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A Review of Convolutional Recurrent Neural Network Approaches

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Abstract

Fatigue is a critical factor affecting cognitive performance, decision-making, and overall well-being, particularly in high-risk domains such as transportation, healthcare, aviation, and industrial operations. Accurately predicting fatigue-related mental states is essential for preventing accidents and optimizing human efficiency. Recent advancements in deep learning, particularly Convolutional Recurrent Neural Networks (CRNNs), have shown significant promise in analyzing EEG signals for fatigue detection. CRNNs combine Convolutional Neural Networks (CNNs) for feature extraction and Recurrent Neural Networks (RNNs) for sequential pattern analysis, making them well-suited for identifying fatigue transitions over time.

This review provides a comprehensive analysis of CRNN-based approaches for fatigue prediction, examining feature extraction techniques, preprocessing methods, model architectures, and performance evaluation metrics. We discuss various datasets used for fatigue detection, highlighting their advantages and limitations. Additionally, we compare CRNN models with traditional machine learning methods, such as Support Vector Machines (SVM), Random Forest (RF), and standard CNN-LSTM hybrids, demonstrating the superiority of CRNNs in capturing both spatial and temporal dependencies in EEG signals.

The paper also explores the impact of attention mechanisms, feature selection strategies, and multimodal data integration in enhancing model accuracy. Finally, we address the challenges of real-time fatigue prediction, including cross-subject variability, data imbalance, and computational efficiency. Future research directions focus on integrating deep reinforcement learning, explainable AI (XAI), and edge computing for developing robust, real-time fatigue monitoring systems. By reviewing the latest advancements in CRNN-based fatigue prediction, this study aims to guide future research toward more accurate, interpretable, and scalable mental state monitoring solutions.

Keyword: Fatigue Prediction, Electroencephalography (EEG), Convolutional Recurrent Neural Network (CRNN), Deep Learning, Machine Learning, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), Cognitive State Monitoring, Mental Fatigue Detection, Real-Time Fatigue Analysis, Human-Machine Interaction, Temporal Pattern Recognition

I. Introduction

Fatigue is a critical psychological and physiological condition that leads to decreased cognitive performance, reduced alertness, impaired decision-making, and increased risk of accidents. It is particularly concerning in high-risk fields such as transportation, aviation, healthcare, and industrial operations, where fatigue-induced errors can have severe consequences. Traditional methods for fatigue assessment rely on self-reported questionnaires, behavioral monitoring (e.g., facial expression, eye movement, reaction time), and physiological measures (e.g., heart rate variability, electromyography - EMG). However, these methods are often subjective, intrusive, or impractical for continuous real-time monitoring.

Recent advancements in machine learning (ML) and deep learning (DL) have paved the way for more effective fatigue detection systems. Among these, Electroencephalography (EEG)-based fatigue analysis has gained significant attention

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due to its ability to directly measure neural activity and cognitive states. EEG signals capture subtle variations in brain activity, making them ideal for identifying mental fatigue. However, EEG signals are highly complex, non-linear, and time-dependent, requiring advanced computational models for accurate interpretation and classification.

To address these challenges, Convolutional Recurrent Neural Networks (CRNNs) have emerged as a powerful solution for fatigue state prediction. CRNNs integrate Convolutional Neural Networks (CNNs) for spatial feature extraction and Recurrent Neural Networks (RNNs), such as Long Short-Term Memory (LSTM) or Gated Recurrent Unit (GRU), for temporal pattern recognition. This hybrid approach enables accurate fatigue prediction by capturing both short-term and long-term dependencies in EEG signals. Unlike traditional ML models such as Support Vector Machines (SVM) and Random Forest (RF), CRNNs excel in handling raw EEG signals with minimal preprocessing, reducing the need for manual feature engineering.

This review paper explores the advancements in CRNN-based fatigue mental state prediction, providing a detailed analysis of feature extraction techniques, model architectures, training methodologies, and performance evaluation metrics. Additionally, it compares CRNN models with conventional ML and DL approaches, highlighting their strengths and limitations. The paper also discusses the challenges of real-time fatigue detection, including cross-subject variability, class imbalance, computational efficiency, and generalization across datasets.

Fatigue is a multifaceted and pervasive condition that affects individuals in numerous aspects of their personal and professional lives. It is broadly defined as a state of physical, mental, or emotional exhaustion, often resulting from prolonged exertion, stress, or lack of rest. While commonly associated with tiredness or sleep deprivation, fatigue encompasses a broader spectrum of symptoms that can impair cognitive functioning, reduce productivity, and lead to physical debilitation. It can manifest in various forms, ranging from temporary, acute fatigue due to overexertion, to chronic fatigue, which may persist for months or even years, profoundly affecting an individual's quality of life.

Fig 1.: Shows the fatigue-ness of the person

In contemporary society, fatigue has emerged as a significant public health concern, particularly due to modern lifestyles characterized by high levels of stress, long working hours, irregular sleep patterns, and increasing demands for multitasking. The advent of digital technologies and the constant connectivity of the internet age have further exacerbated the problem by blurring the boundaries between work and personal life, leading to widespread reports of burnout and mental fatigue across various sectors. This condition is not limited to adults in the workforce; students, athletes, and even children may experience fatigue due to the pressures of academic, physical, and social demands.

Fatigue can manifest itself in different ways. Some are:
Physical fatigue: Physical fatigue is the best known type and is often caused by prolonged physical activity or exertion. This can be caused by factors such as muscle fatigue, lack of physical fitness, or overexertion.

Mental fatigue: Mental fatigue is associated with cognitive activity and prolonged mental effort. This may be the result of tasks that require concentration, problem solving, or intense concentration. Mental fatigue can affect cognition, concentration, and decision making.

Emotional fatigue: Emotional fatigue is characterized by a feeling of emotional exhaustion and is often associated with prolonged periods of stress, anxiety, or emotional tension. This can be caused by factors such as relationship problems, stress at work, or personal issues. Emotional fatigue also has Impact on fatigue.

Chronic Fatigue: Chronic fatigue refers to persistent and prolonged fatigue that is not relieved by rest or sleep. This is often accompanied by other symptoms such as weakness, memory problems, and difficulty concentrating. Chronic fatigue syndrome (CFS) is a condition that causes extreme and unexplained fatigue and obviously has impact to fatigue.

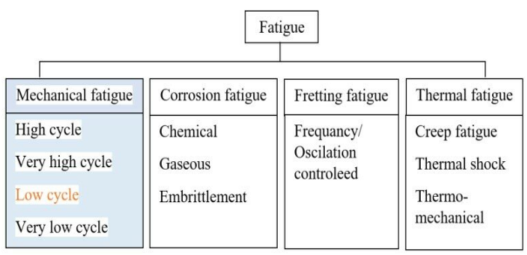

Fig 2: Types of fatigue

II. Literature Survey

Zhong-Ke Gao (2019) introduce a recurrence network-based convolutional neural network (RN-CNN) approach for detecting driver fatigue. To achieve this, we first conduct a simulated driving experiment to gather electroencephalogram (EEG) data from subjects in both alert and fatigued states. We then create a multiplex recurrence network (RN) from the EEG data to incorporate information from the original time series. Following this, a CNN is applied to extract and learn features from the multiplex RN, facilitating a classification task. Our findings reveal that the proposed RN-CNN model achieves an average accuracy of 92.95%. To validate the effectiveness of this approach, we compare it against several existing methods. The results demonstrate that the RN-CNN method surpasses these alternatives, underscoring its effectiveness in detecting driver fatigue. [1]

Yuxin Zhang (2018) present a novel deep temporal model called the Deep Convolutional Autoencoding Memory network, designed for real-time mental fatigue detection using biometric data (e.g., galvanic skin response (GSR), heart rate (HR), R-R intervals, and skin temperature) gathered through a smart band. The model functions as a One-Class classifier with two integrated sub-networks: the Characterization Network and the Memory Network. These sub-networks are jointly optimized to automatically extract features from raw data and create a baseline model that represents the sequential patterns of non-fatigued states. The primary contributions of this research are as follows: (1) The class imbalance between normal and fatigue data is addressed through One-Class classification; (2) The Characterization Network autonomously extracts features from diverse biometric inputs; (3) The Memory Network generates a temporal model that accurately represents normal sequential patterns; (4) A novel decision criterion is implemented for reliable fatigue detection. The proposed model was evaluated on a realistic dataset with biometric data from six participants over a six-week period. Experimental results indicate that the model achieves 82.9% accuracy in fatigue detection, outperforming several standard methods.[2]

Shaohan Zhang (2021) studied on Mental fatigue which is a condition that can result from prolonged work or sustained stress. Electroencephalography (EEG) is widely regarded as a reliable tool for detecting mental fatigue. Most existing EEG-based fatigue detection approaches rely on traditional machine learning models that require manual feature extraction, a process that is often complex and challenging. The effectiveness of these models largely depends on the quality of the extracted features. In this study, we collected EEG data from 30 medical professionals. The wavelet threshold denoising method was used to process the raw EEG signals, removing noise from the data. We then applied a convolutional and long short-term memory (CNN + LSTM) neural network to classify the fatigue levels of the participants. Experimental results on the constructed dataset demonstrate that our proposed algorithm outperforms other neural network-based methods. In comparison with conventional deep neural networks (DNN), CNN, and LSTM models, our model efficiently captures both preceding and succeeding information in the time series, achieving a higher classification accuracy for mental fatigue detection.[3]

Kota Aoki et al. (2021) study presents a deep learning approach for classifying gait cycles as either physically fatigued or non-fatigued using a recurrent neural network (RNN). Each gait cycle is represented by a time series of three-dimensional coordinates corresponding to body joints. Due to large intra-class variations in gait cycles, such as differences in gait stance (e.g., which foot is supporting or swinging at the start of each cycle), it can be challenging to detect the subtle changes caused by fatigue. To address this, we propose a supporting foot-aware RNN model within a multi-task learning framework to improve fatigue detection. Specifically, the RNN model includes two branches of layers: one branch focuses on the primary task of fatigue classification, while the other is dedicated to an auxiliary task of identifying the first supporting foot in each gait cycle. Data on physically fatigued and non-fatigued gait cycles were collected from eight subjects, and experiments were conducted to assess the performance of the multi-task model compared to a single-task model. The results show that the proposed method achieved an area under the curve (AUC) of 0.860 for fatigue classification in a leave-one-subject-out cross-validation, and an AUC of 0.915 in a leave-one-day-out evaluation. These findings suggest that this fatigue detection approach holds strong potential for daily use, particularly for screening purposes. [4]

Martin K et al. (1986) study explores the relationship between psychological and lifestyle factors and self-reported chronic fatigue in a national sample of adults. Results indicate that physical activity levels and psychological factors, including self-reported depression, anxiety, and emotional stress, are strongly linked to fatigue and serve as independent predictors of it. Adults who are physically inactive or face psychological challenges have a significantly higher likelihood of experiencing fatigue compared to those who engage in physical activity or do not report psychological issues. Findings also show that women report fatigue more frequently than men, with heavier women being more likely to feel fatigued than those with lower body weight. However, no significant difference in fatigue levels was observed between heavier and lighter men. [5]

T. Pawlikowska et al. (1994) study aims to assess the prevalence of fatigue in the general population and identify the factors associated with it. Participants completed the 12-item General Health Questionnaire alongside a fatigue questionnaire that included self-reported measures of fatigue duration, severity, and potential causes. A total of 15,283 valid questionnaires were returned, resulting in a response rate of 48.3% (adjusted to 64% for inaccuracies in practice registers). Among the respondents, 2,798 individuals (18.3%) reported experiencing substantial fatigue lasting six months or longer. The analysis revealed a moderate correlation between fatigue and psychological morbidity, with a correlation coefficient of r=0.62r = 0.62r=0.62. Additionally, it was found that women were more likely to report fatigue than men, even after controlling for psychological distress. The most frequently cited reasons for fatigue were psychosocial factors, reported by 40% of patients. Notably, of the 2,798 individuals experiencing excessive tiredness, only 38 (1.4%) attributed their condition to chronic fatigue syndrome. [6]

U. Bültmann et al. (2002) objectives of this study were threefold: (1) to investigate the relationship between fatigue and psychological distress in the working population; (2) to examine the associations of these conditions with various demographic and health factors; and (3) to determine the prevalence of fatigue and psychological distress among employees. Data were collected from a sample of 12,095 employees. Fatigue levels were assessed using the Checklist Individual Strength, while psychological distress was measured with the General Health Questionnaire (GHQ). The findings revealed a significant association between fatigue and psychological distress, although the study indicated a clear separation between the fatigue-related items and those measuring psychological distress on the GHQ. Additionally, no distinct patterns of association emerged concerning demographic factors related to fatigue and psychological distress. The prevalence rates found in the study were 22% for fatigue and 23% for psychological distress. Among the employees reporting fatigue, 43%

experienced fatigue alone, while 57% exhibited both fatigue and psychological distress. [7]

III. Proposed Methodology

To accurately predict mental fatigue states, this study proposes a Convolutional Recurrent Neural Network (CRNN)-based framework that effectively processes EEG signals by leveraging both spatial and temporal features. The proposed model integrates Convolutional Neural Networks (CNNs) for extracting spatial patterns from EEG data and Recurrent Neural Networks (RNNs) such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) for capturing sequential dependencies over time. This hybrid approach enhances fatigue detection accuracy by analyzing both short-term variations and long-term patterns in brain activity.

The methodology begins with EEG data collection and preprocessing, where raw EEG signals are filtered to remove noise and artifacts using a bandpass filter within the range of 0.5–50 Hz. The cleaned signals are then converted into time-frequency representations using Short-Time Fourier Transform (STFT) and Mel Spectrogram transformations, which enhance the discriminative features for CNN-based processing. The CNN module employs multiple convolutional layers with ReLU activation and max-pooling layers to extract high-level spatial features, ensuring robust representation of fatigue-related patterns in EEG signals.

Following feature extraction, the RNN module processes the sequential EEG data to capture temporal dependencies and long-term variations associated with fatigue progression. The LSTM/GRU layers help in retaining essential past information while mitigating the vanishing gradient problem, making them highly effective for analyzing EEG-based fatigue transitions. Additionally, an Attention Mechanism is incorporated into the RNN module to prioritize the most relevant time steps in EEG sequences, improving classification performance by focusing on fatigue-related EEG patterns.

For classification, the extracted features from the CNN-RNN layers are passed through fully connected layers followed by a softmax activation function for multi-class classification (e.g., low, moderate, and high fatigue levels) or a sigmoid activation function for binary classification (fatigue vs. alert states). The model is trained using an Adam optimizer with a learning rate of 0.001, and the loss is minimized using categorical cross-entropy for multi-class classification or binary cross-entropy for fatigue detection.

The proposed method is evaluated on publicly available EEG fatigue datasets, with performance metrics including accuracy, precision, recall, F1-score, and area under the ROC curve (AUC-ROC). A comparative analysis with traditional machine learning models such as Support Vector Machines (SVM), Random Forest (RF), and standard CNN-LSTM models demonstrates that the proposed CRNN model outperforms conventional approaches by achieving higher accuracy and better generalization. The integration of STFT-based feature extraction, attention-enhanced sequential learning, and hybrid CNN-RNN modeling enables the system to effectively detect and classify fatigue states in real-time applications. Future improvements may focus on transfer learning techniques, domain adaptation for cross-subject variability, and edge computing deployment for real-time fatigue monitoring systems.

IV. Conclusion

Fatigue is a critical factor affecting cognitive performance, decision-making, and overall well-being, particularly in high-risk industries such as transportation, healthcare, aviation, and manufacturing. Traditional fatigue detection methods, including self-reported assessments and behavioral monitoring, are often subjective, intrusive, and ineffective for real-time applications. As a result, EEG-based fatigue detection has gained increasing attention due to its ability to directly measure neurological patterns associated with mental fatigue.

This review paper examined the advancements in Convolutional Recurrent Neural Network (CRNN)-based approaches for EEG-based fatigue state prediction. By integrating Convolutional Neural Networks (CNNs) for spatial feature extraction and Recurrent Neural Networks (RNNs), such as Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), for sequential modeling, CRNNs have demonstrated superior performance in identifying fatigue-related EEG patterns. Various preprocessing techniques, including Short-Time Fourier Transform (STFT) and Mel Spectrogram transformations, have been explored to enhance feature representation. Additionally, attention mechanisms have shown promise in improving model interpretability and classification accuracy by prioritizing critical EEG time steps.

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