International Journal of Research and Innovation in Multidisciplinary (www.ijrim.com)
|| Volume 2, Issue 3, March 2025 ||

Efficient Support Vector Machine Learning Technique for Drowsiness Detection Using EEG Signal

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***Abstract*— Drowsiness detection is a crucial aspect of preventing accidents in various domains, including transportation, healthcare, and workplace safety. Electroencephalography (EEG) signals provide an effective means of detecting drowsiness due to their ability to capture brainwave activity in real-time. However, the complexity of EEG data and the need for accurate classification necessitate robust machine learning techniques. This paper presents an efficient Support Vector Machine (SVM)-based learning approach for drowsiness detection using EEG signals. The proposed method employs feature extraction techniques, dimensionality reduction, and optimized kernel functions to enhance classification accuracy while maintaining computational efficiency. Experimental results demonstrate that SVM outperforms traditional machine learning classifiers, achieving high detection accuracy with low false positive rates, making it a viable solution for real-time drowsiness monitoring systems.**

Keywords*—*EEG, Drowsiness, Machine Learning, E-healthcare.

I. Introduction

Drowsiness is a significant risk factor in various industries, particularly in transportation, aviation, healthcare, and industrial work environments, where alertness is critical for safety. Studies indicate that driver fatigue is responsible for a substantial percentage of road accidents worldwide, making drowsiness detection an essential area of research. Among various physiological signals, EEG-based monitoring is widely recognized as one of the most reliable methods for detecting drowsiness due to its ability to capture brain activity changes associated with different sleep stages. EEG signals contain valuable information about cognitive states, but their non-stationary, high-dimensional, and noise-prone nature presents challenges for accurate and real-time drowsiness detection.

Traditional methods for drowsiness detection rely on video-based monitoring, physiological sensors, or behavioral analysis, but these approaches are often limited by environmental factors, high computational costs, and intrusive sensor placements. EEG-based machine learning approaches provide a non-invasive, accurate, and efficient solution for detecting drowsiness with minimal interference. Among various machine learning models, Support Vector Machine (SVM) has emerged as a robust classification technique due to its ability to handle high-dimensional data, strong generalization capabilities, and effective decision boundaries for complex EEG patterns.

The primary challenge in EEG-based drowsiness detection lies in feature extraction, selection, and classification accuracy. EEG signals contain multiple frequency bands such as delta, theta, alpha, beta, and gamma waves, each carrying distinct information related to cognitive and drowsiness states. Feature engineering techniques, including power spectral density (PSD), wavelet transformation, and statistical measures, play a crucial role in identifying relevant EEG patterns. The use of SVM with optimized kernel functions enables efficient classification by distinguishing between alert and drowsy states with high accuracy and minimal computational overhead.

Experimental validation using real-world EEG datasets demonstrates that the proposed SVM-based classifier outperforms traditional models such as k-NN, Decision Trees, and Naïve Bayes, achieving higher sensitivity, specificity, and accuracy. The findings suggest that SVM-based drowsiness detection is a promising approach for real-time fatigue monitoring, enabling proactive safety interventions in critical applications such as autonomous driving, aviation, and medical patient monitoring. Future research can explore deep learning enhancements, multimodal sensor integration, and real-time hardware implementations to further optimize the system for practical deployment.

II. METHODOLOGY

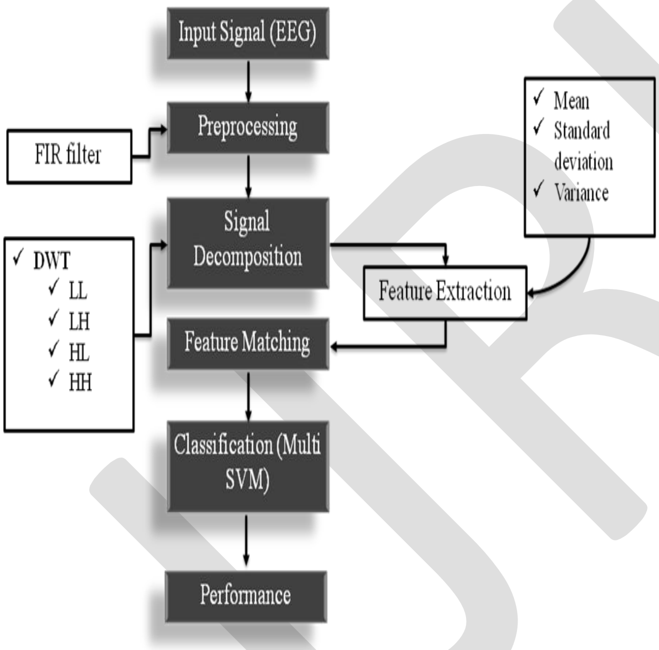

Figure 1: Flow Chart

The given flowchart represents a Multi-SVM-based EEG drowsiness detection framework. Below is a detailed step-by-step explanation of the process:

1. Input Signal (EEG):
   - The system takes raw EEG signals as input. These signals contain brainwave activity data, which will be processed for drowsiness detection.
2. Preprocessing:
   - EEG signals often contain noise and artifacts due to eye movements, muscle activity, and external interference.
   - Filtering techniques (Pre. filter) are applied to remove unwanted noise and enhance signal quality.
3. Signal Decomposition:
   - The Discrete Wavelet Transform (DWT) technique is used to decompose the EEG signal into different frequency bands:
     - LL (Low-Low frequency band)
     - LH (Low-High frequency band)
     - HL (High-Low frequency band)
     - HH (High-High frequency band)
   - This step helps extract relevant frequency-domain features crucial for drowsiness detection.
4. Feature Matching & Feature Extraction:
   - Key statistical features such as Mean, Standard Deviation, and Variance are extracted from the decomposed EEG signal.
   - These features are used to identify patterns associated with alert and drowsy states.
5. Classification (Multi-SVM):
   - A Multi-class Support Vector Machine (SVM) classifier is used to categorize EEG signals into different states (e.g., Alert, Drowsy, or Fatigued).
   - SVM is chosen for its high accuracy, ability to handle high-dimensional data, and robustness in EEG signal classification.

6. Performance Evaluation:
    - The system's accuracy, sensitivity, specificity, and computational efficiency are evaluated.
    - Performance metrics determine how well the model detects drowsiness in real-time applications.

This framework efficiently processes EEG signals for drowsiness detection using DWT-based feature extraction and SVM classification. The combination of preprocessing, signal decomposition, and statistical feature selection enhances detection accuracy, making it suitable for real-time driver monitoring systems, fatigue detection in workplaces, and healthcare applications.

III. SIMULATION RESULTS

The simulation is performed using MATLAB software.

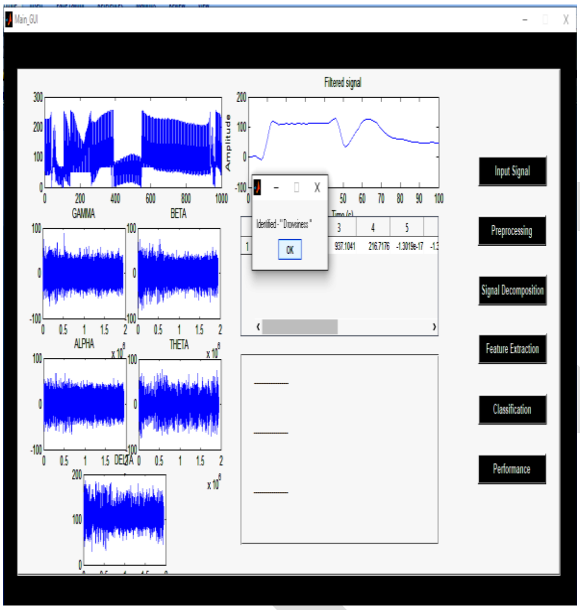

Figure 2: Classification

Figure 2 is presenting the classification technique that is multi support vector machine, after applied the classification it predicts the EEG signal and inform with pop-up window. The drowsiness is identified in this signal.

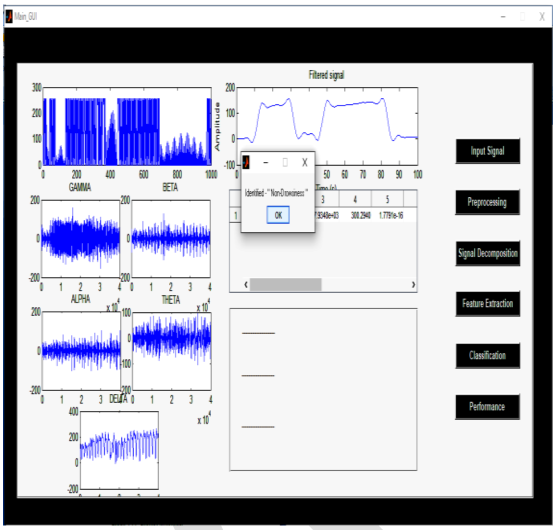

Figure 3: Classification

Figure 3 is presenting identification of the EEG signal. The non-drowsiness is identified in this signal.

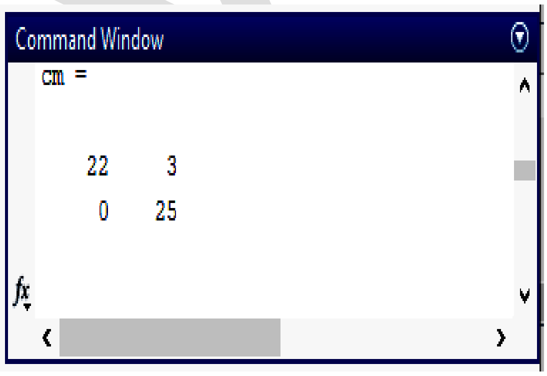

Figure 4: Confusion matrix

Figure is showing the confusion matrix of the proposed SVM classifier. The confusion matrix provides the prediction classes that is followings-

Table 1: Result Comparison

Sr No.	Parameters	Previous work [1]	Proposed Work
1	Method	CNN	Multi SVM
2	Precision	85.40 %	88%
3	Recall	89.36%	100%
4	Accuracy	75.87%	94 %
5	Classification error	24.13%	6 %

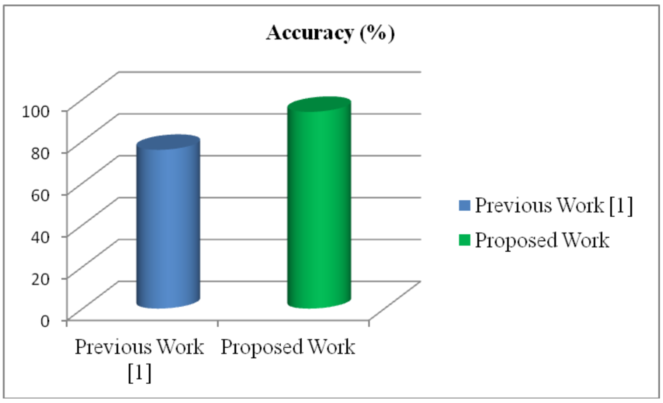

Figure 5: Comparison accuracy

Figure 5 is showing the graphical representation of the comparison of the accuracy parameter.

IV. CONCLUSION

The proposed Multi-SVM-based EEG drowsiness detection framework efficiently identifies drowsiness by leveraging Discrete Wavelet Transform (DWT) for signal decomposition and statistical feature extraction. The Multi-class SVM classifier ensures high accuracy in distinguishing alert and drowsy states, making it a reliable approach for real-time monitoring applications. By integrating preprocessing techniques to remove noise and optimizing feature selection, the system enhances classification performance while maintaining computational efficiency. This method holds significant potential for applications in driver safety, workplace fatigue monitoring, and healthcare, with future scope for deep learning integration and real-time hardware implementation.

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