International Journal for Multidisciplinary Research (IJFMR)
E-ISSN: 2582-2160 ● Website: www.ijfmr.com ● Email: editor@ijfmr.com

Fatigue State Detection for Tired Person in Presence of Driving Periods

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Abstract
Due to the increasing of traffic accidents, there is an urgent need to control and reduce driving mistakes. Driver fatigue or drowsiness is one of these major mistakes. Algorithms have been developed to address this issue by detecting fatigue and alerting the driver to dangerous condition. The major problem of the developed algorithms is their accuracy, well as the time required to detect fatigue status and alert the driver. The accuracy and time represent a critical condition that affects the reduction of traffic accidents. Several datasets have been used in the development of fatigue or drowsy detection techniques. These data gathered from the deriver's brain Electroencephalogram (EEG) signals or from video streaming recordings of the driver behavior. This paper develops two distinct approaches, the first based on the use of machine learning classifiers and the second depends on the use deep learning models to produce a high-performance fatigue detection system. The machine learning approach is used to process EEG signals, whereas the deep learning approach is used to process video streams. In machine learning classifiers, Support Vector Machine (SVM) provides up to 98% of detection accuracy, which is the highest accuracy among the other five deployed classifiers. In deep learning models, Convolution Neural Network (CNN) provides up to 99% detection accuracy, which is the highest accuracy among the other two deployed models. The experimental results demonstrate that the two proposed algorithms provide the highest detection accuracy with the shortest Testing Time (*TT*) when compared to all other recent and efficient fatigue detection algorithms.

Keywords: EEG Signals, Fatigue Detection Systems, Video Streaming, Support Vector Machine, Convolution Neural Network, Testing Time.

1. Introduction

Many projects are currently underway in automobile manufacturing companies to address issue of driver fatigue by developing a fatigue detection system. According to Internet of Things (IOT) components and applications such as sensors, cloud servers, smart phones centralized and decentralized data processing. This idea is promising. Three major techniques are being used to create a robust and effective fatigue detection system. These techniques are classified as behavioral-based, vehicle based and physical based techniques. The three major techniques of fatigue detection systems. First, behavioral-based analyze images and videos captured from the driver using image processing and computer vision. These vital parameters are extracted based on monitoring features such as eye blindness, opening and closing the mouth, eye closure, facial features, and head position and nodding.

Second, vehicle-based techniques employ devices and sensors built into vehicle wheels to create an embedding system for detecting driver fatigue. This embedded system detects driver behavior by monitoring measurements such as Steering Wheel Angle (SWA), Steering Wheel Movements SWM), Steering Wheel Velocity (SWV), hand position, hand absence, and lane deviation. Finally, the physical-based techniques use peripherals that attached to the driver's hands, head, fingers, and chest to monitor various types of body system signals. Electroencephalogram (EEG), Electrocardiogram (ECG), Electro Ocular Gram (EOG), and Percentage of eyelid closure (PERCLOS) are the different types of attached devices. The output signals such as breathing rate, body temperature, respiratory rate, electrical brain activity, pulse rate, heart rate variability and general heart rate are used to detect the driver's status

Attempts to build a fatigue detection system, on the other hand, are divided into traditional-based algorithms and machine learning based algorithms. Support Vector Machine (SVM) and Convolutional Neural Network (CNN) are the most effective and usable classifiers in machine learning algorithms. SVM provides a high precision value in addition to its speed but in the small datasets but it suffers from lower speed and precision value in large datasets. CNN provides the highest precision value as well as stability in both large and small datasets, but it provides slow training with high processing cost. The paper is organized as reviews the related work of fatigue and drowsiness detection algorithms. The full details and discussions of the proposed fatigue detection and prediction algorithm Illustrate in discusses the experimental results obtained by the proposed algorithm with different datasets, as well as results compared to other fatigue detection algorithms. The conclusion of the paper and the future work is presented in section. The paper ended with acknowledge and references.

2. Review of Literature

MAHMOODFATHY [4] says that Improvement of public safety and the reduction of accidents are of the important goals of the Intelligent Transportation Systems (ITS). One of the most important factors in accidents, especially on rural roads, is the driver fatigue and monotony. Fatigue reduces driver perceptions and decision making capability to control the vehicle. Researches show that usually the driver is fatigued after 1 hour of driving. In the afternoon early hours, after eating lunch and at mid nigh, driver fatigue and drowsiness is much more than other times. In addition, drinking alcohol, drug addiction, and using hypnotic medicines can lead to loss of consciousness. In different countries, different statistics were reported about accidents that happened due to driver fatigue and distraction. Generally, the main reason of about 20% of the crashes and 30% of fatal crashes is the driver drowsiness and lack of concentration.

ANIL KUMAR BISWAL [1] says that Driver fatigue has been the main issue for countless mishaps due to tiredness, tedious road condition, and unfavorable climate situations. Every year, the National Highway Traffic Safety Administration (NHTSA) and World Health Organization (WHO) have reported that approximately1.35 million people die due to vehicle crashes across the world. Generally, road accidents mostly occur due to inadequate way of driving. These situations arise if the driver is addicted to alcohol or in drowsiness. The maximum types of lethal accidents are recognized as a severe factor of tiredness of the driver when drivers fall asleep, the control over the vehicle is lost. There is need to design smart or intelligent vehicle system through advanced technology. This paper implements a mechanism to alert the driver on the condition of drowsiness or daydreaming.

MUHAMMAD RAMZAN [5] say that Drowsiness or fatigue is one of the main factors that threaten the road safety and causes the severe injuries, deaths and economical losses. Increased drowsiness deteriorates the driving performance. Lack of alertness, generated the unconscious transition from wakefulness to sleep, and leads to several serious road accidents. U. S. National Highway Traffic Safety Administration (NHTSA) 1 reports that driving resulted in almost 100,000 road accidents and more than 1,500 deaths per year. A fatigue can have multiple causes such as lack of sleep, long journey, restlessness, alcohol and mental pressure. Each of which can lead to serious disaster. Nowadays, road rage in the multiples the past, which causes stress on drivers. Therefore, previous transportation system is enough to handle these hazards on roads. Thus, by embedding the automatic fatigue systems into vehicles, several deadly accidents can be prevented. The drowsiness detection analyzes the drivers' attention level and alerts the driver before the arrival of any serious threat to safety.

JONGSEONG GWAK [3] say that Drowsy driving is one of the main causes of traffic accidents since drivers cannot react to dangerous situations when drowsy, major accidents can occur. To prevent accidents due to drowsy driving, it is necessary to detect driver drowsiness early and accurately. Previous studies showed that the drowsiness level of a driver is related to their facial expression, driving behaviors, and physiological responses. There is a strong correlation between real drowsiness and subjective valuation based facial expressions. Therefore, monitoring a driver’s facial expressions is a widely accepted method for detecting driver drowsiness. Monitoring head position, eye blinks, and body movement has also been used to detect driver drowsiness

AYOUB AL-HAMADI [2] say that globally, an average of 3200 persons die each day around the world due to road traffic crashes (RTCs). It is estimated that driver-related dangerous behaviors such as drowsiness, drug and alcohol use, inexperience and psychological stress, are contributing factors in the vast majority of these crashes, and driver drowsiness is the most commonly reported reason among non-performance errors that accounted for such crashes. For example, in the U.S., the National Highway Traffic Safety Administration (NHTSA) reported that drowsy driving was responsible for an estimated 3662 fatal crashes and 4121 fatalities from2011 to 2015, which corresponds to 2.4 percent of all fatal crashes and 2.5 percent of all crash fatalities recorded in the U.S. during the same period.

MIANKUAN ZHU [6] say that the improvement of people’s living standards, more and more families have bought vehicles. Vehicles play an influential role in transportation because of their flexible transportation capabilities and also promoted the development of many industries and accelerated the economic improvement. According to the public statistics, China had261.5 million vehicles by the end of 2019. The increase in the vehicles will also increase the number of traffic accidents, especially those caused by the drowsy driving of vehicle drivers. In long-distance driving, vehicle drivers will drive for a long time in order to improve driving efficiency. Prolonged driving of vehicle will make the driver feel tired and distracted, which may lead to mortal traffic accidents. On the other hand, vehicle drivers who obtain insufficient sleep on most nights can also cause drowsy driving. The American Automobile

Association (AAA) estimates that one-sixth (16.5%) of fatal traffic accidents and one-eighth (12.5%) of accidents requiring driver or passengers hospitalized are caused by drowsy driving.

YUGANG LIU [8] say that from 1 April 1997 to 18 April 2007, the railway transportation in China experienced six great “improvements” in train speed. The speed of Chinese high speed trains has been raised to 200 km/h, and accordingly, the Chinese high-speed train technology is the worldwide leader. Since the “7.23” Yong-Tai-Wen railway accident (which occurred on 23 July 2011), the most serious railway accident in Chinese railway history, high-speed train accident prevention in China has been changed from passive control modes to active ones. According to the accident investigation report, the causes of the accident was associated with the design, approval, and use of the TCC (the Train Control Centre). Little attention is paid to the important part of the high-speed train Safety Management.

SUKHAN LEE [7] say that Transportation plays a vital role in individual and social welfare, the economy, and quality of life. Its benefits, however, are not a free lunch. Society pays in terms of money (for vehicles’ purchase, operational, and maintenance costs), social ecological costs (resource utilization, exhaust and noise pollution, traffic jams), fatal harmful traffic accidents, and so on. There are several measures to improve the quality of the transportation system at each level of society ranging from government policies to drivers’ performance. A major objective of such improvements is called Vision Zero, which a future where no one is seriously injured or killed in a road accident. Vision Zero has a spectrum, however, this work will concentrate on the studies and systems developed to enhance road safety and driver performance.

3. Related Work

Developing a fatigue detection system is an ambitious project, which aims to establish driving safety rules. The algorithms in this area is divided into two main trends, image and video based techniques and signal processing techniques as highlighted in the following:

3.1 Image and Video Based Techniques

The earlier attempt for the behavioral-based techniques is performed by evaluating a real-time image acquisition for the driver using IR illumination, followed by monitoring driver behavior using software. This proposal employs several parameters as metrics to monitor the driver behavior. These parameters are PERCLOS, blink frequency, face position, nodding frequency, and eye closure duration. A fuzzy classifier to detect the emergency status of the driver evaluates these metrics. This variety of monitoring and analyzing parameters combined with the day and night acquisition conditions, resulted in the system outperforming other algorithms at the time.

Flores proposed an ADAS (Advanced Driver Assistance System) that detects and tracks the driver's face and eyes before analyzing the driver's facial emotions and eyes movement to detect drowsiness. The system had been tested in real time under different lighting conditions. Abtahi developed a straight forward image processing-based technique. Their proposal is based on detecting some signs of fatigue in the driver. These signs can be detected from: monitoring the driver face in the image and then tracking face details such as eye and mouth movements to detect yawning and eye languor.

3.2 Signal Processing Based Techniques

Some algorithms, on the other hand, developed the physical methods based on signals such EEG, ECG, and EOG by combining machine and deep learning models. These methods function as a hybrid of physical-based and behavioral based methods. Proposed an algorithm that used EEG samples to extract Differential Entropy (DE), and a density-connected layer is used for drowsiness decision.

Zhu proposed an algorithm that collected signals from wearable EEG devices and process them using CNN. After collecting EEG signals through brain computer interface, the Alex Net module is deployed with CNN to classify these signals this algorithm has a 94%accuracy rate. The main problem is the time lag between collecting EEG signals and processing them through CNN.

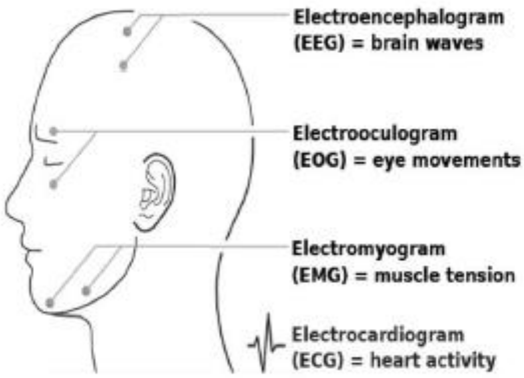
4. Proposed Methodology

This proposed method is divided into two approaches the machine learning approach and deep learning approach. In machine learning approach, the proposed algorithm deployed models such as SVM, Random Forest (RF), Naive Bayes (NB), Logistic Regression (LR), and Decision tree (DT), Multilayer Perceptron (MLP), K-Nearest Neighbor (KNN) and Quadratic discriminant analysis (QDA) models. Furthermore, in deep learning approach, several models are deployed including CNN, Convolutional Long Short-Term Memory (Conv LSTM) and hybrid models that combine CNN and Conv LSTM. The goal of using all of these models is determine which techniques or hybrid of them achieve the best performance, as well as to conduct a detailed analysis of the results of different techniques.

4.1 Machine Learning Approach

In machine learning approach, the proposed algorithm uses the EEG signals as a data input to perform the drowsiness detection process. First, the EEG signals are transformed Discrete Wavelet Transform (DWT) to select the coefficients of high energy signals and discard unwanted signals. Second, discriminant features extracted from the EEG signals are presented. During the pre-processing step, PCA is used to select the important features. In order to facilitate the classification task, a standard scaling is performed in a pre-processing step to examine the differences between features. The extracted and pre-processed features are fed into classifiers, which detect drossiness in the given signal and it display in Figure 1.

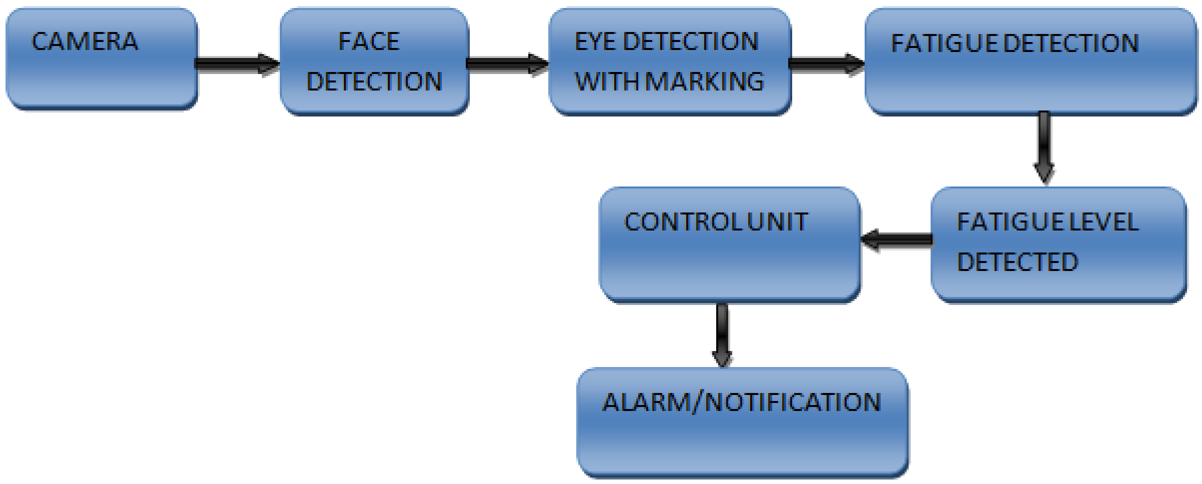
Figure 1: The physical distribution of drowsy polysomnography signals on the driver's head.



4.2 Deep Learning Approach

Unlike the previous approach, deep learning approach handles the driver's visual expressions rather than collecting physical signals. In deep learning approach, the proposed algorithm uses video streaming produced by monitoring the driver through a camera during the driving process as a data input to perform the drowsiness detection process. First, in the video segmentation step, the video streaming for the driver is divided into frames. These segments are ready to be fed into one of the three models described in this section. In deep approach, three deep learning models are proposed to achieve the highest performance drowsiness detection algorithm. The first model is based on CNN, which consists of one input layer, four convolutional layers, four pooling layers followed by one global average pooling layer, one dense layer it displays in Figure 2.

Figure 2: Block diagram



5. Experimental Results

This section contains a comprehensive evaluation of the proposed approaches. First, the dataset is described with its full details. Second, the evaluation metrics used to evaluate the approaches results are displayed. Next, the results as well as the discussions and comments on those results are listed. Finally, well-test comparisons are performed.

5.1 Evaluation Metrics

Various evaluation metrics are used to assess proposed approaches. Accuracy, Sensitivity (equal to True Positive Rate (*TPR*)), False Positive Rate (*FPR*), False Negative Rate (*FNR*), False Discovery Rate (*FDR*), Specificity that is equal to True Negative Rate (*TNR*), Precision, F1 score, and Matthews Correlation Coefficient (*MCC*).

$$\text{Accuracy}= \frac{\text{No. of. Correctly detect images}}{\text{Total No. of images}} \times 100 \qquad (1)$$

5.2 Result

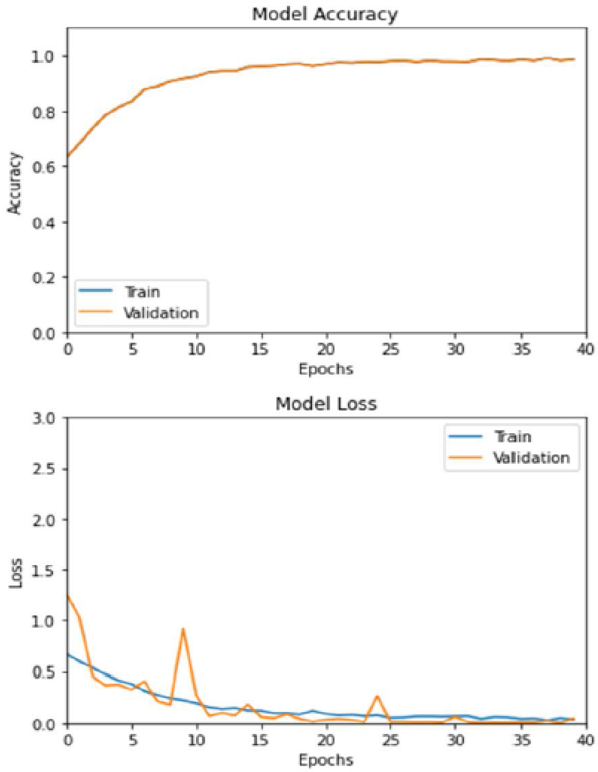
First, a k-fold cross validation process is used to test the performances of the proposed approaches on the DROZY dataset. This k-fold process helps in estimating the optimal hyper parameters combinations to avoid overfitting. The proposed approaches used 10-fold cross validation. This paper proposed two main approaches; machine learning approach and deep learning approach. Then it displays in Table 1.

Table 1: Results of Deep Learning Approach with different model

Metric / Model	ACC %	Sens %	FPR %	FNR %	Spec. %	Prec. %	FDR %	F1 Score %	MCC %	TT(Seconds)
conLSTM	**74.50**	**80**	**39**	**30**	**61**	**67.23**	**32.27**	**73.06**	**41.76**	**19.28**
CNN	**98.8**	**100**	**2.39**	**0**	**97.61**	**97.66**	**2.34**	**98.81**	**97.63**	**10.61**
Hybrid CNN ConvLSTM	**98**	**100**	**4**	**0**	**96**	**96.15**	**3.85**	**98.04**	**96.08**	**26.60**

For the deep learning approach, three models, (Conv LSTM, CNN, and hybrid CNN Conv LSTM), had been employed to reach the best performance. The video streaming samples in the DROZY dataset are segmented into frames and these frames are subjected to image processing and computer vision analysis. In the deep learning approach, the three different models used to predict the best behavior of the data training, validating, and testing using the same strategy displayed before shows the results of each model under different evaluation metrics. Depicts the confusion matrices for all models. Shows the learning curve for each model containing model accuracy and model loss behaviors. Shows the ROC curve of each classifier used in the deep learning approach.

Figure 3: Learning curves for hybrid CNN ConvLSTM Model



6. Conclusion

This paper presents two different approaches machine learning approach and deep learning approach. The main goal of that paper is to develop an effective fatigue detection system for high-performance cars drivers. The machine learning approach addresses the EEG signals processing by predicting driver behavior to detect fatigue status. This proposed machine learning algorithm had been developed by applying different machine learning classifiers such as SVM, RF, LR, MLP, KNN, and QDA. The proposed algorithm used this variety to achieve the best performance, as measured by the highest detection accuracy and the shortest detection time, with a high weight for the accuracy metric. According to the proposed algorithm results and using the DROZYEEG signals dataset, SVM is the best classifier deployed for solving this issue.

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