




# Real-time Dual-feature Mental Fatigue State SVM Classification using EEG Delta Bandpower

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**Abstract**—Reliable fatigue state detection systems recently use electroencephalography (EEG) signals to optimally monitor mental states and decrease the chance of human errors [1]–[5]. The current paper presents a rapid real-time, EEG-based mental fatigue assessment framework based on a linear Support Vector Machine (SVM) model. A low-cost, dry 4-electrode consumer-grade EEG device (Enophone [6]) collected 5-minute data from 24 undergraduate students that answered the Fatigue Assessment Scale (FAS) questionnaire [7] before undergoing an auditory oddball task. Pre-processing consisted in applying a 4th order Butterworth 0.1-100 Hz bandpass filter, as well as a 60 Hz Notch filter, in addition to a linear detrend. Feature extraction consisted of Power Spectral Density (PSD) features via the Welch method via Python’s Brainflow library [8], using one-second windows and half-second overlap. Furthermore, Random Forest (RF) regression’s Gini importance [9] determined the two most relevant features, which were two delta (1-4 Hz) ratios:  $\delta_{A1}^{A2}$  and  $\delta_{A2}^{C3}$ . The binary (No Fatigue / Substantial Fatigue) classification Machine Learning (ML) model achieved 93% accuracy and 0.91 f1-score (7-fold stratified cross-validation). The SVM model was further implemented in a real-time framework and tested using another independent group doing the same task. The reliable, high-accuracy model shows that low-cost EEG devices could be further implemented within the consumer to assess their fatigue level [10]–[14], later including cloud-computing to monitor the user’s mental state and allowing the system to make real-time adjustments to tasks’ complexity and pacing, thus enhancing work efficiency and well-being [15]–[17].

**Index Terms**—eeg, electroencephalography, machine learning, mental fatigue, svm, support vector machine, real-time, wearable

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