DRIVER DROWSINESS DETECTION SYSTEM USING LONG SHORT-TERM MEMORY

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ABSTRACT—Due to absence of rest, persistent driving and not having earlier information about traffic and driving guidelines, the quantity of mishaps are expanding consistently. Drowsiness Detection System plays a significant part in the anticipation of such mishaps by distinguishing drowsy driver from an active driver at the earliest. In the previous few years, A Significant amount of research has been performed using deep learning algorithms to detect drowsiness which ordinarily had a much diminished exactness range that straightforwardly influences the exhibition of the framework. For instance, a facial evaluating technique was created to detect drowsiness which removes facial focuses and groups the driver's facial condition with the help of Random Forest (RF) algorithm. Those frameworks were not fit for obtaining complex features of drivers. They also suffer low reliability and anti-interference ability. To conquer these limits, We propose a drowsiness detection system based on long short-term memory (LSTM) with rectifier linear units and convolutional neural network. The aim of this research is to build better, low-cost , accurate strategies that results in a higher accuracy to overcome this problem of drowsy driving. It is executed using techniques for calling functions such as Recurrent Neural Networks and related functions, using CNN, object cascade classifiers and back propagation algorithm. The results are evaluated with performance metrics such as Frequency Of Mouth ,f1 score, Eye Aspect Ratio to determine accuracy and similar measures to create a highly effective detection system. From the performance calculations, we have obtained an accuracy of 97%. Finally, we discuss some of the key research challenges that could be applied in the future.

Keywords— Driver Drowsiness, Long Short-Term Memory, Deep learning, Convolutional Neural Networks

INTRODUCTION

1. INTRODUCTION

Lately, video footage from mounted cameras [3] and a few different signals have been broadly used to obtain the intricate features of human drivers[19]. Various techniques has been proposed for distinguishing the degree of driver exhaustion. However, at this time, traffic accidents are still one of the main threats to life safety. For example, a lack of awareness of road safety, drunk driving, and tiring driving are the principle factors causing street mishaps. Among them, fatigue driving represents 14-20% of the reasons for accident mishaps, around 43% of serious road accidents, and roughly 37% of road accidents on huge trucks and related vehicles [6]. 1 of every 4 accidents are brought about by drowsy driving, and 1 out of 25 grown-up drivers drivers say they have fallen asleep at the wheel in a month.

International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 05 Issue: 07 | July - 2021 ISSN: 2582-3930

Driving safety is normally affected by numerous components like drowsiness, monotonous environment, drivers who have trouble sleeping, liquor and medication use, the most widely recognized factor being drowsiness while driving [1-8]. As per the World Health Organization, car crashes are one of the main sources of death around the world. Driving in a fatigue state causes in excess of 1,500 deaths and monetary misfortunes of more than $ 12.5 billion every year in a country. Numerous calculations don't separate between driving conditions and driver attributes [2,6]. This causes an increase of error rate. In recent years, artificial intelligent driver monitoring (AI) systems that check driver fatigue and alertness have been developed to address this problem. Nonetheless, the quantity of viable components for ride quality is high. Some sensors may not function properly in low light or bad weather. In addition, some systems only operate at certain speeds. Recently there was a report of a fatal Tesla crash that occurred when the automation failed to detect an obstacle while the driver was not monitoring the automation. Therefore, human drivers must be alert and ready to control the vehicle in an emergency [8].

Designing a complete solution that takes into account the combined effects of these parameters can result in a more accurate system. To overcome the above limitations, a driver-based neural network system is proposed. Accidents and loss reports have shown that there is presently a need to create solutions for distinguish drowsiness, particularly in the beginning phases of accident prevention.

The solution we propose to this issue is to build a detection system with the help of LSTM that will identify key aspects of fatigue behavior before it's too late. LSTM networks are a special type of recurrent neural network (RNN) [1] [7] which can be used to study the long-term dependencies available in the data. A DDF (Driver Fatigue Detection) algorithm was developed here, which is based on a previously trained CNN model [12]. Several computer vision applications have been developed in the past to detect driver fatigue (DDF). They are used to extract visual properties. However, it is not easy to get the visual characteristics to determine the required metric size. This is caused by various factors that are considered to be driving at night or when the head is misaligned and the face is blocked. To solve this problem, a new Fatigue Alert system has been developed in this article [18]. In this article, an effective self-generated data DDF system has been developed that includes images of drivers with different facial reactions obtained from multiple cameras. The proposed fatigue detection system has been pre-trained by multiple Convolutional Neural Network (CNN) [11] models on different data sets for drivers eyes, ears and mouths. On average, the Drowsiness DDF system achieved an recognition accuracy of 97% with different driver data sets in real time.

The rest of this article is structured in the following manner: Section 2 includes the literature work that has different papers that has been referenced which also includes the detail about proposed system. Section 3 exhibits the design of the system implemented with associated flow and architectural diagram. Section 4 explains about the modules, their description and how they are implemented. Experimental results on accuracy of the model is discussed in section 5. Discussions about future work and a summary are presented in Section 6 and Section 7 respectively.

LITERATURE WORK

2.1 Related Work

A Fatigue Driving Detection algorithm based on facial motion information entropy -Feng You, Yunbo Gong, Haiqing Tu, Jianzhong Liang

In [1], the authors developed a driver's face detection method based on the YOLOv3 (You

Only Look Once) -tiny CNN with an open-source dataset WIDER FACE dataset. An eye and mouth SVM classifier is designed which takes driver facial behaviors into account, which judges drowsiness based on actual size of driver's eyes and mouth. An Information library for driver identity is constructed. This system can be divided into three types: driver biometrics, driver eye state classifier, and driver mouth state classifier. Advance training are given in advance and stored into the driver identity information library. Then, Before system startup, identity verification when the classifiers are called. This process simplifies initialization and avoids inaccuracies. The authors reported that they achieved 93.4%.

Real time driver fatigue detection system based on multi-task conNN -BURCU KIR SAVAŞ AND YAŞAR BECERİKLİ : 2019

Here [3], A multi-task ConNN model is used to detect a driver's drowsiness in real time. To accurately classify the driver's eye and mouth information, Dlib algorithm is used. Here, the system is trained with MTCNN models for the determination of drowsiness in drivers which was also proposed in [11]. The frequency range is kept constant within the study and the number of frames will be fixed. These situations are also dynamically tested and coded at certain intervals that also ensures continuity. The accuracy of the system which is tested in real time accounted to be around 95%. The relationship between eye and mouth can be modelled with the provided system in an interactive way as in [11].
Fatigue in the present condition is calculated based on fatigue occurring in a pre-determined time.

Real time Fatigue Detection Based on Facial Behaviour along with Machine Learning Approaches -Sanjay Dey, Monisha Dey, Sajal K.Das : 2019

This paper [7] makes use of the streaming video which is filmed using a webcam and contains facial changes and characters such as eye aspect ratio, mouth opening-closing ratio, and nose length ratio. The system has been performed with the artificial data produced correctly. Then, the feature 's values are stored and algorithms related to machine learning have been used for classification. Here, FLDA, Bayesian classifier, and SVM have been used as used in [1]. In the statistical measurement, the SVM and FLDA sensitivity are 0.948 and 0.896, respectively, while all specificities are 1.

A Fatigue Driving Detection Algorithm Based on Facial Multi-Feature Fusion - Kening Li, Yunbo Gong, Ziliang Ren : 2020

This paper [4] proposes a new drowsy driving identification technique based on facial multi-feature fusion. Here, a driver's face detection method is designed based on the YOLOv3 (You Only Look Once) -tiny CNN is developed with an open-source dataset WIDER FACE dataset. An eye and mouth SVM classifier is designed which takes driver facial behaviors into account, which judges drowsiness based on actual size of driver's eyes and mouth. A library of driver identity information is developed. Driver biometrics, driver eye state classifier, and driver mouth state classifier are the three forms of driver identification information in the system.

Drivers' Drowsiness Detection and Warning Systems for Critical Infrastructures Ioana-Raluca Adochiei; Oana-Isabela Știrbu; Narcis - Iulian Adochiei; Matei Pericle-Gabriel; Ciprian-Marius Larco ; 2020

The main goal of [10],is to create and incorporate a system that can detect and warn the driver's level of fatigue in real time. When the driver's ability to drive and make decisions is reduced, a device like this is supposed to alert him. It is hoped that by tracking the condition of human eyes, signs of driver exhaustion will be identified early enough to avoid a potential road accident, which may result in serious injury or even fatalities. On a BeagleBone Black Wireless development board, the OpenCV library and other necessary packages were mounted. The Python software programme was used to introduce the software that detects the driver's drowsiness. The authors reported that they achieved an accuracy of 94%. The proposed device alerts the driver if his or her eyes are closed for an extended period of time by activating a series of warning lights and sounds. This is also explained in [19].

Driver Fatigue Detection Based on Convolutional Neural Networks Using EM-CNN — Zuopeng Zhao, Nana Zhou, Lan Zhang, Hualin Yan, Yi Xu, and Zhongxin Zhang :2020

Face detection and feature point position are performed using the multitask cascaded convolutional network (MTCNN) architecture, and the region of interest (ROI) is extracted using feature points in the proposed algorithm. To detect the states of the eyes and mouth from ROI videos, an EM-CNN convolutional neural network is proposed. Two parameters used to detect fatigue are the percentage of eyelid closure over the pupil over time (PERCLOS) and the mouth opening degree (POM). The proposed EM-CNN can detect driver fatigue status using driving videos, according to experimental results. Other CNN-based approaches, such as AlexNet and VGG-16, are outperformed by the proposed algorithm EM-CNN. Other CNN-based methods, such as AlexNet, VGG-16, GoogLeNet, and ResNet50, perform worse than EM-CNN, with accuracy and sensitivity rates of 93.623 percent and 93.643 percent, respectively.

Research on Safe Driving Evaluation Method Based on Machine Vision and Long Short-Term Memory Network -Dongmei Shi and Hongyu Tang :2021

An improved dual-stream convolutional network is proposed in this paper for recognising safe driving behavior. The attention mechanism (AM) is incorporated into a long short-term memory (LSTM) neural network structure using convolutional neural networks (CNNs), and a hybrid dual-stream AM-LSTM convolutional network channel is built. The spatial stream channel extracts the spatial characteristic value of a video picture using the CNN approach For the detection of small objects such as faces and eyes, the time stream channel uses a single-shot multibox detector (SSD) algorithm to calculate the adjacent two frames of video sequence. The FDDB database, VOT100 data set, and self-built video image set are used to conduct ROC, accuracy rate, and loss function experiments, respectively. This method's accuracy rate can be increased by at least 1.4 % as compared to SSD, IDT, and dual-stream recognition methods, and the average absolute error in four video sequences can be reduced by more than 2 %.

Driving Fatigue Prediction Model considering Schedule and Circadian Rhythm-Qi Zhang, Chaozhong Wu, and Hui Zhang:2020

A Naturalistic Driving Study (NDS) was performed with the help of one commercial transportation firm, and NDS data from thirty-four middle-aged drivers were selected for research. Participants were also asked how long they slept before driving, with a range of 4 to 7 hours chosen. The discrete KSS data were translated into consecutive values, and curve fitting methods were used to model the fatigue levels of all participants using the Karolinska Sleepiness Scale (KSS). A linear regression model was also proposed to describe the relationship between the four time-related variables and cumulative fatigue level. Finally, the driving efficiency calculation of standard deviation of lateral position was used to validate the prediction model. The findings revealed that fatigue prediction results are highly correlated with driving success.

2.2 Proposed System

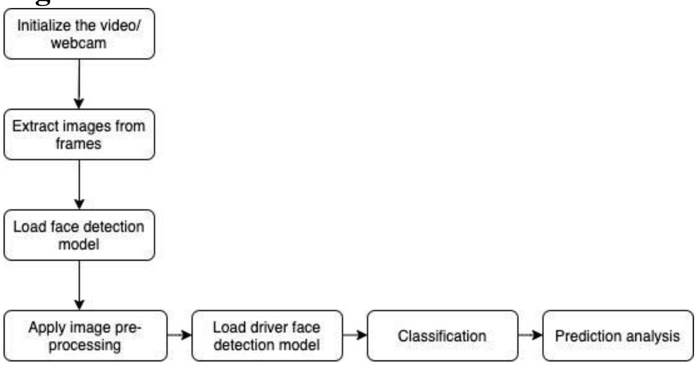
In some of the past works, a two-labelled (fatigue/ non-fatigue) system for driver drowsiness detection was designed which fundamentally included SVM and AdaBoost calculations that were utilized for classification [4]. The proposed approach in this study intends to recognize frames in recordings using convolutional neural network to learn unique spacial facial features. To start, frames are extracted from the video caught by the vehicle's camera. These frames are fed into a face detector based on Haar-like features [5]. Relu function- Rectifier linear unit function is used in the proposed system which helps in a way that will provide inputs directly if it is positive. Otherwise, it would return a value of zero. Edited and resized to 48* 48 square pictures, the detected faces are trimmed and resized. These cropped pictures are standardized by taking away the mean from every pixel and dividing it by the standard deviation. A multi-layer convolutional neural network is fed normalized images of 80 percent of the subjects. The performance of the hidden layers is referred to as the extracted features. The soft-max layer classifier was trained using the extracted features as input. Following the preparation of the classifier, the excess 20% of the pictures retrieved earlier are checked on the classifier. Drowsy driver detection at the frame level is defined in the above scheme. For each frame, a binary signal in the form of a drowsy or non-drowsy face was obtained. To efficiently identify drowsiness, a minimum of 40 to 60 frames should be detected and classified as "drowsy". A buffer of 60 recent frame outputs is maintained, and a signal in the form of an alerting sound is sent to the driver.

3.DESIGN REQUIREMENTS

In our proposed system, we use various features and methods with self-obtained data that has pictures of people with their eyes-opened and closed, mouth-yawn and no yawn.

3.1 WorkFlow of the Proposed System

Fig 1



3.2 Workflow of the Pre-processing module

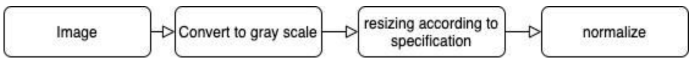


Fig 2

4.MODULE IMPLEMENTATION

4.1 MODULE DESCRIPTION

4.1.1 Data Acquisition:

The main aim of data acquisition is to capture the driver's consecutive facial images in real time. A camcorder is connected to the device which records videos of the driver's different characteristics/actions while driving and converts the pictures into frames. The image here is 92*112 pixels in size. Deep learning algorithms are utilized to classify driver drowsiness rates using new methods and strategies. The framework utilizes a deep learning approach with a a different collection of frames to create automatic classification systems for 30 facial actions in order to generalize drivers' drowsiness; this provides automated measurement of facial features facial during actual somnolence in order to identify new signs of drowsiness.

4.1.2 Pre-processing:

In the self obtained data, The participants were required to drive a car in a controlled environment. Also, To ensure that the subjects fell into a driving fatigue state, they were asked to drive for at least two hours. Pre- Processing involves the removal of non-essential frames, such as blurred areas of the image that aren't required for detection, like the background and listing them under the already labelled part. Image processing is the method of extracting useful information from pictures obtained from mounted camera. We also use the principle of labelling, which is used to identify characteristics so that the computer knows which data to select. It is done to sort images as yawn, no yawn, eyes opened and eyes closed. Separate numbers were allocated to each label.Since we are processing in real time, the images are converted to gray scale. The problem is then solved by applying mathematical operations to images using any type of signal processing and image ROI -Region of Interest extraction (face and eyes orientation), followed by facial expression separation using various techniques mentioned .

4.1.3 Feature extraction:

Feature extraction begins with a collection of data and then builds derived features that are meant to be non-redundant, making the learning and generalisation process easier. It may often contribute to more accurate human interpretations. We use certain functions such as lambda, dense which are important process for using r-CNN. Then, Data augmentation process occurs where every incoming data is collected and is presented for transformation. To model a data for training, augmentation is employed which helps in horizontal and vertical correction. For the image inputted to the system, an array and shape is assigned. We also employ an object cascade classifier to understand the image and create an array according to the same. Array is used to separate the region of interest (ROI) from the unwanted regions such as the background. Another feature of a convolutional neural network (CNN) layer is the softmax layer. It is a software used in deep learning. An adaptive optimizer is used which ensures that there is no loss in accuracy even when most of the data is lost. We also include back propagation algorithm, because While designing a Neural Network, in the beginning, we initialize weights with some random values or any variable for that fact. It is not necessary that whatever weight values we have selected will be correct, or it fits our model the best.The Back propagation algorithm looks for the minimum value of the error function in weight space. The weights that minimize the error function is then considered to be a solution to the learning problem. This process occurs when the error is minimum.

4.1.4 Classification:

4.1.4.1 CNN :

- The first set of layer to accept input values is called a convolutional filter.
- Convolution is the process by which the network tries to show an input value by reference to what has been learned in the past.

- If the input signal / image looks like the image seen previously, the reference signal / image is mixed or kinked with the input signal / image.
- The resulting output / image is then transmitted to the next layer.
- The input obtained as a result of the operation of the preceding convolutional layer can be refined so that the filter sensitivity can be reduced.

The refining process is known as sub-sampling. This can be achieved by averaging / sampling the signal to the maximum.

Examples of scanning methods (for image signals) include resizing / reducing image size or reducing colour contrast in RGB (red, green, blue) channels.

The last set of convolutional layers in the neural network is fully connected, which means that the neurons that were in the previous layer were connected to every other neuron that was in the next layer.

It demonstrates a high level of reasoning that takes into account all possible paths, from entrances to every possible path to exit.

A convolutional neural network (ConvNet / CNN) is a deep learning algorithm that can take input as an image, assign meaning (weight) to various aspects / objects in the image - essentially displaying important properties, leaving out others and differentiating them from one another. The need for preprocessing data required in ConvNet is much lower than that of other classification algorithms. Although filters are designed manually using primitive methods (allowing adequate training during processing itself), ConvNets can certainly learn about these filters.

The ConvNet architecture can be compared to a model of neuron connections in the human brain (inspired by the organization of the visual cortex). There is a limited area of the visual field, known as the receiving field, in which individual neurons respond to stimuli. Such a collection of planes overlaps to cover the entire visual area.

ConvNet manages to capture spatial and temporal dependencies in an image with the help of appropriate filters. Its architecture provides better customization of image sets due to the use of repeated weights. In other words, to better understand the complexity of the image, the network can be trained.

4.2 Long Short Term Memory(LSTM)

One way to handle sequential data is to use the LSTM model. LSTM networks are a special type of recurrent neural network (RNN) [1] [7] which can be used to study the long-term dependencies available in the dataWe have added Rectifier linear unit to the model to obtain a much efficient model. The Relu unit, short for piecewise linear function, is basically an activation function that will output the input directly if it is positive, otherwise, it will output zero. A recurring neural network is a neural feedback network with internal memory that allows stability of the information.

We chose the LSTM network because it is easier to work with long sequences without the gradient loss problems that traditional RNNs experience and much easier to learn and use [7]. In LSTM network there are three ports for each time step: Forget port, input port and output port.

Forget Gate: The gate tries to “forget” part of the memory from the previous output.

$$f_t = \sigma(W_f.[h_{t-1}, x_t] + b_f)$$

Input Gate: The gate decides what should be kept from the input in order to modify the memory.

Output Gate: The gate decides what the output is by combining the input and memory.

$$O_t = \sigma(W_o[h_t, x_t] + b_o)$$

$$h_t = o_t * tanh(C_t)$$

After hyper-parameter tuning, our optimised LSTM model achieved an overall accuracy of 97% with a much lower false-negative rate of 0.3 compared to the false-negative rate of our kNN model (0.42) [10].

4.3 FATIGUE LABELING

PERCLOS is a widely used method of measuring the degree of sleepiness [2] [3]. Considering traditional fatigue detection methods, PERCLOS calculations are highly influenced by environmental changes. A new and effective approach is to use eye tracking glasses (which are more like video cameras) to record detailed eye movement data. With the technology provided for tracking we are able to detect the expected status of the eye, eg.CLOS is another status defined as long duration of eyelid closure and slow lid closure. The PERCLOS index can be calculated as follows:

$$PERCLOS = \frac{blink + CLOS}{interval}$$

$$interval = blink + saccade + fixation + CLOS$$

5. EXPERIMENTAL RESULTS

5.1 Description:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \quad \tilde{C}_t = tanh(W_C \cdot [h_{t-1}, x_t] + b_C)$$

In the result graph, the proposed graph depicts the estimated value of output expected from the system and the existing graph depicts the value obtained from our system for the input data.

The accuracy of the model is measured using F1–score . It is calculated as,

*F1 = 2 * (precision * recall) / (precision + recall)* where, precision = (True Positives) / (True Positives + False Positives)recall = (True Positives) / (True Positives + False Negatives)

5.2 Result Analysis:

	precision	recall	f1-score	support
yawn	0.90	0.89	0.90	53
no_yawn	0.91	0.94	0.93	66
Closed	0.99	0.97	0.98	181
Open	0.98	0.99	0.99	194
accuracy			0.97	494
macro avg	0.95	0.95	0.95	494
weighted avg	0.97	0.97	0.97	494

Table 1

5.3 Performance Table:

Method	**Metric**	**Classifier**	**Accuracy**
Viola Jones	Eye state	SVM	93.4%

CMOG	Visual Features	HMM	95.7%
Eye state and mouth	Eye state	MTCNN	91.6%
LSTM with relu units	Visual Features	CNN with soft-max	97.6%

Table 2

6. FUTURE WORK

Although the proposed evidence of sleepiness based on in-depth training may yield reasonable results for diverse data sets, there is still room for improvement in their effectiveness. Drowsiness causes the driver to accidentally roll or fall while driving. This can be a valuable indicator of a successful detection of driver fatigue. Most of these events also occurred at night. I.R.- An LED-based tracking approach can be used to detect drowsiness in such situations and thus make the circuit usable in all lighting conditions. In addition, the proposed scheme makes frame level decisions by applying 2D CNN (Convolutional Neural Networks) to each frame to extract properties. The 3-D convolution network can be applied to a more efficient sleep state detection system using the spatio-temporal link.

7. CONCLUSION

Driver Drowsiness Detection is an active area of research, considering the increasing number of accidents now. Different models have been developed for the same. LSTM model with its related functions provide better performance when compared with some other traditional approaches. The classification accuracy obtained by employing CNN is higher compared to the basic classification techniques. In this article, we have applied various methods that could best identify driver drowsiness conditions. In our case, the f1 score provides the required accuracy to the LSTM model. The proposed LSTM model with Relu units provides a more optimized performance result when compared with the existing models. Model training acts as a significant and crucial part in obtaining a greater accuracy rate since the data has to be clear and accurate to obtain the required result. Finally, the system gained an accuracy rate of 97.6%.

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