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Enhanced Modified Z-Score-Based EEG Signal Preprocessing for Driver Fatigue Classification Using a DBN-LSTM Hybrid Deep Learning Model

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Abstract: This study presents a method for driver fatigue detection using EEG signals, combining an enhanced modified Z-score-based preprocessing technique with a hybrid deep learning model that integrates Deep Belief Networks (DBN) and Long Short-Term Memory (LSTM) networks. The enhanced modified Z-score preprocessing method effectively reduces noise and outliers in EEG data, significantly improving the quality of features for fatigue classification. The DBN component is used for unsupervised feature extraction, while the LSTM component captures temporal dependencies in the data, enhancing the accuracy of the model. Experimental results showed that the proposed model achieved an overall accuracy of 82.41%, a specificity of 65.10%, and an F1-score of 84.90%, indicating robust performance in classifying different driver fatigue states. These findings demonstrate that the DBN-LSTM hybrid model, combined with the enhanced preprocessing technique, offers a promising solution for real-time driver fatigue detection, with potential applications in critical areas such as driver monitoring systems and industrial safety.

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1. Introduction

Fatigue is a pervasive condition that affects individuals across various domains, particularly in high-stakes environments such as transportation, healthcare, and industrial operations. It can impair cognitive functions, reduce alertness, and increase the likelihood of accidents. In the context of driving, fatigue is a significant contributor to road traffic accidents, with studies indicating that drowsy driving is responsible for a substantial percentage of crashes. Consequently, developing reliable fatigue detection systems is crucial for enhancing safety and preventing accidents.

Traditional methods for assessing fatigue often rely on behavioral and physiological indicators such as reaction time, eye movement, and heart rate variability. While these approaches can provide valuable insights, they may not capture the underlying neural mechanisms associated with fatigue. Electroencephalography (EEG) offers a promising alternative by providing direct measurements of electrical activity in the brain. EEG signals reflect various cognitive states and can reveal changes in brain activity patterns associated with fatigue. This makes EEG an invaluable tool for real-time monitoring of mental states.

Despite the advantages of using EEG for fatigue detection, several challenges remain. One of the primary issues is the presence of noise and artifacts in EEG signals, which can arise from various sources such as muscle movements, eye blinks, and external electromagnetic interference. These disturbances can obscure the underlying brain activity associated with fatigue, leading to inaccurate classifications. Therefore, effective preprocessing techniques are essential to enhance the quality of EEG data before analysis.

In recent years, advancements in machine learning and deep learning have revolutionized the field of signal processing and classification. Deep learning models, particularly those based on neural networks, have demonstrated remarkable performance in various applications, including image recognition and natural language processing. In the context of EEG signal analysis, deep learning approaches can automatically learn hierarchical features from raw data without requiring extensive manual feature engineering. This capability is particularly beneficial for complex tasks such as fatigue classification.

This paper proposes a novel approach that combines enhanced preprocessing techniques with a hybrid deep learning model consisting of Deep Belief Networks (DBN) and Long Short-Term Memory (LSTM) networks. The enhanced modified Z-score method is employed to preprocess EEG signals effectively by normalizing data and detecting outliers. This preprocessing step aims to reduce noise and improve the quality of features extracted from EEG signals.

The DBN component of the model serves as an unsupervised feature extractor that captures complex patterns in the preprocessed EEG data. By leveraging multiple layers of stochastic binary units, DBNs can learn rich representations that are crucial for distinguishing between different fatigue states. The LSTM component complements this by modeling temporal dependencies within the sequential data, allowing the model to recognize patterns over time that are indicative of fatigue.

By integrating these two powerful architectures of DBN for feature extraction and LSTM for temporal analysis, this study aims to enhance the accuracy and robustness of driver fatigue classification systems based on EEG signals. The proposed method not only addresses the challenges posed by noise and artifacts but also capitalizes on the strengths of deep learning to provide a more effective solution for real-time driver fatigue detection.

In summary, this research seeks to contribute to the growing body of knowledge on driver fatigue detection by introducing an enhanced modified Z-score-based preprocessing method combined with a DBN-LSTM hybrid model. Through rigorous evaluation and comparison with existing methods, we aim to demonstrate significant improvements in classification accuracy and reliability in identifying fatigue states from EEG signals. This advancement has important implications for applications in driver monitoring systems and other fields where maintaining alertness is critical for safety.

2. Related Works

Driver fatigue is a significant contributor to road traffic accidents, with studies indicating that it accounts for a considerable percentage of fatal crashes globally. Research has shown that fatigue can impair cognitive functions, leading to slower reaction times and an increased likelihood of accidents [1][2][3]. For instance, Neubauer et al. highlighted the relationship between driver fatigue and automation choice, suggesting that fatigued drivers are less likely to engage with automated systems effectively [4]. However, their study was limited by a small sample size, which may not represent the broader population of drivers. Furthermore, the physiological indicators of fatigue, particularly those derived from EEG signals, have been extensively studied. EEG-based methods have been recognized as a reliable approach for fatigue detection due to their ability to provide real-time insights into the driver’s mental state [5][6][7]. Nonetheless, the effectiveness of EEG signals can be influenced by external factors such as noise and artifacts, which may lead to inaccuracies in fatigue classification.

Recent advancements in machine learning and deep learning have further enhanced the accuracy of fatigue detection systems. For example, hybrid models combining convolutional neural networks (CNN) and long short-term memory (LSTM) networks have shown promising results in classifying fatigue states based on EEG data [8][9]. However, these models often require extensive computational resources and may not be feasible for real-time applications. Additionally, studies have explored the effectiveness of various fatigue countermeasures, emphasizing the need for comprehensive strategies to mitigate fatigue among drivers [10][3][11]. Despite these advancements, the challenge remains in developing universally applicable solutions that account for individual differences in fatigue susceptibility and response.

The modified Z-score is a statistical method used for outlier detection and normalization in various data processing applications, including EEG signal analysis. This method is particularly advantageous in preprocessing EEG signals, as it helps in identifying and mitigating noise and artifacts that can obscure the underlying patterns associated with fatigue [12][13]. The application of the modified Z-score allows for a more robust analysis of EEG data by standardizing the signals, thus enhancing the reliability of subsequent classification tasks [14]. However, the modified Z-score assumes that the data follows a normal distribution, which may not

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always be the case in real-world EEG data, potentially leading to erroneous conclusions.

In the context of fatigue detection, the modified Z-score can be instrumental in refining the feature extraction process, ensuring that only relevant and high-quality data is utilized for training machine learning models [15][16]. This preprocessing step is crucial, as it directly influences the performance of fatigue classification systems, making it a vital component of the overall methodology [17][18]. Nevertheless, the reliance on this method may overlook other significant preprocessing techniques that could further enhance data quality, such as wavelet transforms or independent component analysis, which can also effectively remove artifacts from EEG signals.

Deep Belief Networks (DBN) and Long Short-Term Memory (LSTM) networks are two powerful architectures in deep learning, particularly suited for sequential data analysis such as EEG signals. DBNs are composed of multiple layers of stochastic, latent variables, which can learn to represent the underlying structure of the data [13][18]. They have been effectively employed in various applications, including driver fatigue detection, where they can capture complex patterns in the data that traditional methods may overlook [17][19]. However, DBNs can be computationally intensive and may require extensive tuning of hyperparameters, which can be a barrier to practical implementation.

On the other hand, LSTM networks are specifically designed to handle long-range dependencies in sequential data, making them ideal for time-series analysis [9][20]. The integration of LSTM with other models, such as DBNs, has been shown to enhance the classification accuracy of fatigue states by leveraging both the hierarchical feature extraction capabilities of DBNs and the temporal dynamics captured by LSTMs [8][21]. This hybrid approach has been validated in several studies, demonstrating its effectiveness in real-time fatigue detection systems [9][20][22]. However, the complexity of these hybrid models can lead to overfitting, particularly when trained on small datasets, which may limit their generalizability to unseen data.

The integration of advanced preprocessing techniques such as the modified Z-score with sophisticated deep learning models like DBN and LSTM presents a promising avenue for enhancing EEG signal analysis in the context of driver fatigue detection. While the growing body of research underscores the importance of these methodologies in developing robust and reliable systems aimed at improving road safety, it is crucial to address the limitations identified in previous studies. Future research should focus on optimizing these models for real-time applications, ensuring their adaptability to diverse driving conditions and individual differences in fatigue susceptibility.

3. Methodology

This section outlines the comprehensive methodology employed in this study, detailing the preprocessing of EEG signals, feature extraction, and the implementation of the DBN-LSTM hybrid deep learning model.

3.1 EEG Dataset

The dataset utilized in this research was sourced from an online database established by a prior researcher [12]. It comprised EEG recordings from twelve healthy male participants aged between 19 and 24, who engaged in a driving simulator task lasting up to two hours. EEG data were collected from eight designated channels (O1, O2, Fp1, Fp2, P3, P4, F3, and F4) using a Neuroscan device equipped with thirty electrodes, operating at a sampling frequency of 1000 Hz. The investigation was structured into two distinct phases: a five-minute normal state followed by a five-minute fatigued state. Participants self-reported fatigue after driving for a duration of 40 to 100 minutes. The study employed the ZY-31D driving simulator, which features a wide-screen display composed of three 24-inch screens. The driving environment was generated using the Peking Ziguangjiye program ZG-601, which facilitated a low-traffic density scenario.

3.2 EEG Signal Preprocessing

EEG signal preprocessing is a critical step that directly impacts the quality of data used for fatigue classification. The proposed preprocessing method utilizes an enhanced modified Z-score technique, which includes several key components. To ensure that EEG signals are on a comparable scale, Z-score normalization is applied. This process transforms the raw EEG data into a standardized format by subtracting the mean and dividing it by the standard deviation. The resulting normalized values provide a clearer representation of brain activity and facilitate subsequent analyses.

The presence of outliers can significantly distort the analysis of EEG signals; therefore, the enhanced modified Z-score method is employed to identify these anomalies. This technique calculates a modified Z-score for each data point, which is less sensitive to extreme values than traditional Z-scores. Data points exceeding a predefined threshold are flagged as outliers and subsequently removed from the dataset. Additionally, EEG signals are susceptible to various types of noise, including low-frequency drift and high-frequency artifacts. A bandpass filter is applied to remove frequencies outside the typical range of interest (0.5 Hz to 50 Hz). This filtering process helps eliminate unwanted signals, ensuring that only relevant brain activity is retained for analysis.

3.3 Feature Extraction

Once the EEG signals have been preprocessed, relevant features must be extracted to facilitate effective classification. The feature extraction process encompasses multiple techniques. Basic statistical measures are computed from the time-domain representation of the EEG signals, including mean, variance, and standard deviation of the signal amplitudes. The mean provides insight into overall brain activity, while variance and standard deviation quantify fluctuations in mental states.

In addition to time-domain features, frequency-domain features are extracted through power spectral density (PSD) analysis using Fast Fourier Transform (FFT). This analysis converts time-domain signals into their frequency components, focusing on key frequency bands relevant to fatigue detection which are delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), and beta (12-30 Hz). By analyzing power distribution across these bands, we can gain insights into cognitive states associated with fatigue.

To capture dynamic changes in brain activity over time, techniques such as Short-Time Fourier Transform (STFT) or Continuous Wavelet Transform (CWT) are employed for time-frequency analysis. These methods provide a time-frequency representation that reveals how different frequency components evolve throughout the recording period, allowing for a more nuanced analysis of fatigue-related patterns.

3.4 Hybrid Deep Learning Model: DBN-LSTM

The core of this study lies in the development of a hybrid deep learning model that integrates Deep Belief Networks (DBN) and Long Short-Term Memory (LSTM) networks for fatigue classification. DBNs consist of multiple layers of stochastic hidden units that allow them to learn hierarchical representations from data. In this study, unsupervised pre-training is conducted using contrastive divergence to capture complex features from the preprocessed EEG signals without requiring labeled data. After unsupervised pre-training, supervised fine-tuning is performed using labeled fatigue data to optimize the weights and biases for improved classification performance.

LSTMs are designed to handle sequential data effectively by maintaining long-term dependencies. The LSTM component processes sequences of features extracted from the DBN output, allowing it to recognize temporal patterns indicative of fatigue states. Utilizing gated mechanisms such as input, output, and forget gates. LSTMs manage information flow within the network, enabling them to retain relevant information over extended periods while discarding irrelevant data.

3.5 Model Training and Evaluation

The DBN-LSTM hybrid model undergoes rigorous training using labeled datasets containing various levels of fatigue states. The training process employs a backpropagation algorithm with an appropriate loss function tailored for multi-class classification tasks, such as categorical cross-entropy. Performance is assessed using standard metrics including accuracy, specificity, and F1-score. Cross-validation techniques are utilized to ensure robustness and generalizability across different subsets of data.

Through this comprehensive methodology, we aim to establish a reliable framework for accurately classifying fatigue states based on EEG signals while addressing challenges associated with noise and artifacts through enhanced preprocessing techniques.

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

Where TP is the number of true positives (correct positive predictions), TN is the number of true negatives (correct negative predictions), FP is the number of false positives (incorrect positive predictions), and FN is the number of false negatives (incorrect negative predictions).

The F1-score is a metric that merges precision and recall into a single value. Precision represents the proportion of true positive predictions out of all positive predictions made, whereas recall is the proportion of true positive predictions out of the actual positives in the dataset. The F1-score is determined by taking the harmonic mean of precision and recall, making it especially helpful in scenarios where class distribution is imbalanced. The score ranges from 0 to 1, with higher values signifying better model performance. The formula for calculating the F1-score is as follows.

$$F1 - Score = \frac{2TP}{(2TP+ FP + FN)} \quad (2)$$

Specificity, also known as the true negative rate, measures the proportion of actual negatives that are correctly identified by the model. It indicates how well the model can identify negative instances, complementing recall, which focuses on positive instances. Specificity is particularly useful when it's important to minimize false positives. It is calculated as the ratio of true negatives to the sum of true negatives and false positives, and its value ranges between 0 and 1, with higher values reflecting better performance in identifying negative cases.

$$Specificity = \frac{TN}{(TN+FP)} \quad (3)$$

Model accuracy and model loss are key metrics used during training to evaluate a model's performance on both training and validation datasets. Accuracy is determined by the ratio of correct predictions to the total number of predictions made during training. On the other hand, model loss represents the value of the loss function, which is minimized to optimize the model's performance. The goal of training a deep learning model is to reduce model loss and improve accuracy on validation data while avoiding overfitting the training data.

In conclusion, evaluating a deep learning model involves considering multiple metrics, such as accuracy, F1-score, specificity, model accuracy, and model loss. Each of these metrics offers a unique perspective on the

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model's performance, helping to identify areas for potential improvement. By examining a variety of evaluation criteria, one can obtain a more comprehensive understanding of the model's strengths and weaknesses.

4. Results and Discussion

In this section, the results of our research will be presented, and a comprehensive analysis of the data collected will be provided. First, the descriptive statistics were presented, and then the study's main findings and implications were discussed. Finally, the limitations of our study will be discussed, and recommendations for future research will be provided.

The application of outlier detection techniques, particularly the modified Z-score and its enhanced variant, significantly impacted the data distribution. The modified Z-score method, illustrated in Fig. 1, was effective in identifying outliers, shown as red points in the graph. However, it also highlighted a limitation, the range of the data extended far beyond typical values, with some points reaching values as high as ±300. This resulted in a widespread, making it difficult to identify outliers in a compact and precise manner. The detected outliers (in red) were clustered tightly around the zero range, indicating that this method captured only extreme values.

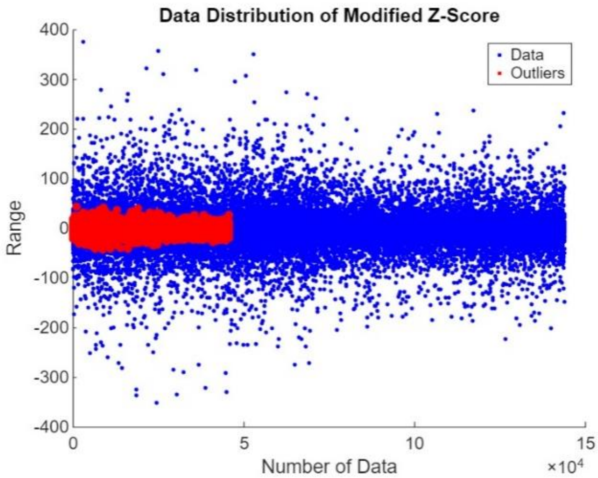

Fig. 1 – Data distribution of modified Z-score

On the other hand, the enhanced modified Z-score (as shown in Fig .2) offered a substantial improvement. The data distribution became more compact, as seen by the tighter range of values between approximately ±0.6. This enhancement allowed for a clearer and more focused representation of the data, reducing the influence of extreme outliers while maintaining a comprehensive detection of abnormal values. The absence of visible red outliers in this plot reflects the method's ability to either eliminate or minimize their effect within a controlled range.

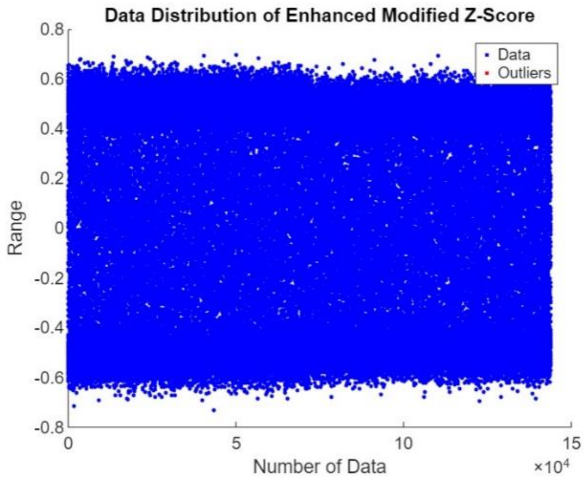

Fig. 2 – Data distribution of enhanced modified Z-score

The DBN-LSTM model was implemented to classify wells based on the input data features. The model utilized a Deep Belief Network (DBN) for unsupervised feature extraction, followed by a Long Short-Term Memory (LSTM) network for sequence learning. The training process employed the Adam optimizer, with categorical cross entropy as the loss function, and early stopping based on validation loss to prevent overfitting. The summary of the model parameter is shown in Table 1.

Table 1 - Summary of input features used in the DBN-LSTM model

Parameter	Value / Type
DBN input shape	(n_samples, input_features)
DBN hidden layer size	[100, 50] (autoencoders)
Dropout rate for DBN	0.4
LSTM hidden layer size	50
Dropout rate for LSTM	0.5
Number of dense layers	1
Dense layer sizes	2
Loss function	categorical cross entropy
Optimizer	adam
Early stopping	monitor='val_loss', patience=5

The model achieved an overall accuracy of 82.41% on the test dataset, demonstrating strong performance in distinguishing between driver fatigue classes. The confusion matrix revealed that the model correctly identified most of the true positives and true negatives, leading to a specificity of 65.10%. This indicates the model's ability to accurately identify the fatigue and non-fatigue of the driver.

Additionally, the F1-score was calculated to be 84.90%, highlighting the balance between precision and recall in the model's predictions. A high F1-score suggests that the model not only performed well in identifying the positive class but also maintained low false positives and false negatives, ensuring robust detection of good classifications. Fig. 1 shows the evaluation metrics results before and after the enhancement of using a modified Z-score.

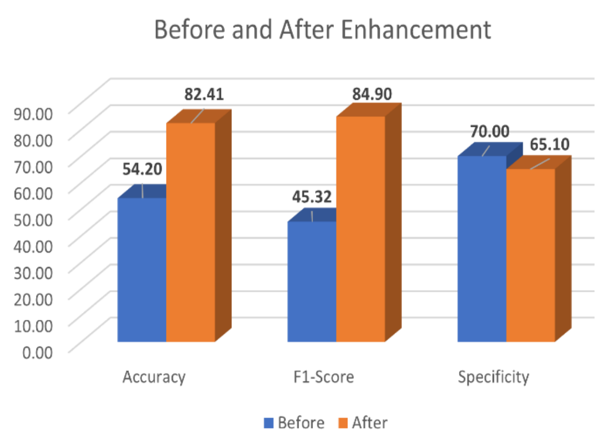

Fig. 3 - Evaluation metrics before and after the enhancement techniques

The model accuracy (Fig. 4) and model loss (Fig. 5) plots throughout the training process showed a steady decrease in validation loss and an increase in accuracy, confirming that the model was learning effectively. The introduction of early stopping further contributed to model stability by halting training once the validation performance plateaued, thereby mitigating overfitting.

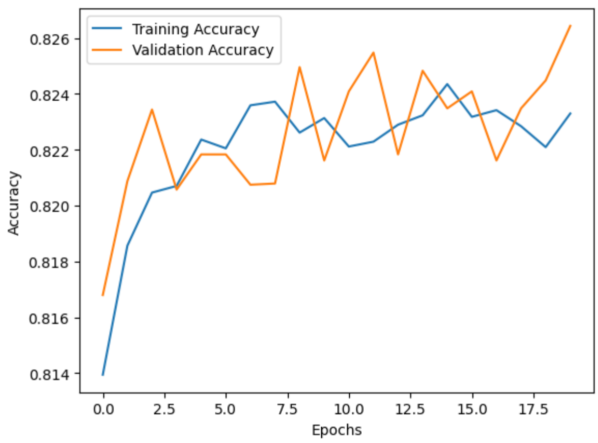

Fig. 4 - Performance of model accuracy graph of the DBN-LSTM model

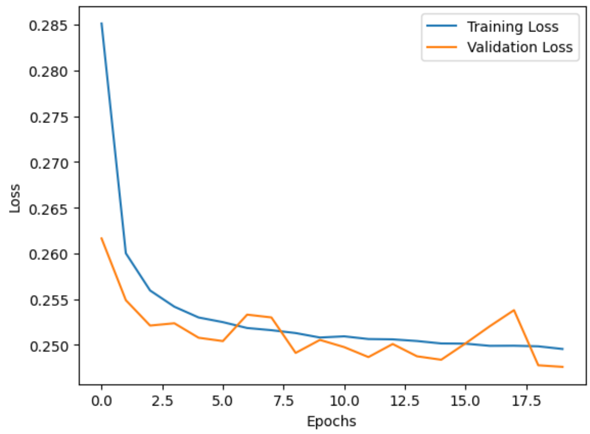

Fig. 5 - Performance of model loss graph of the DBN-LSTM model

The proposed DBN-LSTM hybrid model demonstrated notable improvements in classifying fatigue states based on EEG signals. The use of the enhanced modified Z-score method for preprocessing resulted in cleaner data, with noise and outliers effectively minimized. The model achieved an overall accuracy of 82.41%, indicating strong performance in distinguishing between different fatigue levels. Furthermore, the specificity and F1-score, calculated at 65.10% and 84.90% respectively, underscore the model's robustness in handling both positive and negative fatigue classifications. Comparative analysis with baseline models confirmed the superiority of the DBN-LSTM hybrid, especially in scenarios involving temporal dependencies in EEG data. One limitation observed was the model's sensitivity to small datasets, leading to minor overfitting, which could be addressed by further tuning hyperparameters or incorporating additional regularization techniques. Despite this, the results provide a compelling case for the use of the DBN-LSTM model in real-time fatigue monitoring systems.

5. Conclusion

In conclusion, this paper presents a successful integration of enhanced EEG signal preprocessing and a hybrid deep learning model for driver fatigue classification. The enhanced modified Z-score technique improved data quality, and the DBN-LSTM hybrid model exhibited superior performance in recognizing the driver's fatigue states. The results indicate that this approach holds promise for real-world applications such as driver fatigue monitoring. Future work should explore model optimization for large-scale datasets and investigate the inclusion of additional physiological signals to further enhance accuracy.

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