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Machine Learning Techniques for Drowsiness Detection: A Review

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Abstract : Electroencephalogram (EEG) plays an important role in E-healthcare systems, especially in the mental healthcare area, where constant and unobtrusive monitoring is desirable. EEG signals can reflect activities of the human brain and represent different emotional states. Drowsiness can also be a result of your mental, emotional, or psychological state. It can come from any event or thought that makes you feel frustrated, angry, or nervous. Drowsiness has become a social issue and could become a cause of functional disability during routine work. A machine learning (ML) framework is effective for electroencephalogram (EEG) signal analysis. This paper review of machine learning method for drowsiness detection using EEG signals.

Index Terms **– EEG, Emotion, Drowsiness, Drowsiness, Machine Learning, E-healthcare.**

I. INTRODUCTION

This work explores study for drowsiness detection using EEG signals in a sustained-attention driving task considering pre-event time windows, and focusing on cross-subject zero calibration. Driving accidents are a major cause of injuries and deaths on the road. A considerable portion of those are due to fatigue and drowsiness. Advanced driver assistance systems that could detect mental states which are associated with hazardous situations, such as drowsiness, are of critical importance. EEG signals are used widely for brain-computer interfaces, as well as mental state recognition. However, these systems are still difficult to design due to very low signal-to-noise ratios and cross-subject disparities, requiring individual calibration cycles [1]. Driver fatigne is often the direct cause of many road accidents. Therefore, developing an accurate system that senses and informs the driver of his inadequate psychophysical situation is necessary.

The Electroencepbalogram (EEG)-based two-channel real-time test was conducted on 30 healthy subjects on a driving simulator to monitor the significant change in the subject's EEG signal, which happens during the transition of the subject's normal state to a normal drowsiness state [2]. Facts reveal that numerous road accidents worldwide occur due to fatigue, drowsiness, and distraction while driving. Few works on the automated drowsiness detection problem, propose to extract physiological signals of the driver including ECG, EEG, heart variability rate, blood pressure, etc. which make those solutions non-ideal. While recent ones propose computer vision-based solutions but show limited performances as either they use hand-crafted features with conventional techniques like Naïve Bayes and SVM or use excessively bulky deep learning models which are still low on performances [4]. Drowsiness detection is still an open issue, especially when detection is based on physiological signals. In this sense, light non-invasive modalities such as electroencephalography (EEG) are usually considered. EEG data provides informations about the physiological brain state, directly linked to the drowsy state.

Electrocardigrams (ECG) signals can also be considered to involve informations related to the heart state [5]. For EEG-based drowsiness recognition, it is desirable to use subject-independent recognition since conducting calibration on each subject is time-consuming. In this work, we propose a novel Convolutional Neural Network (CNN)-Long Short-Term Memory (LSTM) model for subject-independent drowsiness recognition from single-channel EEG signals. Different from existing deep learning models that are mostly treated as black-box classifiers, the proposed model can “explain” its decisions for each input sample by revealing which parts of the sample contain important features identified by the model for classification [6].

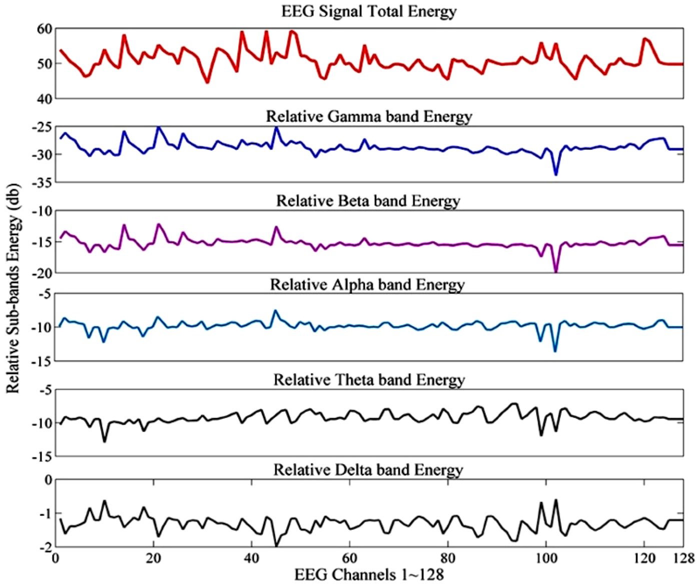

Figure 1: EEG Signal [1]

Decreasing road accidents rate and increasing road safety have been the major concerns for a long time as traffic accidents expose the divers, passengers, properties to danger. Driver fatigue and drowsiness are one of the most critical factors affecting road safety, especially on highways. EEG signal is one of the reliable physiological signals used to perceive driver fatigue state but wearing a multi-channel headset to acquire the EEG signal limits the EEG based systems among drivers [11]. The road accidents are a common cause to the injury and death of people. As reported by The American National Highway Traffic Safety Administration (NHTSA), the drivers drowsiness accounts for nearly 100,000 accidents per year in the United States. Thus, we present a novel drivers drowsiness detection system in this work using the techniques of deep learning(DL), mobile computing, wearable device and Electroencephalography (EEG). We employ the deep learning architecture designed by ourselves that can be easily implemented on the mobile phone to detect the drowsiness with a high accuracy. The EEG signal we use is only single channel that can be easily obtained by the wearable device [12].

II. BACKGROUND

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.

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.

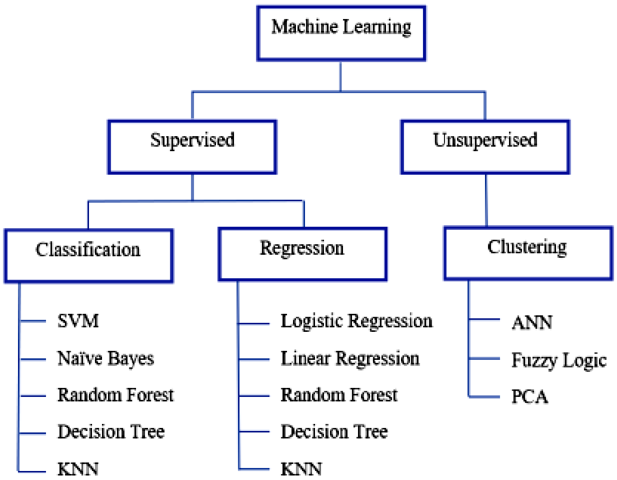

Figure 2: Machine learning Techniques [5]

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 overload, 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.

To evaluate the performance of algorithms for drowsiness from EEG detection problem, various evaluation metrics have been used. In this subsection, we review the most widely used metrics for detection. The machine learning approaches generate the confusion matrix and find the accuracy and other parameters through this.

- True Positive (TP)
- True Negative (TN)
- False Negative (FN)
- False Positive (FP)

By formulating this as a clarification problem, we can define following metrics,

$$
\begin{aligned}
Precision &= \frac{|TP|}{|TP| + |FP|} \\
Recall &= \frac{|TP|}{|TP| + |FN|} \\
F1 &= 2 \cdot \frac{Precision \cdot Recall}{Precision + Recall} \\
Accuracy &= \frac{|TP| + |TN|}{|TP| + |TN| + |FP| + |FN|}
\end{aligned}
$$

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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