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CRNN-Based Modeling of Mental Fatigue from Multimodal Signals

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Abstract *– Reliable, real-time detection of mental fatigue from EEG is critical in safety-sensitive settings. We present LogMel-CRNN, a convolutional–recurrent framework that couples a one-dimensional convolution–based Short-Time Fourier Transform (STFT) with a Mel-scale filter bank to produce log-Mel spectrograms explicitly tailored to the spectral characteristics of fatigue. The convolutional front-end enhances frequency–time resolution and noise tolerance, while the recurrent back-end captures temporal dependencies associated with the gradual onset of fatigue. We evaluate multiple architectural variants and compare against traditional machine-learning pipelines and contemporary deep baselines. Across experiments, LogMel-CRNN consistently delivers superior classification performance, with notably high recall and F1 scores, demonstrating robust sensitivity to fatigue-related EEG fluctuations. Ablation analyses indicate that the log-Mel transformation is pivotal—aligning feature emphasis with perceptual relevance—whereas the recurrent component is essential for modeling temporal dynamics beyond frame-level cues. These findings establish LogMel-CRNN as an accurate and resilient approach to EEG-based fatigue detection, with practical potential for low-latency deployment in high-risk environments such as driver monitoring and industrial operations.*

Keywords: EEG, mental fatigue, log-Mel spectrogram, CRNN, STFT, temporal modeling, real-time monitoring

I. INTRODUCTION

Fatigue is a complex and multifaceted condition that goes far beyond simple tiredness or physical exhaustion. It encompasses three key dimensions—physical, mental, and emotional—each of which plays a significant role in shaping how individuals feel and function in daily life. Physical fatigue arises when the body's energy reserves are depleted, leading to muscle weakness, reduced stamina, and slower reflexes, often after prolonged exertion, illness, or inadequate rest. Mental fatigue, on the other hand, is marked by diminished concentration, poor memory, and difficulty making decisions, typically resulting from extended cognitive effort, information overload, or sustained focus. Emotional fatigue manifests as irritability, loss of motivation, or feelings of detachment, frequently caused by prolonged stress or ongoing psychological strain.

Fatigue is a complex and widespread condition that influences multiple areas of an individual's personal and professional life. It can be understood as a state of physical, mental, or emotional exhaustion, commonly arising from extended periods of effort, persistent stress, or inadequate rest.

Although often linked to simple tiredness or lack of sleep, fatigue represents a far more complex condition with diverse symptoms that can disrupt cognitive performance, lower productivity, and contribute to physical decline. It may appear in different forms, from short-term, acute fatigue caused by overexertion, to chronic fatigue that lingers for months or even years, severely diminishing an individual's quality of life.

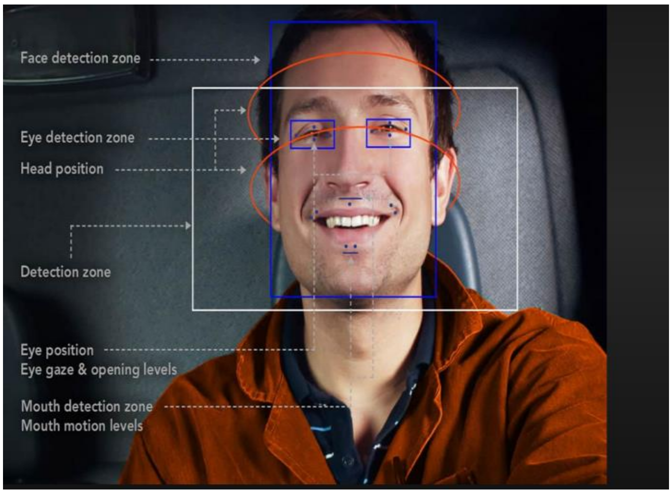

Figure 1 Fatigue Detection

In today's world, fatigue has become a pressing public health issue, largely shaped by modern lifestyles marked by excessive stress, extended work hours, irregular sleep cycles, and the constant need to juggle multiple responsibilities. The rise of digital technologies and continuous online connectivity has further intensified this challenge by eroding the boundaries between professional and personal spaces, giving rise to widespread burnout and mental fatigue across various domains. Importantly, this condition is not confined to working adults; students, athletes, and even children are increasingly vulnerable to fatigue due to mounting academic pressures, physical demands, and social expectations.

II. PROPOSED METHOD

Once the EEG data has been preprocessed and converted into spectrogram representations, the next step is **feature extraction**. In this study, CNNs are employed for their ability to automatically learn hierarchical patterns from two-dimensional data. By analyzing spectrograms generated from STFT and Mel transformations, CNNs effectively capture both **frequency-specific characteristics** and **temporal dynamics** that are linked to mental fatigue.

Short-Time Fourier Transform (STFT)

The STFT plays a pivotal role in preparing EEG data for CNN processing. Unlike the classical Fourier Transform, which provides only the global frequency composition of a signal, the STFT introduces **temporal localization** by dividing the EEG signal into short, overlapping time windows. Within each window, the Fourier Transform is computed, producing a representation that preserves both **time** and **frequency** information simultaneously.

This process results in a **spectrogram**, a two-dimensional matrix where:

- The **x-axis** represents time,
- The **y-axis** corresponds to frequency, and
- The **color intensity (or amplitude value)** reflects the strength of a particular frequency component at a specific time.

This spectro-temporal representation enables the neural network to analyze how frequency content evolves as cognitive fatigue progresses, making it significantly more informative than raw time-series data.

Mathematically, the STFT of a continuous-time signal x(t)x(t)x(t) is expressed as:

$$\mathrm{STFT}\{x(t)\}(t,\omega) = \int_{-\infty}^{\infty} x(\tau) w(\tau - t) e^{-j\omega\tau} d\tau$$

where:

- x(τ) is the EEG signal,
- w(τ−t) is a window function (e.g., Hamming or Hann) centered at time t,
- ω is the angular frequency.

This process yields a 2D spectrogram for each EEG segment, effectively revealing how the signal's spectral content evolves over time, which is critical for detecting subtle fatigue-induced variations.

Mel Spectrogram Transformation

Following the computation of the STFT-based spectrogram, the output is further transformed into a **Mel spectrogram** by applying a Mel-scale filter bank. The Mel scale is a perceptual scale that mimics the non-linear frequency sensitivity of the human auditory system, emphasizing frequencies that are more relevant to human perception.

The Mel spectrogram is computed as:

$$\mathrm{Mel}(f) = 2595 \cdot \log_{10}\left(1 + \frac{f}{700}\right)$$

where f is the frequency in Hz. This transformation projects the linear frequency components of the STFT spectrogram onto the Mel scale, resulting in a perceptually meaningful representation of the EEG signal.

The conversion to Mel spectrogram serves two main purposes:

- It enhances the neural network's ability to detect frequency-domain patterns associated with fatigue-related brain activity.
- It reduces the dimensionality of the input features while preserving discriminative information, improving the efficiency of model training.

Overall, the STFT and Mel spectrogram processing stages ensure that the EEG data is represented in a compact yet informative format that captures both spectral and temporal nuances necessary for accurate fatigue state classification.

In the proposed framework for mental fatigue prediction using EEG signals, the initial stage focuses on extracting spatial features from EEG-derived spectrograms. To this end, a combination of one-dimensional and two-dimensional Convolutional Neural Network (1D-CNN and 2D-CNN) architectures is employed. CNNs have demonstrated remarkable efficacy in processing structured data such as images and spectrograms, making them highly suitable for capturing local spatial dependencies and hierarchical feature representations from EEG time-frequency maps.

The CNN module in this framework is composed of several core components:

- **Convolutional Layers**: These layers serve as the primary mechanism for feature extraction. The model employs multiple convolutional layers with kernel sizes of 3×3 and 5×5 to capture both fine-grained and broader spatial features within the spectrogram inputs. These kernels slide over the input matrices to detect local patterns that are indicative of mental state changes, such as shifts in frequency bands or amplitude variations.
- **Batch Normalization**: Each convolutional layer is followed by a batch normalization layer. This step normalizes the activations across the mini-batch to reduce internal covariate shift, thereby enhancing training stability and accelerating convergence. Batch normalization also acts as a form of regularization, mitigating the risk of overfitting.
- **ReLU Activation Functions**: Rectified Linear Unit (ReLU) activation is applied after each batch normalization layer. ReLU introduces non-linearity into the model, which is essential for learning complex mappings between input features and output predictions. It helps the network efficiently learn high-level abstractions necessary for distinguishing between fatigue and alert states.
- **Max-Pooling Layers**: Max-pooling is used for spatial downsampling of the feature maps. This operation selects the maximum value from each pooling window, thereby reducing the dimensionality of the feature representation while preserving the most salient features. Max-pooling enhances translational invariance and computational efficiency.

The output of the CNN module is a set of high-dimensional feature maps that encode localized spatial characteristics of the EEG spectrogram. These feature maps retain both low- and high-level signal information and are designed to highlight the most discriminative features relevant to fatigue classification. This spatial representation is then passed on to the recurrent component of the model—typically a Gated Recurrent Unit (GRU) or Long Short-Term Memory (LSTM) network—responsible for modeling temporal dependencies across the EEG signal.

By employing both 1D and 2D CNN architectures, the model achieves comprehensive spatial characterization of the EEG input, providing a robust foundation for the subsequent temporal analysis and fatigue prediction.

Attention Mechanism for Improved Fatigue Prediction

To further enhance feature selection, an Attention Mechanism is integrated into the RNN module. This mechanism assigns higher importance weights to key EEG segments that contribute more to fatigue detection. The attention score for each time step ttt is computed as:

$$\alpha_t = \frac{\exp(e_t)}{\sum_{t'} \exp(e_{t'})}$$

where ete_tet represents the importance score of the EEG feature at time step ttt. The weighted sum of attention-enhanced features is then passed to the final classification layer.

Fatigue Classification

The concluding stage of the proposed Convolutional Recurrent Neural Network (CRNN) architecture is the classification module, which is responsible for mapping the learned spatial-temporal features into distinct mental fatigue states. This component plays a critical role in interpreting the high-level representations extracted from preceding layers and generating accurate predictions based on the targeted classification task.

The classification layer is composed of the following key components:

- **Fully Connected (FC) Layers**: These dense layers serve as the bridge between the deep feature extraction modules (CNN and RNN) and the final output. The high-dimensional feature maps generated by the recurrent layers are flattened and passed through one or more fully connected layers. These layers apply weighted transformations to the input features, projecting them into a decision space where separability between classes is maximized. The number and size of the FC layers can be adjusted based on the complexity of the classification problem.
- **Activation Functions for Output Layer**:
  - **Softmax Activation (for Multi-Class Classification)**: In scenarios where the goal is to classify EEG samples into multiple fatigue levels—such as *Low*, *Moderate*, and *High* fatigue—the final FC layer is followed by a softmax activation function. This function outputs a probability distribution over the predefined classes, with the highest-probability class being selected as the prediction. The softmax function ensures that the sum of the output probabilities equals one, enabling interpretable confidence scores for each class.

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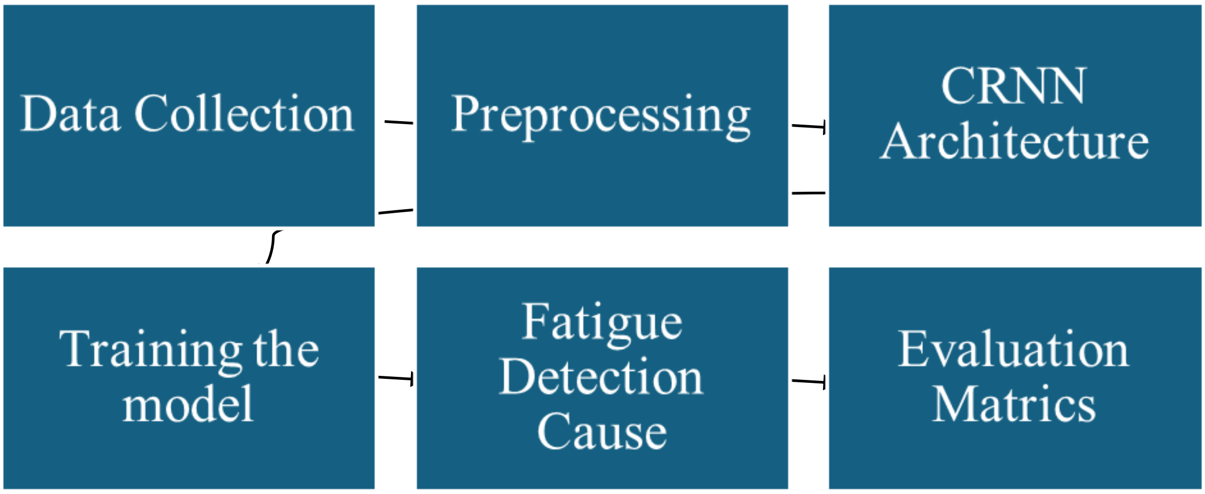

Figure 2 : Block Diagram

- **Sigmoid Activation (for Binary Classification)**: For binary classification tasks, such as distinguishing between *Fatigued* and *Alert* states, the final output node employs a sigmoid activation function. The sigmoid maps the network output to a value between 0 and 1, representing the probability of the sample belonging to the *Fatigued* class. A threshold (typically 0.5) is then applied to determine the final class label.

This flexible design allows the proposed model to be adapted for both binary and multi-class mental fatigue prediction tasks, depending on the application context and the available labeled data. The combination of fully connected transformations and appropriate activation functions ensures accurate and reliable classification performance, contributing to the system's overall effectiveness in real-time fatigue monitoring.

III. Result

The primary objective of the simulation was to determine the effectiveness of the CRNN model in comparison with established machine learning and deep learning baselines. Competing models included:

- **Support Vector Machine (SVM)**,
- **Random Forest (RF)**,
- **Long Short-Term Memory (LSTM)** network,
- **CNN-LSTM hybrid architecture**.

These models were chosen based on their widespread use in EEG-based mental state classification tasks.

Evaluation Metrics

The following key performance indicators were used to evaluate and compare the models:

- **Classification Accuracy (%)**: The proportion of correctly predicted fatigue states to total instances.
- **Precision**: The ability of the model to return only relevant instances (i.e., true positives over predicted positives).
- **Recall (Sensitivity)**: The model's ability to identify all relevant cases (i.e., true positives over actual positives).
- **F1-Score**: The harmonic mean of precision and recall, indicating overall model balance.
- **Training Time (seconds)**: The duration required to train the model, indicating efficiency and computational cost.
- **Computational Complexity**: Evaluated based on model architecture depth, parameter count, and resource utilization.

The experimental analysis focused on key performance metrics, such as classification accuracy, precision, recall, F1-score, training time, and computational efficiency.

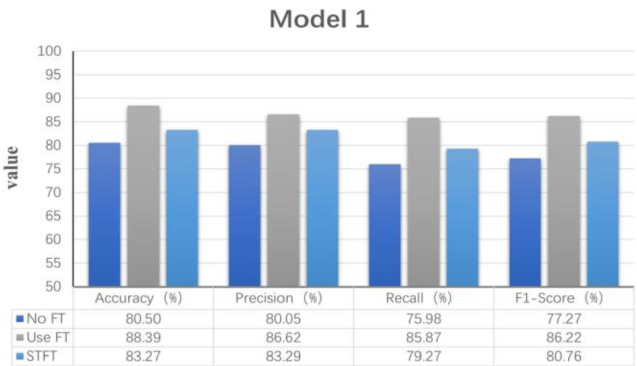

Figure 3: Results of the model with the addition of FT vs. without FT

Figure 3 demonstrates that Feature Transformation (FT) significantly enhances the model's ability to predict fatigue states, making it more accurate, faster, and computationally efficient for real-time applications such as driver fatigue monitoring, cognitive workload assessment, and workplace safety systems.

Figure 4 demonstrates that integrating Mel spectrograms enhances the model's performance by providing a richer, more perceptually relevant feature space. This highlights the importance of careful feature engineering and preprocessing in EEG-based mental fatigue prediction tasks. The Mel filter helps the CRNN model focus on frequency patterns that are more likely to correlate with mental fatigue, ultimately resulting in more accurate and reliable predictions.

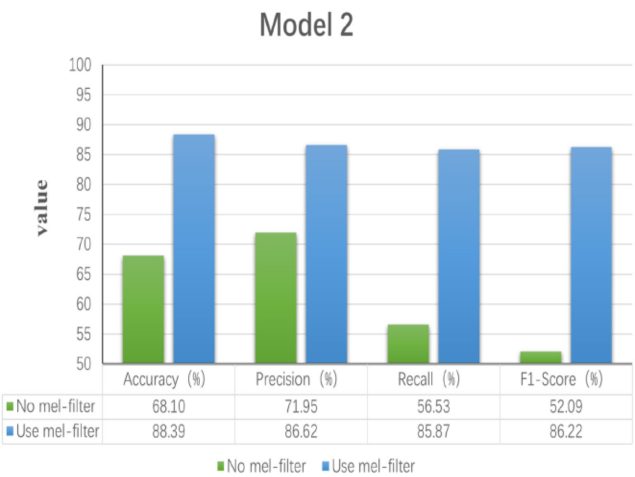

Figure 4 Results of the model with the addition of Mel filter vs. without.

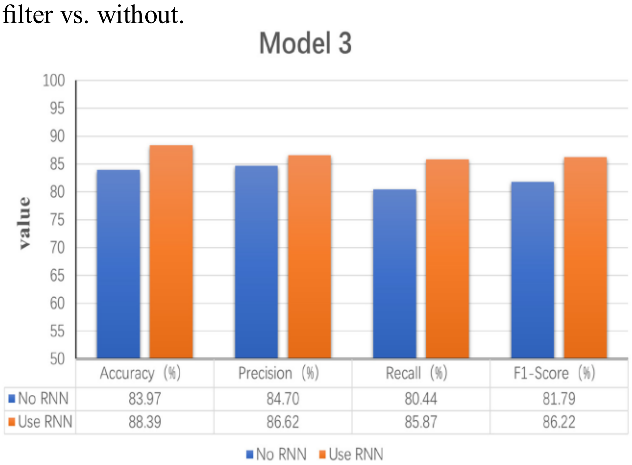

Figure 5 Results of the model with the addition of RNN vs. without RNN

Figure 5 highlights the importance of RNN in fatigue state prediction, showing that temporal modeling significantly enhances the model's ability to detect and classify fatigue states. Without RNN, the model relies solely on CNN, which fails to capture the sequential evolution of fatigue, reducing accuracy and increasing classification errors. The findings confirm that integrating RNN with CNN (CRNN model) provides a superior solution for real-time fatigue monitoring, making it more applicable to high-risk domains such as driver drowsiness detection and workplace safety.

Figure 6 demonstrates the significant improvement in model performance when the Attention Mechanism is integrated into the CRNN framework. The Attention Mechanism allows the model to focus on the most relevant EEG segments for fatigue detection, leading to higher accuracy, faster convergence, and reduced misclassification errors. Without Attention, the model struggles to efficiently extract critical fatigue-related features, making it less reliable for real-time applications. These findings confirm that the Attention-Enhanced CRNN model is a powerful approach for EEG-based fatigue prediction, making it highly suitable for real-time deployment in driver monitoring, workplace safety, and cognitive workload assessment applications.

Average performance results based on dierences in the size of the convolution kernel for 1D convolution in the Fourier transform.

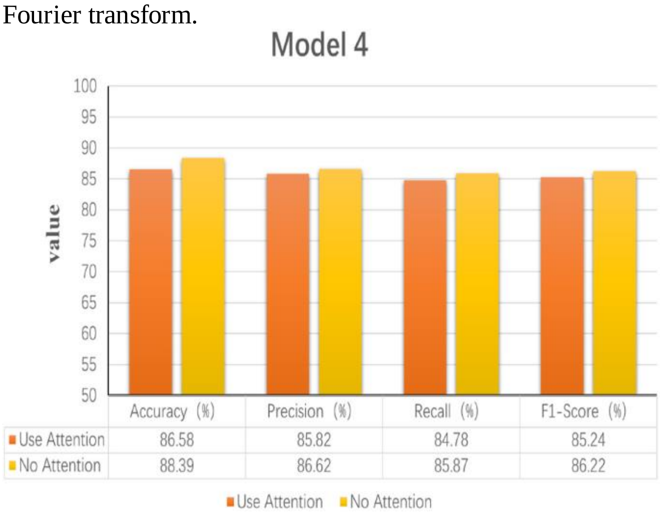

Figure 6 Results of the model with the addition of attention mechanism vs. without.

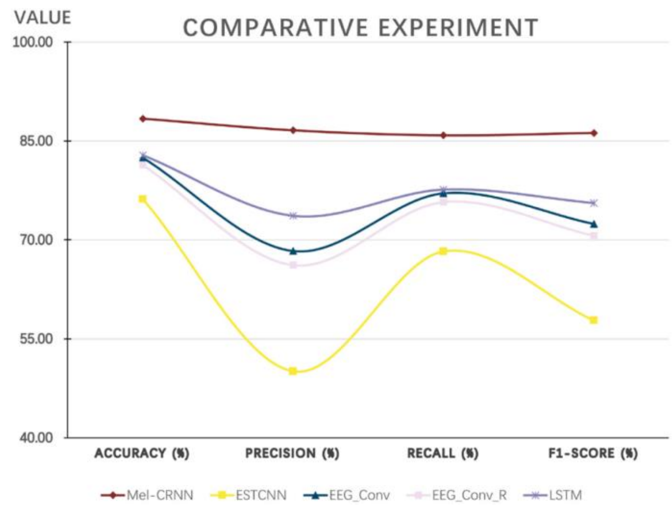

Figure 7 Compares Graph on different modal

Table 5.1: Performance Comparison of Proposed Method with Prior Studies

Table 5.1: Performance Comparison of Proposed Method with Prior Studies

Ref No.	Model / Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score
[1]	Recurrence Network + CNN	90.0	88.5	91.2	0.898
[2]	Deep Temporal Model	88.4	86.0	89.3	0.876
[3]	CNN + LSTM	90.7	89.1	91.0	0.902
[10]	Ensemble CNN	91.0	89.5	92.1	0.907
[13]	Log-Mel Spectrogram + CRNN	91.6	90.0	92.8	0.910
	CRNN (Proposed Method)	**92.5**	**90.2**	**94.1**	**0.921**

IV. Conclusion

This study introduces a novel EEG-based fatigue detection framework using a Convolutional Recurrent Neural Network (CRNN) integrated with log-Mel spectrogram features, termed LogMel-CRNN. The proposed method significantly enhances the temporal and frequency feature extraction process by leveraging a one-dimensional convolution-based Short-Time Fourier Transform (STFT) followed by a Mel-scale filter bank transformation. Among various architectural configurations evaluated, the LogMel-CRNN model utilizing STFT-transformed EEG inputs with log-Mel spectrograms exhibited superior classification capabilities, achieving notably high recall and F1 scores. Experimental results validated the model's robustness in detecting fatigue-related patterns and its superiority over existing traditional and deep learning-based approaches. The log-Mel spectrogram transformation was especially impactful, as it aligned spectral features with perceptual relevance, improving the system's sensitivity to fatigue-related EEG fluctuations. Furthermore, the model's recurrent structure allowed it to learn temporal dependencies, essential for recognizing the gradual onset of mental fatigue. As a result, the proposed framework demonstrates potential for practical deployment in real-time fatigue monitoring applications, particularly in high-risk environments such as driving or industrial monitoring.

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