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Fatigue driving detection technology based on EEG signal

Zhe Yang *

Department of Computer Science and Engineering, The Chinese University of Hong Kong, Hong Kong, China

* Corresponding Author: 1155174022@link.cuhk.edu.hk

Abstract. Fatigue, significantly impacting daily work and life, is a common state triggered by overexertion. Given these statistics, the development of reliable fatigue driving detection technology becomes critical to enhancing road safety. Therefore, fatigue driving detection technology is essential to reduce accidents and improve traffic safety. Effectively detecting fatigue has become a significant topic of interest among researchers. Methods for detecting fatigue that rely on physiological data are viewed as the most objective and precise. Current methods mainly rely on facial expression observation and physiological signal monitoring, such as yawning and blinking. Although these methods are effective, lighting and environmental changes may affect the results of facial expression-based detection. In contrast, electroencephalography (EEG) signals, as physiological signals that directly reflect human mental states, can reduce environmental interference with detection results. This paper reviews recent advancements in classification algorithms for EEG-based fatigue detection. In the majority of studies, traditional machine learning algorithms and manual feature extraction methods are commonly employed as the primary techniques for fatigue detection. In addition, deep learning algorithms, which have demonstrated significant results on large-scale datasets, have also been applied to fatigue detection. However, training for long-term calibration against subjects remains challenging in practical applications. Given the increasing demands in this field, researchers must continually explore efficient decoding algorithms and design rational experimental paradigms. Additionally, they need to gather and accumulate standardized data to enable the widespread application of fast and accurate fatigue detection methods or systems.

Keywords: EEG; Fatigue Detection; Machine Learning Algorithms; Deep Learning Algorithms.

1. Introduction

Fatigue refers to a decline in physical or mental strength caused by sustained activity and is divided into physical and mental fatigue [1]. Compared to physical fatigue, mental fatigue is more intricate and can have more severe consequences, affecting cognitive functions and overall well-being. Driving fatigue, a prevalent form of mental fatigue, is a key factor contributing to traffic accidents [2]. According to the World Health Organisation, 20% to 30% of road traffic accidents are caused by fatigued driving [3]. Therefore, effectively detecting fatigued driving is essential to reducing injuries and preventing accidents. Researchers have used various methods to detect fatigue, including heart rate monitoring, electromyography-ECG, facial expression analysis, EEG data detection, and skin resistance measurements [4]. Among them, EEG is widely utilized in detecting driving fatigue because it directly reflects brain activity and can accurately and in real-time monitor the degree of fatigue [5].

EEG-based fatigue detection technology includes three partitions: signal acquisition, signal processing and analysis, feedback and application [6]. Specifically, EEG caps or other devices are used to collect EEG signals from subjects in both fatigued and awake states during the signal acquisition. In the signal processing and analysis part, the signals are processed and analyzed through preprocessing (e.g., filtering, removing artifacts), feature extraction (e.g., wavelet transform, autoregressive modeling), and classification (e.g., machine learning, deep learning). Ultimately, the user's current state (the fatigue or awake state) is fed back through applying a trained classification model in time to take appropriate measures to avoid potential safety risks.

In recent years, significant progress has been made in fatigue detection techniques based on EEG signals. Researchers have employed various algorithms to enhance the accuracy and reliability of detection, including machine learning algorithms like Support Vector Machines (SVM) and K-Nearest Neighbors (KNN), etc. In addition, to solve the problem of insufficient data, deep learning techniques such as Convolutional Neural Network (CNN) and Long Short-Term Memory Network (LSTM) have also been introduced into the fatigue detection research to improve the model's generalization ability. This paper reviews current EEG-based fatigue detection techniques and provides a theoretical foundation for future algorithmic research. Although these techniques have made significant progress, challenges such as portability, robustness, and real-time performance remain to be overcome. The article concludes with a discussion of these techniques' issues and an analysis of future trends. These discussions are essential for promoting the further development of EEG-based fatigue detection techniques.

2. EEG-based Fatigue Detection Technology

This paper will review recent research progress on fatigue detection techniques based on EEG signals. As illustrated in Fig. 1, the classification algorithms are categorized into traditional machine learning and deep learning methods. In the field of traditional machine learning, commonly used classifiers include SVM, Random Forest (RF), and KNN, which mainly rely on manually designed features and are suitable for small datasets [7-9]. On the other hand, deep learning algorithms leverage network properties to extract effective features and enhance classification performance. CNN is used to extract frequency domain features and adapt to the spatial frequency complexity of EEG, while LSTM excels at processing time-series data and capturing the temporal dependencies of EEG. With technological advances and computational resources, deep networks such as Generative Adversarial Network (GAN) and Graph Convolutional Network (GCN) are also being utilized for fatigue detection [10]. The application of deep learning in fatigue driving detection has become more mature, with substantially improved accuracy and robustness; this provides effective technical support for fatigue driving prevention and intervention.

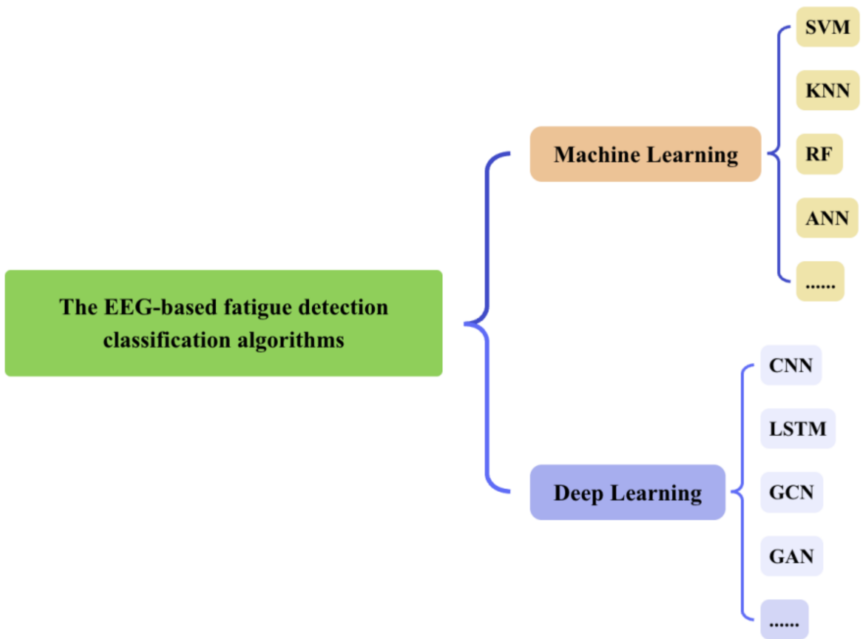

Figure 1. The EEG-based fatigue detection classification algorithms [6]

3. Traditional Machine Learning Algorithms Applicated in Classification

Table 1 summarises the authors, feature extraction methods, classification algorithms and accuracy rates of all the traditional machine learning articles mentioned in this section.

3.1. Combined with Traditional Feature Extraction Methods

In the study conducted by Chai et al., EEG data from 48 subjects experiencing driving fatigue were processed. They employed an autoregressive (AR) model to extract features from the data and used an independent component analysis (ICA) algorithm to optimize the feature downscaling. Using ICA helps in reducing the dimensionality of features while preserving essential information, which is crucial for improving the performance of the AR model in fatigue detection. This step ensures that the most relevant aspects of the data are preserved, resulting in more accurate and efficient detection of fatigue states. By applying a Bayesian classifier for data classification, they achieved a classification accuracy of 88.2%. Nevertheless, a significant limitation of this study is its relatively low classification accuracy [11]. SVM has demonstrated significant classification accuracy in a variety of complex data analysis and signal processing strategies [12]. Zhao et al. utilized the MVAR model to extract multi-channel EEG signal features and then employed KPCA-SVM, achieving an accuracy of 81.64% [13]. Using the same PCA preprocessing technique, Alharbey et al. applied multiple classifiers [7]. The SVM classifier alone achieved nearly 98% detection accuracy in under 0.18 seconds. This result significantly outperformed other well-known and efficient fatigue detection algorithms using driver EEG signals, further emphasizing the power and advantages of SVM in complex and high-dimensional data analysis. However, the biggest drawback of SVM is the difficulty in tuning its key parameters to achieve optimal performance [14]. Nugraha et al. used the EMOTIV EPOC+ technique and collected EEG data from 30 subjects performing either 33 minutes or 60 minutes [15]. They applied the KNN classification method by analyzing data for mean, standard deviation, correlation, and features extracted through the Fast Fourier Transform (FFT), achieving 96% classification accuracy. Subasi et al. used a Flexible Analytic Wavelet Transform (FAWT)-based approach to efficiently process EEG signals and extract key features from them [16]. These features were integrated into several machine learning models, including SVM, CART, KNN, ANN (Artificial Neural Network), RF, etc. In particular, the model shows up to 97.90% accuracy in distinguishing between fatigue and rest states in the MultiBoost-SVM setting. In addition, the model's high F-score, AUC, and k values validate its effectiveness and reliability in real-world applications. Kumar et al. employed various machine learning methods to automatically detect driver fatigue [17]. These methods included multidimensional scaling (MDS), singular value decomposition (SVD), three-phase mean-based support vector regression, adjustable q-wavelet transforms, and extreme learning machines (ELM). Additionally, they used classifiers such as Adaboost and SVM to classify the feature matrix, ultimately achieving up to 99% accuracy in distinguishing between normal and fatigued states. These results demonstrate the effectiveness of various methods and underscore the importance of combining multiple techniques in complex signal processing and machine learning. By combining CSD and Lyapunov exponential mapping of multidimensional signal levels based on manifolds with SVM classification, a classification accuracy of 99.13% was achieved.

Table 1. Summary of Traditional Machine Learning Algorithms Applicated in EEG-Based Fatigue Detection

Reference	Feature Extraction Method	Classification Algorithm	Accuracy (%)
Chai et al. [11]	ERBM-ICA, AR	BNN	84.3/83.0
Zhao et al. [13]	MVAR	KPCA-SVM	81.64
Alharbey et al. [7]	PCA	SVM	98
Nugraha et al. [15]	EMOTIV EPOC+	KNN	96
Subasi et al. [16]	FAWT	SVM, CART, k-NN, ANN, RF	97.9 (max)
Kumar et al. [17]	MDS, SVD	ELM-SVM	98
Ma et al. [18]	PCA, PCANet	SVM	95.14 ± 4.87
Tuncer et al. [9]	NCA, ReliefF, PCA	KNN	97.29
Bo Peng et al. [19]	NCA, ReliefF, PCA	T-A-MFFNet	85.65

3.2. Combined with Feature Extraction Network Methods

Conventional feature extraction methods have limitations in processing EEG signals for fatigue driving detection, mainly because they usually perform only shallow feature extraction, making it challenging to capture complex deterministic signal features. These methods often rely on manually designed features, which are time-consuming, may introduce personal bias, and have weak generalization to new data. Due to the high complexity and non-linear characteristics of EEG signals, traditional shallow learning methods are difficult to cope with these challenges. To overcome these problems, in recent studies, researchers have used networks that combine multiple feature extraction techniques to automatically learn and extract useful features from large amounts of data. Automated feature extraction overcomes the limitations of shallow feature extraction in traditional methods by using deep learning techniques that can analyze data at a deep level through a multi-layer network structure. This approach improves the efficiency and quality of feature extraction, significantly reduces human intervention and bias, and enhances the model's adaptability and generalization to new data types and unknown conditions. Therefore, automated feature extraction techniques can effectively address the limitations of traditional methods in fatigue driving detection and provide more accurate and efficient analysis results.

In 2019, Ma et al. proposed a feature extraction strategy that combines Principal Component Analysis (PCA) and PCANet to optimize EEG-based driving fatigue detection [18]. The strategy first preprocesses the EEG data using PCA, which ensures the retention of key signal features by reducing the complexity of the data and avoiding the dimension explosion problem. Then, the feature representation capability is further enhanced by PCANet, which provides richer features for the classification model. Considering that EEG datasets usually have small sample sizes, SVM with superior small-sample processing capabilities were selected for classification in the study. This integrated approach attained a high classification accuracy of 95.14% ± 4.87 in driving fatigue detection tasks, significantly surpassing the performance of traditional feature extraction methods.

Unlike Ma et al., Tuncer et al. generated features by combining Dynamic Centre based Binary Pattern (DCBP) and Multi Threshold based Ternary Pattern (MTTP), which are two approaches to the modifications of the traditional Binary Pattern (BP) and Ternary Pattern (TP) [9]. This feature generation network is designed to efficiently capture complex patterns in EEG signals. It reduces the computational cost and improves the representativeness of the classification. Tuncer's team used a three-layer feature selection method that combines ReliefF, NCA (Neighborhood Components Analysis), and PCA to optimize the feature selection process. This hybrid approach first filters out statistically significant features through ReliefF, then further extracts the most relevant features for the classification task using NCA, and performs dimensionality reduction through PCA, ultimately streamlining down to 108 highly discriminative features. In the classification phase, several benchmark classifiers were used for comparison, including KNN, ANN, RF, and SVM. Among these, the KNN algorithm based on the Manhattan Distance metric performed the best in the experiments. It achieved a high classification accuracy of 97.29%, a sensitivity of 97.08%, and a specificity of 97.50%. The effectiveness and efficiency of the DCBP-MTTP feature generation network and the RFNCAPCA feature selection method in fatigue detection are demonstrated by these results.

Although Tuncer et al. have already achieved some results in the field of driving fatigue detection, the study by Bo Peng et al. further expands the depth and breadth of the technique on this basis [19]. They introduced a new multi-feature fusion network (T-A-MFFNet) that combines time-domain analysis with attention mechanisms, enabling comprehensive analysis and utilization of EEG signal information. By integrating differential entropy and time-series features automatically learned by a deep learning network, the T-A-MFFNet not only boosts the accuracy of fatigue detection but also enhances the model's ability to process complex EEG signals. The network achieves an accuracy of 85.65% on the SEED-VIG dataset, surpassing existing models. This highlights the potential of combining deep learning technology with advanced feature processing methods to enhance real-time accuracy and suggests a new direction for the future development of fatigue detection technology.

4. Deep Learning Algorithms Applicated in Classification

Compared to traditional machine learning techniques, deep learning demonstrates a greater ability to utilize large datasets and achieve improved classification performance [20]. This advantage stems from the multi-layered architecture of deep neural networks, which can autonomously learn and extract complex features from raw data. The ability of these models to handle extensive data is further augmented by efficient training on advanced hardware such as GPUs, which utilize parallel processing to accelerate computation. Moreover, deep learning models are adept at capturing intricate patterns and high-level abstractions, resulting in significantly improved classification accuracy relative to conventional machine learning algorithms. In recent years, driven by advancements in machine learning technology, particularly deep learning, researchers have begun to investigate various neural network models to enhance the accuracy and efficiency of fatigue driving detection. Table 2 summarises the authors, classification algorithms and classification results of the four deep learning articles mentioned in this paper.

Recurrent Neural Networks (RNN) are widely used in analyzing physiological EEG signals due to their advantages in processing time-series data. Gao et al. proposed an integrated model that fuses Recurrent Network (RN) and CNN, RN-CNN, to monitor fatigue driving behavior [21]. The advantages of RN and CNN are effectively combined by using the information matrix of the RN as a convolutional neural network input. The model utilizes multiple RNs to encode the deep features of time-series data, followed by CNN for efficient feature extraction and classification. The RN-CNN model demonstrated an average classification accuracy of 92.95%, proving its efficient performance in complex classification tasks. However, when dealing with long time series data, recurrent networks are prone to the problem of gradient vanishing or exploding, as the gradient may gradually decay to almost zero or abnormally increase to overflow during backpropagation, which seriously affects the learning efficiency of the network and the stability of the model [22]. The vanishing gradient problem causes weights to update very slowly, preventing the network from learning long-term dependencies, while the exploding gradient problem leads to large, unstable weight updates, causing the model to behave erratically. Both issues hinder the network's ability to learn effectively from data, making training challenging and unreliable. To solve this problem, LSTM, as a special kind of RNN, is widely used to overcome the gradient problem in long sequence training.

The research by Sheikhabad et al. introduces a system for automatically detecting driver fatigue by integrating Compressed Sensing (CS) and deep learning methods [23]. Specifically, it utilizes LSTM and CNN for a two-stage classification of driver fatigue using EEG signals. Initially, the researchers applied Compressed Sensing (CS) theory to the recorded EEG data to minimize computational load. The compressed data were then input into the proposed deep convolutional neural network (DCLSTM), which is composed of seven convolutional layers and three LSTM layers. This network can fully utilize CS and deep learning to perform feature extraction and classification automatically. The LSTM layers perform well in overcoming the gradient problem in long sequence training, which enables the system to maintain the accuracy at different compression rates at a high level, e.g., 95% accuracy when the compression rate is 40. However, while LSTM addresses the gradient issues encountered by traditional RNNs, it also adds more parameters and complexity, thereby increasing the difficulty of network training [21]. For example, consider a sequence prediction task with an input dimension of 10, a hidden layer of 100 neurons, and an output dimension of 1. In a traditional RNN, the total number of parameters is 11,100. However, for an LSTM with the same configuration, the total number of parameters increases to 44,400. In recent years, researchers have increasingly investigated the use of various deep learning algorithms for EEG signal classification to discover more optimal solutions.

Jia et al. proposed an alternative to deep learning networks with their end-to-end fatigue driving detection algorithm, based on temporal and graph convolution (MATCN-GT) [24]. The MATCN-GT model integrates two core components: the Multi-scale Attentional Temporal Convolutional Neural Network Block (MATCN Block) and the Graph Convolutional Transformer Block (GT Block). The MATCN Block is responsible for extracting features directly from raw EEG signals, operating without any prior information. Meanwhile, the GT Block handles the processing of EEG signal features across various electrodes. Additionally, the researchers developed a multi-scale attention module to preserve critical information about electrode correlations. They also incorporated a transformer module into the GCN to enhance the capture of dependencies between distant electrodes. Capturing these long-range dependencies is crucial for fatigue driving detection because fatigue-related signals in EEG data are often spread out across different regions of the brain. Effective detection of these signals requires understanding the complex interactions and dependencies between distant electrodes. By incorporating a transformer module, the model can more accurately capture these long-range dependencies, leading to better detection and prediction of fatigue states, ultimately improving the reliability and effectiveness of the fatigue detection system. The experimental results demonstrate that the MATCN-GT model achieves an accuracy of 93.67% on the public SEED-VIG dataset, surpassing the performance of existing algorithms. Specifically, the accuracy of the GT block is enhanced by 3.25% compared to traditional graph convolutional neural networks. Moreover, the MATCN block exhibits superior accuracy relative to existing feature extraction methods across different topics. Notably, the accuracy is improved by approximately 16%-13% compared to traditional machine learning methods (KNN, SVM), by about 9%-7% compared to CNN-based methods, and by around 1%-3% compared to GCN-based methods.

Ardabili et al. proposed an innovative driver fatigue detection system combining GAN and GCN to process and classify EEG signals [10]. They designed a standard driving simulator and recorded the EEG signals from 20 participants across five distinct fatigue levels (fully awake, mildly fatigued, moderately fatigued, severely fatigued, and highly fatigued) to form a comprehensive database. To validate the effectiveness of the system, they used a self-reported questionnaire and analyzed physiological pattern changes. The proposed deep learning model consists of five convolutional graph layers, one dense layer, and one fully connected layer, structured to optimize performance. It achieves 99%, 97%, 96%, and 91% accuracy in four real-world application scenarios, including different noisy environments, respectively. This demonstrates the model's excellent classification ability and robustness. Compared with traditional methods, the model performs well when dealing with small amounts of data, with higher convergence speed and accuracy. In the model evaluation, the GCN model demonstrated higher accuracy and faster convergence than algorithms such as AlexNet, ResNet 60, and Inception V3. This study tested the GCN model in a noise-free environment and specifically considered the effect of engine and cabin noise on classification accuracy, which has been generally ignored in recent studies. Therefore, they introduced Gaussian white noise at various signal-to-noise ratios to evaluate the model's robustness. The results show that the proposed GCN model maintains more than 90% classification accuracy until the signal-to-noise ratio is 0 dB, proving the model's reliability and stability in noisy environments. This further demonstrates the significant potential of GCN in the application of automatic driving fatigue detection. It indicates that, in practical applications, the GCN model can effectively manage and resist environmental noise interference, providing a crucial guarantee for enhancing the safety and stability of autonomous driving systems.

Table 2. Summary of Deep Learning Algorithms Applicated in EEG-Based Fatigue Detection

Reference	Classification Algorithm	Accuracy (%)
Gao et al. [22]	RNN, CNN, RN-CNN	92.95%
Sheykhivand et al. [23]	DCLSTM, CNN, CNN-LSTM	95% (compression rate = 40)
Jia et al. [24]	MATCN-GT	93.67%
Ardabili et al. [10]	GAN, GCN	≈ 96%

5. Conclusion

In today's society, the prevalence of fatigue triggered by a fast-paced life has far-reaching effects on individual health, public safety, and occupational efficiency. Fatigue detection systems are an area that requires continuous research, and their development will help mitigate the social problems caused by fatigued driving. This study concentrates on the application of EEG technology in fatigue detection, ,which, with its unique advantages, provides a solid theoretical foundation and a wide range of application prospects for fatigue monitoring. By comprehensively analyzing various technological approaches ranging from traditional signal processing to deep learning, this study points out that technological innovation improves the accuracy and practicality of fatigue monitoring and promotes the innovation of the human-computer interaction interface. Although facing difficulties in data acquisition, algorithmic complexity, and practical application challenges, existing research is moving towards optimization of algorithms, expansion of data resources, and diversification of experimental protocols, aiming to improve detection accuracy and expand application scope. Looking ahead, cross-disciplinary collaboration through cognitive science, neuroscience, and artificial intelligence will provide a more solid scientific foundation and strong support for fatigue monitoring technology. With advances in wearable device technology, the development of real-time and portable fatigue monitoring systems will soon be possible, greatly enhancing the systems' practicality and user acceptance. These technological advances will significantly improve fatigue monitoring performance and contribute to health protection, work efficiency, and public safety. With the deepening of research and the improvement of technology, EEG-based fatigue detection is poised to play a more significant role in both daily life and professional fields, opening a new chapter of healthier and safer life.

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