



FATIGUE STATE DETECTION FOR TIRED PERSONS 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. Many algorithms have been developed to address this issue by detecting fatigue and alerting the driver to this dangerous condition. Several datasets have been used in the development of fatigue or drowsy detection techniques. These images recognize live motion of action behavior in our dataset. And the evaluated data are trained using Machine learning techniques mysterious data estimated using Deep learning techniques. The machine learning approach is used to process Image dataset, whereas the deep learning approach is used to process video streams. In deep learning models, VGG16 architecture, provides up to 98% detection accuracy, which is the highest accuracy among the deployed models.

Keywords: *Machine learning, Convolutional Neural Network Algorithm.*

1. Introduction

Driver tiredness pose a major threat to highway safety, and the problem is particularly severe for commercial vehicle operators. Twenty-four-hour operations, high annual mileage, exposure to challenging environmental conditions, and demanding work schedules all contribute to this serious safety issue. Monitoring the driver's state of fatigue and vigilance and providing feedback on their condition so that they can take appropriate action is one crucial step in a series of preventive measures necessary to address

this problem. Human eyes are the stable feature than compared with the other facial features. Therefore, in recognizing facial features, it is advantageous to recognize the eyes. Using the eye position we can estimate the location of certain facial features. Furthermore, only with the presence of both eyes the scale orientation and rotation of the face in the picture plane can be normalized. In this paper, CNN Approach has been proposed to detect the driver drowsiness. Currently there is not adjustment in zoom or direction of the camera during operation.

2. Related Work

This work presents the development of an ADAS (advanced driving assistance system) focused on driver drowsiness detection, whose objective is to alert drivers of their drowsy state to avoid road traffic accidents. In a driving environment, it is necessary that fatigue detection is performed in a non-intrusive way, and that the driver is not bothered with alarms when he or she is not drowsy. Our approach to this open problem uses sequences of images that are 60 s long and are recorded in such a way that the subject's face is visible. To detect whether the driver shows symptoms of drowsiness or not, two alternative solutions are developed, focusing on the minimization of false positives. The first alternative uses a recurrent and convolutional neural network, while the second one uses deep learning techniques to extract numeric features from images, which are introduced into a fuzzy logic-based system afterwards. The accuracy



obtained by both systems is similar: around 65% accuracy over training data, and 60% accuracy on test data. However, the fuzzy logic-based system stands out because it avoids raising false alarms and reaches a specificity (proportion of videos in which the driver is not drowsy that are correctly classified) of 93%. Although the obtained results do not achieve very satisfactory rates, the proposals presented in this work are promising and can be considered a solid baseline for future works.[1]

Road traffic accidents (RTA) account for a significant proportion of mortality and morbidity worldwide, especially the developing countries. 'Hidden pandemics' such as deaths due to RTA often receive minimal attention globally. If not addressed adequately, the forecast looks bleak, especially for the developing countries in the coming decades. Healthcare professionals have an important role in advocating measures to reduce injuries following RTA and, along with like-minded social individuals, can act as a powerful lobby to implement change. Following a 'Public Interest Litigation or PIL' by the Indian Orthopedic Association (IOA) in 2012 – which challenged the Government to accept responsibility for this glaring problem and form an apex body to enforce road safety – the Supreme Court of India identified the existing road-safety laws to be inadequate. It created an 'Empowered committee' which oversaw various new road safety measures implemented by respective state governments. A public movement called 'UYIR' (meaning 'life' in Tamil) was launched at Coimbatore to reduce RTA. Early results following the implementation of this program showed promising results with a reduction in major accidents. It emphasized that well-planned programs involving the general public could be the way forward in reducing accidents across the country. Hence, Social Advocacy is crucial when an individual or group supports and influences political, economic, and social decisions. Such advocacy aims to gain support in an adverse environment to create the necessary change for the better.[2]

Continuous advancements in computing technology and artificial intelligence in the past decade have led to improvements in driver monitoring systems. Numerous experimental studies have collected real driver drowsiness data and applied various artificial intelligence algorithms and feature combinations with the goal of significantly enhancing the performance of these systems in real-time. This paper presents an up-to-date review of the driver drowsiness detection systems implemented over the last decade. The paper illustrates and reviews recent systems using different measures to track and detect drowsiness. Each system falls under one of four possible categories, based on the information used. Each system presented in this paper is associated with a detailed description of the features, classification algorithms, and used datasets. In addition, an evaluation of these systems is presented, in terms of the final classification accuracy, sensitivity, and precision. Furthermore, the paper highlights the recent challenges in the area of driver drowsiness detection, discusses the practicality and reliability of each of the four system types, and presents some of the future trends in the field.[3]

Driver drowsiness and fatigue plays a great impact in causing road accidents. Drowsiness can lead to inattentiveness or even micro sleep, which involves brief intermittent moments of sleep sometimes without the person even noticing it, and this can sometimes be fatal when driving. In this paper, a drowsiness detection an alert system is proposed to identify the drowsiness level of a driver and trigger an audible alarm, status display on LCD, and a light indicator to alert the driver. The input is captured using Mind Link Neuro Sensor which is a wearable dry EEG headset which is wirelessly connected to the microcontroller. The common activities that activate certain brain wave, as well as the activities that deactivate the respective brain wave is examined and presented in the results. It can be seen that a few brain waves can be associated with drowsiness as they are triggered during



yawning such as the alpha, beta, and theta waves, but the Mind Link EEG headset used in this experiment featured 2 nodes placed at the front of the forehead and is most sensitive to changes in the alpha wave, so alpha wave is used as a drowsiness determinant.[4]

Driver drowsiness is one of the main factors leading to road fatalities and hazards in the transportation industry. Electroencephalography (EEG) has been considered as one of the best physiological signals to detect drivers' drowsy states, since it directly measures neurophysiological activities in the brain. However, designing a calibration-free system for driver drowsiness detection with EEG is still a challenging task, as EEG suffers from serious mental and physical drifts across different subjects. In this paper, we propose a compact and interpretable Convolutional Neural Network (CNN) to discover shared EEG features across different subjects for driver drowsiness detection. We incorporate the Global Average Pooling (GAP) layer in the model structure, allowing the Class Activation Map (CAM) method to be used for localizing regions of the input signal that contribute most for classification. Results show that the proposed model can achieve an average accuracy of 73.22% on 11 subjects for 2-class cross-subject EEG signal classification, which is higher than conventional machine learning methods and other state-of-art deep learning methods. It is revealed by the visualization technique that the model has learned biologically explainable features, e.g., Alpha spindles and Theta burst, as evidence for the drowsy state. It is also interesting to see that the model uses artifacts that usually dominate the wakeful EEG, e.g., muscle artifacts and sensor drifts, to recognize the alert state. The proposed model illustrates a potential direction to use CNN models as a powerful tool to discover shared features related to different mental states across different subjects from EEG signals.[5]

3. Objective

Signs of drowsiness are detected, and takes action to be stayed alert, for reducing the risk of

damage. Enhancing road safety. Improving the driver health's to raise awareness among driver about the dangerous of driving. To ensure seamless operations and widespread adoption of the technology. Maintaining the accurate eye closure rate and fatigue blink frequency.

4. Proposed System

The proposed algorithm employs a variety of techniques to achieve the highest performance in the shortest amount of time and with the least amount of processing complexity. By using image processing, it raises the image's quality so that we can analyze it more effectively and it not limited the adjustments of size, orientation and color. By using feature extraction, it transforms raw data into numerical features that can be processed while preserving the information in the original data set. By using convolutional neural network, we achieve the best performance, as well as to conduct a detailed analysis of the results of different forms. By using convolutional neural network, we achieve the best performance, as well as to conduct a detailed analysis of the results of different forms.

5. Architecture Diagram

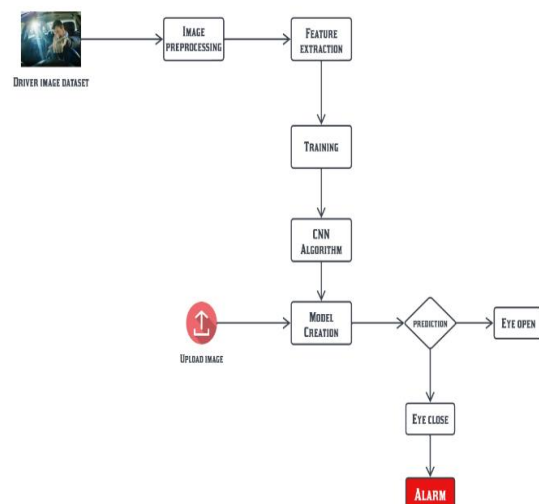


Fig.5.1 Architecture Diagram



6. Algorithm

A Convolutional Neural Network (CNN) is a type of Deep Learning neural network architecture commonly used in Computer Vision. Computer vision is a field of Artificial Intelligence that enables a computer to understand and interpret the image or visual data. When it comes to Machine Learning, Artificial Neural Networks perform really well. Neural Networks are used in various datasets like images, audio, and text. Different types of Neural Networks are used for different purposes, for example for predicting the sequence of words we use Recurrent Neural Networks more precisely an LSTM, similarly for image classification we use Convolution Neural networks. In this blog, we are going to build a basic building block for CNN.

Input Layers: It's the layer in which we give input to our model. The number of neurons in this layer is equal to the total number of features in our data (number of pixels in the case of an image).

Hidden Layer: The input from the Input layer is then fed into the hidden layer. There can be many hidden layers depending on our model and data size. Each hidden layer can have different numbers of neurons which are generally greater than the number of features. The output from each layer is computed by matrix multiplication of the output of the previous layer with learnable weights of that layer and then by the addition of learnable biases followed by activation function which makes the network nonlinear.

Output Layer: The output from the hidden layer is then fed into a logistic function like sigmoid or SoftMax which converts the output of each class into the probability score of each class.

The data is fed into the model and output from each layer is obtained from the above step is called feedforward, we then calculate the error using an error function, some common error functions are cross-entropy, square loss error, etc. The error function measures how well the network is performing. After that, we backpropagate into the model by calculating the derivatives. This step is called backpropagation

called which basically is used to minimize the loss.

Convolutional Neural Network (CNN) is the extended version of artificial neural networks (ANN) which is predominantly used to extract the feature from the grid-like matrix dataset. For example, visual datasets like images or videos where data patterns play an extensive role.

7. Implementation

7.1 Image Preprocessing

An image classification task determines the category of a given input image in the human driving the vehicle dataset. It recognizes the facial zone from the received images. The collected data is preprocessed to enhance quality, remove noise, and standardize the format. It is a basic task in high-level image understanding and can be divided into binary- and multi classification tasks. After multiple convolution-and-pooling operations via VGG16 architecture, an image is classified in the output layer following the requirements. It easily identified and then necessary actions can be taken to prevent accidents is a high performance in natural image classification.



Fig:7.1 Image Preprocessing

7.2. Feature Extraction

When the input data to an algorithm is too large to be processed and it is suspected to be redundant, then it can be transformed into a reduced set of features. It automatically extracts features from the input data. Determining a subset of the initial features is called feature selection. The selected features are expected to contain the relevant information from the input data. So that the desired task can be performed by using this reduced representation.



7.3. Convolutional Neural Network

Convolutional Layer in a typical neural network each input neuron is connected to the next hidden layer. Only small region of the input layer neurons connects to the neuron hidden layer. Pooling Layer is used to reduce the dimensionality of the feature map. There will be multiple activation & pooling layers inside the hidden layer of the CNN. Fully Connected Layers form the last few layers in the network. The input to the fully connected layer is the output from the final Pooling or Convolutional Layer, which is flattened and then fed into the fully connected layer.



Fig:7.3 Convolutional Neural Network for model creation

7.4. Model Creation of Drowsiness

It performs from the different types of images that evaluates from trained models. Then, it analyses and interpret data to identify signs of drowsiness. Based on the analysis the different types of images has been finalised.

7.5. Image Prediction

Generates alerts or warnings when the model detects signs of drowsiness. It provides continuous monitoring to improve the model performance. Then, it updates based on comparison between 0% to 100% alerting strategies based on image prediction. It alerts when 50 % of eye movement is close.



Fig:7.5 Image Prediction

8. Experimental Results

This result discusses about the implementation of the fatigue state detection for tired persons in presence of driving periods using machine learning and deep learning. Various cases are identified and the below Fig.8.1 shows the model loss, Fig.8.2 shows the model accuracy, Fig.8.3 shows the facial detecting process, Fig.8.4 shows the drowsiness alert.

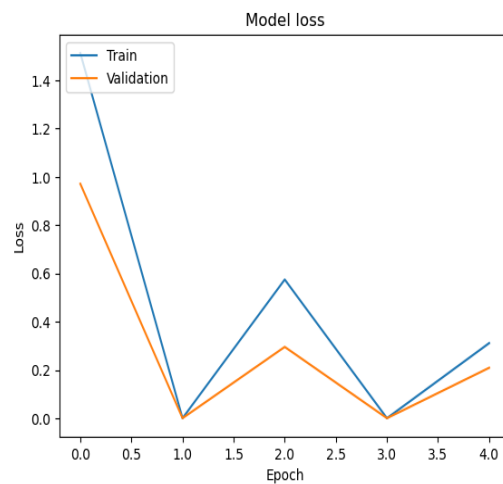


Fig:8.1 Shows the Model Loss

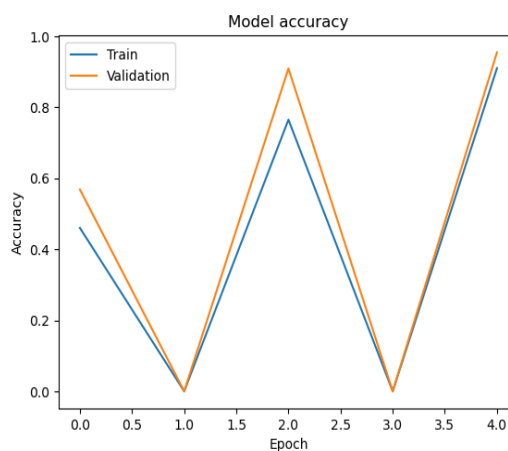


Fig:8.2 Shows the Model Accuracy



Fig:8.3 Shows the facial detecting Process

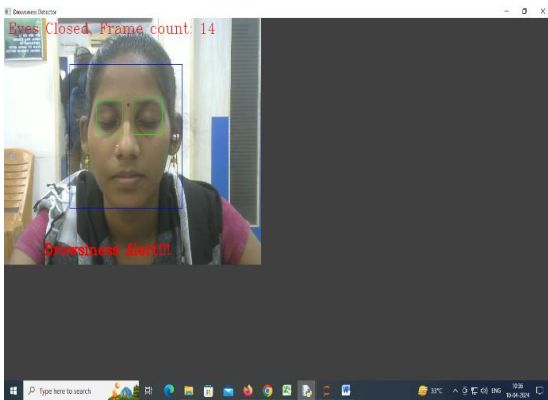


Fig:8.4 Shows the Image Prediction

9. Conclusion & Future Work

The drowsiness detection and correction system developed is capable of detecting drowsiness in a rapid manner. The system which can differentiate normal eye blink and drowsiness which can prevent the driver from entering the state of sleepiness while driving. During the monitoring, the system is able to decide if the eyes are opened or closed. When the eyes have been closed for about five seconds, the alarm beeps to alert the driver. By doing this many accidents will reduce and provides safe life to the driver and vehicle safety. A system for driver safety and car security is presented only in the luxurious costly cars. Using drowsiness detection system, driver safety can be implemented in normal cars also.

Future Enhancement: Firstly, advancements in sensor technology hold the potential to enhance fatigue detection systems by incorporating additional physiological and behavioural markers beyond the current standard measures like eye movements and steering patterns. Integrating biosensors capable of monitoring factors such as heart rate variability, skin conductance, and brainwave activity could provide a more comprehensive understanding of driver fatigue levels, enabling more accurate and timely interventions.

10. References

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