International Journal of Recent Development in Engineering and Technology
Website: www.ijrdet.com (ISSN 2347-6435(Online) Volume 12, Issue 12, December 2023)

# Artifical Intelligence Approach for Drowsiness Detection Using EEG Signal : A Review

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***Abstract*— Drowsiness detection holds immense significance in ensuring safety across various domains, such as transportation and healthcare. This review explores the intersection of artificial intelligence and neuroscience in addressing the critical task of drowsiness detection using EEG signals. Electroencephalogram (EEG) signals provide valuable insights into the brain's electrical activity and serve as a non-invasive window into the cognitive and physiological states associated with drowsiness. The review begins by delving into the process of feature extraction, highlighting the extraction of relevant information from raw EEG data. Various features, including power spectral density, band power ratios, entropy measures, and statistical moments, are discussed.**

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

## I. INTRODUCTION

In an increasingly interconnected world, where human activities span across domains such as transportation, healthcare, and industrial operations, ensuring vigilant and alert states is paramount to both individual safety and overall operational efficiency. Drowsiness, characterized by a decline in cognitive awareness and alertness, poses a significant threat, particularly in safety-critical contexts such as driving, aviation, and medical procedures. Addressing this challenge has spurred the convergence of artificial intelligence (AI) and neuroscience, giving rise to innovative approaches for detecting and mitigating drowsiness.

Electroencephalogram (EEG) signals, which capture the electrical activity of the brain in real-time, have emerged as a valuable tool for monitoring the cognitive and physiological states associated with drowsiness. The intricate patterns of neural activity reflected in EEG data offer insights into changes in brain functioning, making them a promising avenue for developing robust drowsiness detection systems. Leveraging AI techniques to interpret these EEG signals has led to the development of sophisticated models capable of discerning between alert and drowsy states with increasing accuracy and reliability.

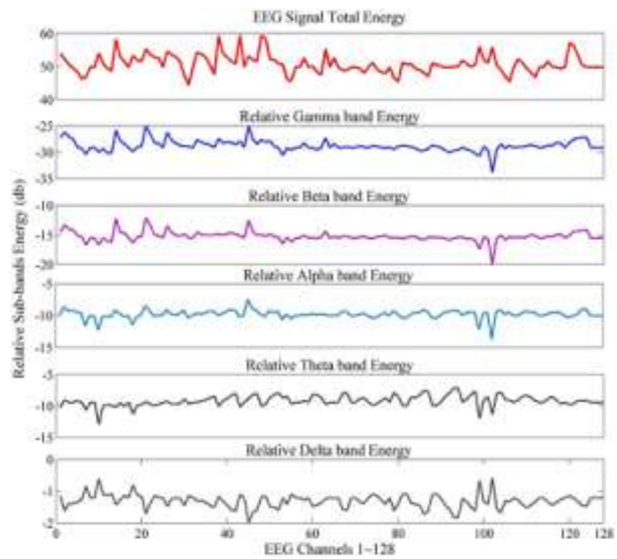


**Figure 1: EEG Signal [1]**

This review embarks on a comprehensive exploration of the strides made at the crossroads of AI and EEG-based drowsiness detection. The journey begins by elucidating the process of feature extraction, wherein relevant information is distilled from raw EEG data to form a foundation for subsequent analysis. Subsequently, the review delves into the diverse repertoire of machine learning algorithms that have been harnessed to transform these features into actionable insights. The evolution from traditional approaches to cutting-edge deep learning methodologies underscores the dynamism of the field.

Recognizing the indispensable role of data preprocessing, this review navigates the techniques employed to enhance the quality and reliability of EEG signals. Noise reduction, artifact removal, and feature scaling emerge as crucial steps in preparing the data for subsequent analysis. As EEG data often presents with high dimensionality, the exploration extends to feature selection and dimensionality reduction strategies, which not only enhance computational efficiency but also contribute to refining the accuracy of drowsiness detection models.

Decreasing Performance evaluation, a cornerstone of any scientific endeavor, occupies a prominent place within this review. A panorama of evaluation metrics and cross-validation techniques employed to rigorously assess the efficacy of drowsiness detection models is presented. Real-time monitoring considerations are also contemplated, acknowledging the need for timely interventions in safety-critical contexts.

As the review unfolds, it confronts the challenges inherent in drowsiness detection using EEG signals. Inter-subject variability, individual idiosyncrasies, and the complexities of real-world scenarios emerge as persistent hurdles. The integration of EEG data with complementary physiological signals is proposed as a potential avenue for enhancing the robustness of drowsiness detection systems. Looking ahead, the review glimpses into the future by envisioning the infusion of transfer learning, generative models, and advanced AI paradigms, poised to push the boundaries of accuracy and applicability.

## II. Literature Survey

J. R. Paulo et al.,[1] explore drowsiness detection based on EEG signals' spatiotemporal image encoding representations in the form of either recurrence plots or gramian angular fields for deep convolutional neural network (CNN) classification. Results comparing both techniques using a public dataset of 27 subjects show a superior balanced accuracy of up to 75.87% for leave-one-out cross-validation, using both techniques, against works in the literature, demonstrating the possibility to pursue cross-subject zero calibration design.

M. A. Asghar et al.,[2] To discriminate the correct parts of the signal from the acquired EEG signal, we use preprocessing. The features were extracted using deep neural networks and defining an optimal set of characteristics and representing the signal in the frequency-time domain. The k-NN (k-Nearest neighbor), and SVM (Support vector machine) classification methods are used to achieve high classification performance, considering the differences between the controllers. The algorithm we propose in this work uses a discrete wavelet transform to eliminate noise in the data. The classification accuracy achieved was 79.7% using the proposed system. Hence, there is a possibility to identify and distinguish the state of drowsiness of the driver.

M. Zhu et al.,[3] presents an EEG-based driver drowsiness estimation method using deep learning and attention mechanism. First of all, an 8-channels EEG collection hat is used to acquire the EEG signals in the simulation scenario of drowsiness driving and normal driving. Then the EEG signals are pre-processed by using the linear filter and wavelet threshold denoising. Secondly, the neural network based on attention mechanism and deep residual network (ResNet) is trained to classify the EEG signals. Finally, an early warning module is designed to sound an alarm if the driver is judged as drowsy. The system was tested under simulated driving environment and the drowsiness detection accuracy of the test set was 93.35%. Drowsiness warning simulation also verified the effectiveness of proposed early warning module.

M. Ahmed et al.,[4] propose an ensemble deep learning architecture that operates over incorporated features of eyes and mouth subsamples along with a decision structure to determine the fitness of the driver. The proposed ensemble model consists of only two InceptionV3 modules that help in containing the parameter space of the network. These two modules respectively and exclusively perform feature extraction of eyes and mouth subsamples extracted using the MTCNN from the face images. Their respective output is passed to the ensemble boundary using the weighted average method whose weights are tuned using the ensemble algorithm.

G. Geoffroy et al.,[5] propose a method for drowsiness detection using joint EEG and ECG data. The proposed method is based on a deep learning architecture involving convolutional neural networks (CNN) and recurrent neural networks (RNN). High efficiency level is obtained with accuracy scores up to 97% on validation set. We also demonstrate that a modification of the proposed architecture by adding autoencoders helps to compensate the performance drop when analysing subjects whose data is not presented during the learning step.

J. Cui et al.,[6] This is achieved by a visualization technique by taking advantage of the hidden states output by the LSTM layer. Results show that the model achieves an average accuracy of 72.97% on 11 subjects for leave-one-out subject-independent drowsiness recognition on a public dataset, which is higher than the conventional baseline methods of 55.42%-69.27%, and state-of-the-art deep learning methods. Visualization results show that the model has discovered meaningful patterns of EEG signals related to different mental states across different subjects.

B. V. Bharath Chandra et al.,[7] Drowsiness has become one of the major causes of road accidents now-a-days. In order to alleviate this issue, a system has been developed, which uses electroencephalogram (EEG) signals to detect drowsiness with sufficient reliability. This experiment was conducted on a small population and the EEG signals were acquired using a 14-channel wireless headset, while they were in a virtual driving environment.

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C. Lee et al.,[8] aimed to detect drowsiness and find optimal electrode set by collecting and classifying the EEG dataset labeled with three classes: awakeness, drowsiness, and sleep. Blindfolded subjects were presented short audio stimulus in random duration and instructed to push button according to audio stimulus. For classification of 3 classes, EEG signal was segmented and labeled according to the sequence of button response. The proposed drowsiness detection deep learning network resulted 82.8% accuracy with 18 channels, and 79.8% accuracy with 3 channels located at premotor area of right hemisphere.

W. Ko et al.,[9] Estimating driver fatigue is an important issue for traffic safety and user-centered brain-computer interface. In this work, based on differential entropy (DE) extracted from electroencephalography (EEG) signals; we develop a novel deep convolutional neural network to detect driver drowsiness. By exploiting DE of EEG samples, the proposed network effectively extracts class-discriminative deep and hierarchical features. Then, a densely-connected layer is used for the final decision making to identify driver condition.

A. Rochmah et al.,[10] Driving is a very monotonous job that results in fatigue and drowsiness. Fatigue and drowsiness can have a big effect on safety and security on the road. It can be prevented by using technological capabilities. Development of drowsiness detection uses the reading mechanism of electroencephalogram (EEG) with the classification of artificial neural networks. The method of the artificial neural network used is ANN Backpropagation. ANN Backpropagation method is a supervised artificial neural network.

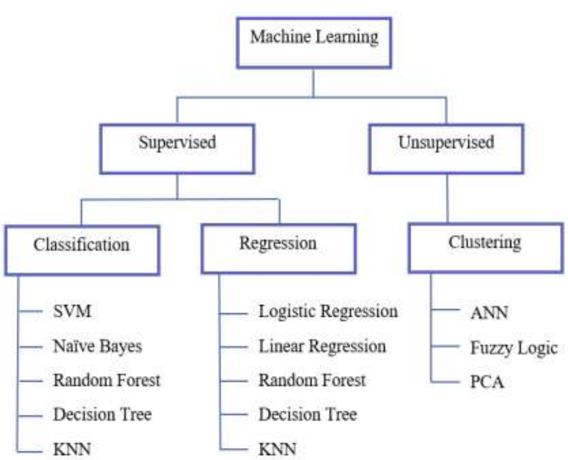


**Figure 2: Machine learning Techniques [5]**

W. M. Shalash et al.,[11] suggested using a driver fatigue detection system using transfer learning, depending only on one EEG channel to increase system usability.

The system firstly acquires the signal and passing it through preprocessing filtering then, converts it to a 2D spectrogram. Finally, the 2D spectrogram is classified with AlexNet using transfer learning to classify it either normal or fatigue state.

S. Ding et al.,[12] The EEG signal collector is designed and made by ourselves, which is like a hair band that makes the driver easier and more comfortable to wear it. The web platform provides an interface for the monitor to observe the condition of the driver. Our system achieved an accuracy of 97.09% detecting the drivers drowsiness, which surpasses the SOTA methods. The model's size and predict latency are also within a smaller scale than present models that make it more applicable to mobile and embedded system.

## III. Drowsiness Detection In Various Environments

### *1) Drowsiness Detection in Different Driving Conditions*

There can be many drowsiness ful events that may occur while driving like maintaining the speed limit, heavy traffic, and unsafe weather conditions, etc. Driving in such conditions may lead to violations of rules and possibly car accidents. Hence the identification of the drowsiness level of a driver while driving is an important issue for safety, security, and health purpose. In such cases, wearable devices can be helpful by alerting the driver about the elevated drowsiness levels and advising them to take necessary precautionary measures.

### *2) Drowsiness Detection in Academic Environment*

The study is one of the main sources of mental Drowsiness among adolescents especially students which generally comes from the excessive curriculum, preparation for exams, unsatisfactory academic performance, over expectations from parents, strict teachers, lack of interest in a particular subject, etc. These factors can affect the physical and mental health of students. Wearable sensors can be useful to detect drowsiness and its level among students allowing them to perform better in their studies.

### *3) Drowsiness Detection in Office-Like Working Environment*

The office-like environments can create mental loads which can be responsible for health issues like anxiety, Drowsiness and depression of the employees. There can be many sources of drowsiness like long working hours, tight deadlines, work over load, job insecurity in private sectors, working in teams, and peer pressure.

The identified challenges are described below-

- Improperly worn devices and the unrestricted movement of the subjects are the main significant challenges.
- In controlled environments, the movements and the Drowsiness ors are constrained and limited, thereby, giving an opportunity to researchers to intervene with the subjects to wear the device properly and to get precise results. But in a real-time environment, movements are unrestricted and unmonitored. Also, the subjects may incline to do more than one activity at a time, making the detection process more complicated and thereby could reduce the performance of drowsiness detection systems.
- Health issues such as those related to blood pressure, blood sugar, sleep patterns, alcohol or smoking habits, etc., are very likely to cause massive changes in subjects' physiology. Hence, it is vital to pay more attention to the said issues as they may affect the accuracy of the system.
- Collecting data in a real-time environment, removing artifacts and noise, and ensuring data accuracy are the most challenging aspects in developing any drowsiness detection model.

## IV. CONCLUSION

Drowsiness is an escalated psycho-physiological state of the human body emerging in response to a challenging event or a demanding condition. Environmental factors that trigger Drowsiness. This paper study the drowsiness detection approaches adopted in accordance with the sensor devices such as wearable sensors, Electrocardiogram (ECG), Electroencephalography (EEG), and Photoplethysmography (PPG), and also depending on various environments like during driving, studying, and working. The machine learning techniques is very effective to identify the types of emotion with high accuracy. The Drowsiness ors, techniques, results, advantages, limitations, and issues for each study are highlighted and expected to provide a path for future research studies.

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