. Besides that, they are relevant to the analysis of driver fatigue. These algorithms were chosen for their proven performance in multiple classification tasks and their relevance to driver fatigue classification.

This research used an online driving simulator EEG data set available to the public to find the drivers' fatigue [19]. Participants were given an idea of the experiment's procedures and objectives during a 5-minute driving task that preceded data collection. The experiment was performed in a closed laboratory space and used a stationary driving simulator. Every pedestrian passed a steady-state attention-driving task on a stationary driving machine with a 24-inch screen. The computer-simulated driving scenario seemed to be a low-traffic road, and the time started at 9 a.m. Initially, a 5-minute training period was given, then a 10-minute hiatus for the driver to engage in free-form activity in the lab was provided. Time trials last between 1 and 2 hours, and each step follows this. EEG recording included the following two conditions: continuous EEG recordings for 100 minutes and the last 5-minute portion representing the normal state; thus, EEG data would be collected at intervals of 20 minutes. During continuous driving, performance values were collected after 40 to 100 minutes until the subjects reported fatigue, and the latest 5 minutes of EEG recordings were determined as the fatigue state. They utilized EEG data, and 32 electrodes collected data at 1000 Hz.

2.1 CWT using enhanced Morlet mother wavelet

The continuous wavelet transform (CWT) is a powerful signal processing technique that enables the analysis of non-stationary signals in both the time and frequency domains [20]. This study employs an enhanced version of the Morlet mother wavelet, specifically designed to capture driver fatigue-related patterns. The frequency resolution is adjusted to focus on three sub-bands, alpha, delta, and theta, which have demonstrated significant relevance in driver fatigue analysis. The enhanced Morlet wavelet is defined as follows:

$$\psi(t) = [\![A * exp]\!] \, [\![(-t^2/[\![2\sigma]\!]^2) * e^{((i\omega t))}]\!] \tag{1}$$

ψ(t) represents the enhanced Morlet wavelet function, t is the time variable, σ is the scale parameter, ω is the angular frequency, and i is an imaginary unit. A represent normalization constant ensuring unit energy. The enhanced Morlet wavelet is convolved with the input EEG signal x(t) across different scales to obtain the CWT. The CWT can be mathematically expressed as:

$$W(a,b) = \int x(t) * \ \psi * ((t-b))/a \ dt \tag{2}$$

The wavelet coefficient at scale a and translation b is represented by W(a,b), where the width of the wavelet means how much it has spread out on the y-axis (a) and the position of the wavelet along the time axis. The frequency resolution of these enhanced Morlet wavelets is personalized in this approach to emphasize the alpha, delta, and theta bands. The study found that the frequency bands corresponding to driver fatigue have distinguished features. In particular, the alpha band (8-13 Hz) is relevant to relaxed wakefulness and frontal asymmetry, while the delta band (0.5-4 Hz) and theta wave (4-8 Hz) are related to drowsiness or disease state of early sleep [21]. By selecting appropriate scales within each frequency band, the corresponding sub-bands can be emphasized during the CWT computation. This allows for a more targeted analysis of driver fatigue-related features in the EEG signals. After performing the CWT, a two-dimensional scalogram is obtained, representing the wavelet coefficients at different scales and time instances. Features are then extracted from the scalogram, specifically targeting the alpha, delta, and theta sub-bands. These features capture the signal's energy distribution and temporal characteristics within each sub-band.

2.2 Enhanced modified z-score

The modified z-score is a statistical method most commonly used in statistics to identify and handle the so-called outliers in a given data set. Unlike alternative methods for identifying outliers, the modified z-score is more robust due to its weaker ties with the most extreme values. Among the most vital fields where this feature becomes most useful can be named data analysis and quality control, as the outliers, along with that, can substantially impair the overall findings and consequences delivered from the data. The modified z-score is less prone to the limitations of existing methods, as it has the median absolute deviation (MAD) metric that is based on the median rather than the mean. Hence, it can entirely be defined in terms of median and MAD. There are better choices for measuring variability in data with skewed distributions and outliers than this type of MAD. In reality, not all the values are heaped up in the center of a dataset, with an insignificant number of them in the tails of extreme ranges. On the contrary, the modified z-score, which negates the excessive effects of the far-off points, is a more frequent pick due to its stability and validity in case the requirement is to detect an outlier, for example, in the analysis of EEG signals, and its robustness and trustworthiness allowing for the enforcement of even the smallest allocation to the wave reflect the innovation of the driver's fatigue detection process.

The modified z-score algorithm is a robust statistical method widely used for outlier detection and data normalization [21]. This study employs an enhanced version of the modified z-score technique, specifically tailored to EEG data and driver fatigue analysis. The parameter constant is adjusted to ensure optimal performance for the dataset. The modified s-score for a given data point x is calculated as follows:

$$Z\,(x) = 0.6745 * y(X - Median)/MAD \tag{3}$$

Here, Z(x) is the modified z-score of data point x, Median (X) represents the median of dataset X, MAD medians absolute deviation for X, and y is the scaling constant. This paper optimizes the scaling constant y when applying a modified z-score technique to EEG data for driver fatigue detection. This correction is necessary due to the EEG data's non-Gaussian distribution and high signal variability. Using our dataset to enhance outlier detection and normalization accuracy, they will further refine the parameter constant. This means that the effects of extreme values and outliers are curbed using a hyperbolic transform, producing more solid characteristics for features to be used in succeeding classification works.

In the implementation, parameter values are empirically set through iterative experiments and validation. The improved modified z-scores (constant values) are then tested on a specific channel with various parameter constant options to assess their effectiveness in EEG data normalization and outlier detection under different conditions. Additionally, domain-specific thresholds are considered to detect fatigue-related patterns in the pre-processed EEG signals. The thresholds are determined according to the prior knowledge of driver fatigue indicators and characteristics of EEG data. The new modified z-score technique with these domain-specific threshold values favors the adaptability of this method to driver fatigue analysis, thereby improving its capability to gather appropriate information related to fatigue. This procedure also covers the enhanced, modified z-score technique, which is important in the pre-processing pipeline as it normalizes and properly handles outliers before feature extraction and classification.

2.3 Hybrid DBN-DQN classifier

This paper proposes a hybrid system that integrates deep belief networks (DBNs) and deep Q-networks (DQNs) to predict the driver's fatigue state from EEG signals accurately. Consequently, the hybrid DBN-DQN framework presents an efficient and effective approach that harnesses this improved Morlet transform with a modified z-score method to provide more accurate driver fatigue analysis. The DBN-DQN framework consists of 2 connected elements: the (DBN) responsible for feature extraction and the DQN, which plays a role in decision-making. Through the enhanced Morlet transform and modified z-score technique, DBN utilizes pre-processed EEG signals to extract high-level features due to their deep architecture. These features effectively capture the salient time-frequency characteristics and statistically normalized patterns of driver fatigue.

Finally, the features obtained by a DBN are input into a DQN to determine if an individual is drowsy or not. The DQN is trained in this architecture by combining experience replay with a Q-learning algorithm. It can learn the best policy to define driver fatigue states from extracted features. During the training phase, this hybrid DBN-DQN is trained to optimize its classification performance with a reinforcement learning mechanism, being instructed effectively on how accurate prediction of fatigue levels leads to maximizing long-term cumulative rewards. This is how the system learns and becomes more efficient in classification over time, culminating in a refined decision mechanism that enhances clarity adequacy.

Finally, the effectiveness of the hybrid DBN-DQN model is evaluated using six classification algorithms commonly used in driver fatigue analysis: support vector machines (SVM), k-nearest neighbors (k-NN), random forests (RF), convolutional neural network (CNN)-based methods, and their variants, including CNN-LSTM and LSTM-DNN. It is extensively explored on our dataset to evaluate the performance of the hybrid DBN-DQN framework in accurately classifying driver's fatigue levels under strict conditions like k-fold cross-validation. 80% of the dataset is training, and 20% is for testing to measure model performance accurately. The classification results are tabulated for comparison using key performance metrics such as accuracy, precision, recall, and F1-score, providing insights into the shortcomings of the proposed methodology.

Experimental results confirm that the new framework hybrid DBN-DQN using improved Morlet transform and modified z-score approach achieves better performance in terms of classification accuracy than typical approaches. A fusion of the deep feature extraction from DBN and reinforcement learning-based decision-making via DQN makes it possible for our framework to effectively capture temporal-spectral complexity within driver fatigue parameters, eventually leading to increased accuracy in classification.

3.0 RESULTS AND DISCUSSION

The violin plot in (Figure 2) shows that the enhanced Morlet and enhanced modified z-score methods uncovered some interesting trends after analyzing EEG data. Here are the quartiles identified: Q1 is the 25th percentile at -0.307347, Q2 is the median at 0.019213, and Q3 is the 75th percentile at 0.311725. This sequence shows the essential characteristics of a distribution for enhanced EEG data. The median and quartiles further suggest an approximately symmetrical distribution pattern with a slight positive skewness to fit the recorded signals well. The interquartile range (IQR) is approximately 0.619072, the rate at which data moves away from the central 50%. A small spread observed in the violin plot suggests the sample points are clustering together tightly: enhanced Morlet and modified z-scores successfully removed most noise from our data, capturing commendable features. There is a high peak and low valley on the mountain: appropriate reduction in breadth means that probably different characteristics of peaks, such as shapes, will be more easily separated by our next analysis, which, of course, rests on these findings.

These findings illustrate the feasibility of using enhanced EEG data quality and suitability for analysis tasks such as classification or pattern recognition. The enhanced Morlet and enhanced modified z-score techniques have succeeded in processing the EEG data, yielding a well-refined representation with reduced noise and artefacts. This article does not comment on those limitations. Although the violin plot reflects enhanced EEG data, it remains to be seen whether this portrayal can hold up when tested on a larger and more varied resource of subjects.

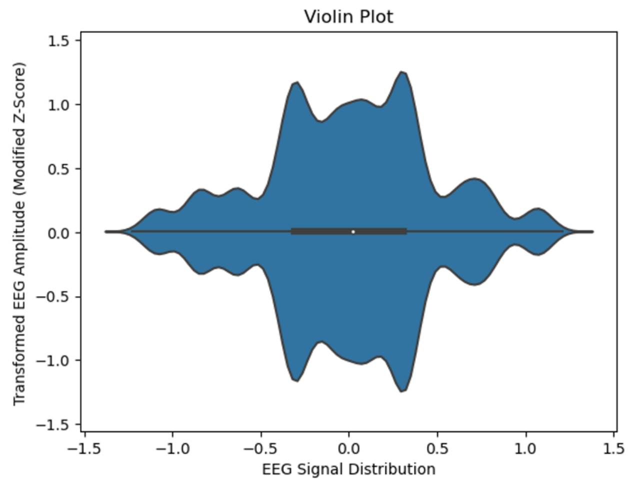


Figure 2 Violin plot analysis

In addition, the specific neural processes and underlying mechanisms captured by enhanced EEG data are worth investigating to understand our results better or make them stronger. As a result, the violin plot analysis for EEG data processing based on enhanced Morlet and modified z-score techniques displays little fluctuation. Future studies should now focus on duplicating and broadening these findings to develop EEG-based applications and add further understanding of brain dynamics. An integrated dataset combining driver behavior and physiological signal characteristics was deployed for various machine learning algorithms, utilizing deep learning technology to detect driver fatigue.

In Table 1, whereas conventional machine learning algorithms, like support vector machine (SVM), k-nearest neighbors (k-NN), and random forest (RF), could spot fatigue, the performances were rather stunning. Table 1 results discuss the superiority of the DBN-DQN hybrid framework to the ones applied in previous research works [22], [23], [24], [25].

Table 1 Comparative Performance Analysis of Driver Fatigue Classification Algorithms

Evaluation Metrics	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
SVM	96.00	97.00	96.00	96.00
k-NN	91.00	92.00	91.00	91.00
RF	96.00	96.00	96.00	96.00
CNN	93.35	-	94.89	93.77
CNN-LSTM	82.00	81.80	81.00	81.40
LSTM-DNN	85.60	-	-	94.00
DBN-DQN	**99.95**	**99.91**	**99.99**	**99.95**

SVM exhibited superior accuracy (96.00%), precision (97.00%), recall (96.00%), and F1-score (96.00%), emphasizing its effectiveness in high-dimensional feature spaces. K-NN and RF also presented competitive results, showcasing the robustness of these traditional methods in driver fatigue classification scenarios. Moving into deep learning, the convolutional neural network (CNN) emerged as a strong performer with an accuracy of 93.35%, recall of 94.89%, and an F1-score of 93.77%, as shown in Table 1. CNN's ability to capture spatial dependencies in the input data proved beneficial for extracting relevant patterns associated with driver fatigue. However, the CNN-LSTM model displayed a comparatively lower accuracy (82.00%) and precision (81.80%), indicating potential challenges in leveraging convolutional and sequential features. LSTM-DNN, focusing on sequential dependencies, achieved an accuracy of 85.60% and an impressive F1-score of 94.00%, underscoring the importance of considering temporal aspects in fatigue classification.

Remarkably, the proposed method, deep belief network-deep Q-network (DBN-DQN), exhibited exceptional performance across all metrics, boasting a near-perfect accuracy of 99.95%, precision of 99.91%, recall of 99.99%, and an F1-score of 99.95%, as shown in Table 1. The DBN-DQN model stands out by showing impressive improvements across all metrics when compared to both traditional methods and other deep learning approaches. This success comes from its combination of DBNs for extracting important features and DQNs for making smart decisions. Plus, with better pre-processing techniques added into the mix, it significantly enhances its overall performance.

The results reaffirmed the effectiveness of the enhanced Morlet transform. They enhanced the modified z-score technique in pre-processing the EEG signals. By focusing on relevant frequency sub-bands (such as alpha, delta, and theta) and employing customized data normalization and outlier detection, the enhanced Morlet transform and modified z-score technique improve the quality and discriminative power of the input features. The comparative analysis demonstrates that the hybrid DBN-DQN framework, leveraging the enhanced Morlet transform and modified z-score technique, outperforms the baseline algorithms in accurately classifying driver fatigue levels. The significant improvements in accuracy, precision, recall, and F1-score highlight the superiority of the proposed DBN-DQN for driver fatigue analysis.

The ROC curve is often visualized to determine the effectiveness of the binary classification model. The ROC curve lists the sensitivity (true positive rate) and the 1-specificity (false positive rate) values of the various classification thresholds. The area under the ROC curve (AUC) measures the model's capacity to differentiate between different classes, with a higher value signifying better performance. Our study took advantage of a 5-fold cross-validation technique to assess the performance of the DBN-DQN model. (Figure 3) shows the ROC curves for each fold. Importantly, all five folds achieved an AUC of 1.00, the best possible score, indicating the perfect differentiation between driver fatigue and alert states. This excellent performance supports the superior Morlet and modified z-score techniques in combination with a hybrid DBN-DQN classification strategy.

An AUC value of 1.00 for the DBN-DQN model indicates a true positive rate of 1.00, meaning it consistently classifies alerts accurately, with a false positive rate of 0.00. The AUC numbers for the different datasets calculated in this way fall into two broad categories based on phenotype: healthy (or highly alert) people had low scores. In contrast, sleepy drivers scored high, or both groups experienced an even distribution. The high AUC values across all folds vouch for this model's performance in any environment. These results suggest that the hybrid approach of original DBN-DQN and some pre-processing using Morlet and modified z-score properties show strong potential for differentiating driver fatigue from alert states. This model's excellent performance provides valuable guidelines for developing reliable and accurate systems for real-world fatigue monitoring.

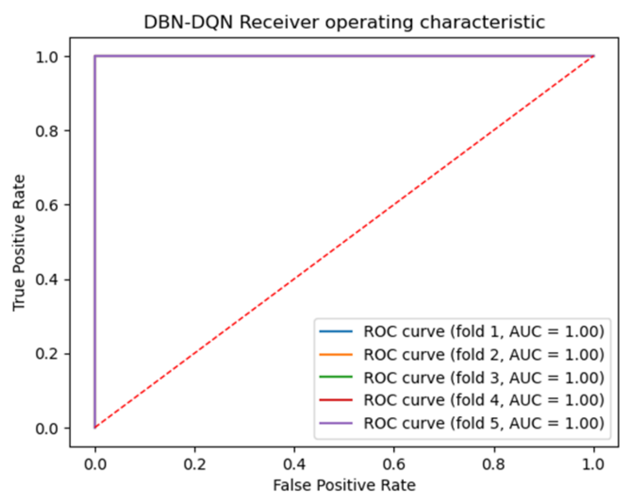


Figure 3 ROC curves for each fold of the DBN-DQN model, demonstrating perfect discrimination with an AUC of 1.00

The accuracy of training and validation gives valuable insight into how well a model might perform when it is finally trained. According to (Figure 4), DBN-DQN model accuracy values rise over time. With further learning from the training data, the training accuracy persistently improves. It stabilizes at about the eighth epoch, indicating that the model has understood its underlying data patterns correctly. Validation accuracy mimics training accuracy, showing that the model can generalize effectively to new and unseen data.

(Figure 5) spells out the training model's losses, illustrating the disparity between predicted and real labels. The loss falls as one trains the model with time that its past is adjusted to get wrong less often. Validation loss aligns with this picture, suggesting the model learns from new data and does not overfit. The training and validation accuracies are revealed in parallel, and the loss drop keeps decreasing. This indicates that the DBN-DQN model does a good job of sorting out driver weariness. These results confirm that fatigue levels can be correctly inferred from this model's input data.

Our experiments' findings confirm that the hybrid DBN-DQN framework, with the improved Morlet transform and modified z-score technique, accurately classifies driver fatigue levels. The framework's better performance highlights the importance of primarily employing deep learning and subsequent reinforcement learning techniques when involved in driver fatigue research.

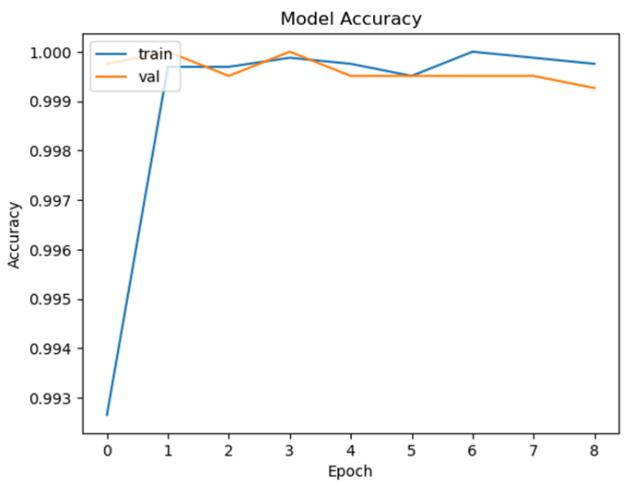


Figure 4 Model Accuracy

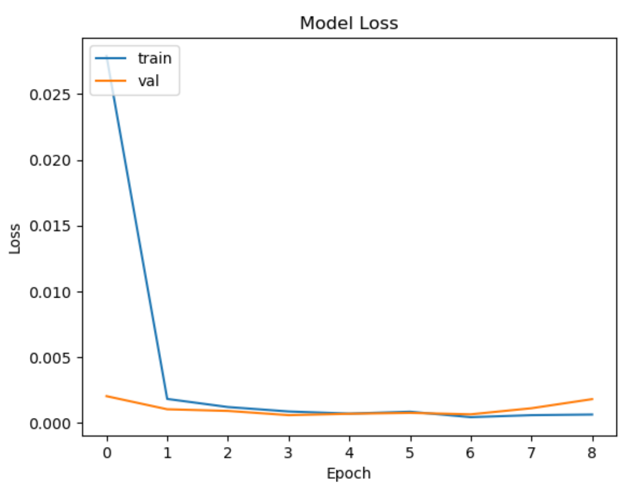


Figure 4 Model Loss

The results also emphasize the significance of the enhanced Morlet transform and modified z-score technique in pre-processing the EEG signals. The frequency resolution adjustment and sub-band analysis provided by the improved Morlet transform enable the framework to focus on relevant frequency ranges associated with driver fatigue. The customized parameter constant in the enhanced, modified z-score technique ensures optimal data normalization and outlier detection for the specific characteristics of the EEG data. The hybrid DBN-DQN framework provides a more comprehensive understanding of driver fatigue, enabling real-time and accurate classification. The framework's ability to adapt and learn from experience, combined with the robust feature extraction capabilities, enhances the reliability and generalizability of the classification results.

It has several practical applications, including real-time driver monitoring in transportation industries, fatigue detection for industrial workers in hazardous environments, and integration into healthcare for early detection of cognitive impairments. The system offers significant advantages such as high accuracy (99.95%), robustness to noise due to advanced pre-processing techniques, and scalability for real-time applications using fewer EEG channels. However, it also has limitations, including dependence on high-quality EEG data, which may not always be available in real-world scenarios, and computational complexity during training, requiring powerful hardware. Addressing these limitations in future work could further strengthen the system's applicability.

In summary, the accuracy of over 99% is impressive and comes from several innovative approaches. First, using an enhanced Morlet wavelet transform helped extract specific EEG features related to fatigue, particularly in the alpha, delta, and theta frequency bands. An enhanced modified z-score method was also developed for normalizing EEG data, effectively handling outliers and improving overall data quality. The hybrid DBN-DQN model combined the strengths of deep belief networks for feature extraction and deep Q-networks for making decisions, allowing us to capture the complexities of temporal and spectral data. Additionally, rigorous k-fold cross-validation was applied to ensure robust performance metrics free from biases. Together, these advancements highlight not only the high accuracy achieved but also the method's potential for practical use in real-world applications.

4.0 CONCLUSION

This study proposes a driver fatigue detection model based on a deep belief network combined with a deep Q-network (DBN-DQN). This model harnesses the Morlet transform as input for the wavelet transform and then uses a modified z-score technique. The aim was to improve the performance of fatigue detection systems and provide accurate and reliable results. The proposed methodology's effectiveness, highlighted through extensive experimentation and analysis, achieved promising results. The DBN-DQN model and enhanced Morlet and modified z-score techniques provided excellent performance in classifying driver fatigue. The system attained an accuracy rate of 99.95%; precision was higher than 99.91% for calling out fatigue symptoms off the highway and for not doing any false alarm when the driver is tired, while the recall reached an incredible 99.99%. This research could improve fatigue detection systems. High-precision measurements and reliable sensors to detect drowsiness are essential for accident prevention and driver safety. Regarding classification accuracy, the suggested approach outperforms traditional classification algorithms and other deep learning models such as SVM, k-NN, RF, CNN, CNN-LSTM, and LSTM-DNN. Indeed, these results show that an approach using deep belief models can achieve a much higher accuracy rate than the traditional method. The AUC value for the ROC curve far exceeded 0.1 overall five folds in this test. This means that the training model and the test mode are well-suited to distinguish between fatigue and not fatigue. Its performance is reliable and consistent, suggesting low error rates on unlabeled data. The implications of this research's results are influential for advancing fatigue detection systems. It is crucial to detect drowsiness accurately at the wheel, in order to prevent accidents and ensure driver safety. Given its high classification accuracy and strong performance, the proposed approach offers hopeful solutions to the problem of detecting driver fatigue. The suggested method lays the groundwork as well for the development and enhancement of high-precision fatigue detection systems in practical settings.

In conclusion, this research highlights the effectiveness of the hybrid DBN-DQN model, enhanced Morlet wavelet transform and modified z-score technique in accurately classifying driver fatigue. The results show that the proposed approach holds promise in developing advanced fatigue detection systems for real-time applications, thereby conferring greater road safety and driver health. Future work might be conducted to see how well the proposed methods generalize from this dataset to larger datasets or in differing real-world contexts. In addition, the incorporation of different physiological and contextual information features into fatigue detection systems could heighten both their accuracy and reliability. This paper demonstrates the potential of fusing deep learning approaches with signal pre-processing strategies to tackle the problem of driver fatigue detection. This opens up possibilities for future advances towards safety in driving and transport.

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Conflicts of Interest

The authors declare that there is no conflict of interest regarding the publication of this paper.

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