Mental Fatigue Detection using EEG Signals: A 1D-CNN Approach

Bhavna Kakkar
M.A. Clinical Psychology

1. Project Overview and The Challenge

Mental fatigue is a critical cognitive state resulting from prolonged mental activity, leading to impaired attention, reduced decision-making ability, and increased risk of errors, particularly in high-stakes professional environments (e.g., healthcare, transportation).

Existing methods for detecting mental fatigue are largely subjective (surveys, self-reports) and often fail to provide objective, real-time monitoring. This project addresses the need for a robust, non-invasive system by **leveraging Electroencephalogram (EEG) signals**—a direct measure of brain activity—combined with deep learning for automated, objective classification.

2. Research Goals

The primary objective of this project is to develop and validate an end-to-end deep learning pipeline for classifying mental fatigue.

- To explore the relationship between time-series EEG signals and defined levels of cognitive fatigue.
- To design and implement a **1-Dimensional Convolutional Neural Network (1D-CNN)** model capable of autonomously extracting temporal features from EEG data.
- To classify mental workload into discrete levels (**Low, Medium, and High**) based solely on EEG recordings.
- To evaluate the model's performance rigorously using standard machine learning metrics.

3. Technical Implementation & Pipeline (Methodology)

This project follows a three-stage pipeline: Data Preparation (Completed), Model Development (In Progress), and Evaluation.

3.1 Data Source and Preprocessing (Phase 1: Complete)

- **Dataset:** The study utilizes the publically available **Mental Fatigue Level Detection (FatigueSet)** dataset, which includes raw and pre-filtered EEG recordings across various frequency bands (Alpha, Beta, Delta, Theta, Gamma). The goal is to classify the three intensity levels present in the dataset.
- **Standardization:** The most critical step involves converting the raw data, which contains variable-length EEG trials, into a standardized 3D tensor format for the CNN input.

  - EEG trials are individually loaded, cleaned (e.g., removal of index columns), and segmented.
  - **Zero-Padding:** All trials are programmatically standardized to the same sequence length using zero-padding based on the maximum trial length found in the dataset.
  - **Final Input Shape:** The data is transformed into the required 3D NumPy array shape: ($N_{samples} \times N_{timepoints} \times N_{channels}$). This processed data forms the input for the 1D-CNN.

Data Source Attribution: The project uses the **Mental Fatigue Level Detection (FatigueSet)** dataset. As per the authors' request for citing the publication associated with the data, the source paper is listed below:

- **Dataset Link:** https://www.esense.io/datasets/fatigueset/
- **Citing Publication:** Manasa Kalanadhabhatta, Chulhong Min, Alessandro Montanari and Fahim Kawsar. *FatigueSet: A Multi-modal Dataset for Modeling Mental Fatigue and Fatigability*. In 15th International Conference on Pervasive Computing Technologies for Healthcare (Pervasive Health), December 6–8, 2021.

3.2 1D-CNN Model Architecture (Phase 2: In Progress)

The model is designed as a sequential 1D-CNN to effectively capture local dependencies and temporal patterns across the EEG signal.

- **Input Layer:** Accepts the 3D tensor input of shape ($N_{timepoints}$ x $N_{channels}$).
- **Feature Extraction Blocks:** The model will employ two main blocks:
  - **Block 1:** Conv1D layer (e.g., 64 filters, kernel size 5, ReLU activation) → Batch Normalization → MaxPooling1D (pool size 2) → Dropout (0.3).
  - **Block 2:** Conv1D layer (128 filters, kernel size 5, ReLU activation) → Batch Normalization → MaxPooling1D (pool size 2) → Dropout (0.3).
- **Classification Head:** The output is flattened → passed through a **Dense** hidden layer (100 neurons, ReLU) → and terminates in a final Dense layer with **Softmax** activation for 3-class classification (Low, Medium, High).
- **Compilation:** The model will be compiled using the **Adam** optimizer and **Categorical Crossentropy** loss function.

3.3 Evaluation Metrics

The model's classification performance will be evaluated on a separate test set using standard metrics:

- **Accuracy:** Overall correctness of predictions.
- **Precision, Recall, and F1 Score:** Essential for evaluating performance in multi-class classification, ensuring the model performs reliably on each fatigue level.

4. Tools and Resources

Category	Tools and Libraries
Programming	Python
Data Handling	NumPy, Pandas
Deep Learning	TensorFlow / Keras
Hardware	Local machine or cloud resources (e.g., Google Colab with GPU support)
Dataset	Mental Fatigue Level Detection (FatigueSet)

5. Project Deliverables and Commitment

This project demonstrates a fully functional, custom data preparation pipeline capable of transforming the raw, variable-length FatigueSet data into the standardized **3D tensor input** required for deep time-series analysis. The completed data preparation phase serves as a foundation for a high-accuracy classification model.

The current deliverable is a documented codebase, which includes:

- Scripts demonstrating robust data loading, cleaning, and standardization via zero-padding.
- The research proposal outlining the intended 1D-CNN architecture.

6. Conclusion

This project aims to contribute significantly to the fields of clinical neuropsychology and machine learning by developing a model that can objectively and non-invasively detect mental fatigue using EEG data. Despite being a work in progress, the foundational data engineering is complete, demonstrating proficiency in handling complex, real-world biological signals. Completion of the **1D-CNN implementation and evaluation** is the final committed step toward realizing a prototype for a highly practical real-time fatigue monitoring system.