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Driver Drowsiness Detection Using Hybrid Algorithm

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ABSTRACT

In this work we focus on the discernment of sleepiness in drivers' drowsiness proposing a hybrid algorithm which aims to confirm whether the driver's level of attention has decreased owing to a nap or any other medical issue, such as brain problems. Therefore, the proposed hybrid algorithm uses both Haarcascade classifier and Convolutional Neural Network (CNN) algorithm to detect drivers' drowsiness. The driver's eyes will be monitored and an alert sound will be generated by Raspberry Pi module, but the face must be moving in real time, and the aspect ratio must be between 16:9 and 1.85:1. People often feel sleepy since activities like driving call for a proper mental state, and bad work-life balance has additional negative repercussions. When we give input through normal camera it analyses drivers state of eyes and mouth, actually it checks aspect ratio of eye. We proved in comparative trials that our hybrid algorithm beats current driving fatigue detection algorithms in speed as well as accuracy.

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1. INTRODUCTION

Accidents on the road ways are becoming one of the leading causes of early mortality. Drivers would regularly get negligent and have unfortunate crashes. This reduction in the driver's tiredness and sleepiness contributes to their increased awareness.

When the driver is alone, the situation becomes extremely dangerous. Accidental micro-sleeps, or small lapses in consciousness that happen when a motorist is tired and weary, are the primary cause of the loss of attention. Drowsiness or weariness represents one of the leading reasons for poor road safety, serious injuries, revenue losses, and occasionally fatalities. These factors, taken together, increase the likelihood of an accident while driving. Some bad events can be avoided by utilizing a computer to identify fatigue remotely. Several techniques are currently devised to detect the driver's tiredness and issue warnings in response, as accidents are frequently caused by drivers who are fatigued. Both benefits and drawbacks can be found in any approach.

Although there exist several outstanding initiatives in this area, there is still an opportunity for improvement. The purpose of this research is to identify driver sleepiness while handling the issue of late alerts because analysis in discrete time periods by previous techniques results in late warning. This work demonstrates the development and utensilation of a machine Learning-based approach to identifying eye states, as well as the inclusion of the previously mentioned concepts into an algorithm to identify driver drowsiness.

According to research conducted in the United States, 37% of drivers surveyed acknowledged to dozing off behind the wheel. In the previous five years, an estimated 1.35 million drivers were involved in accidents involving sleepy driving. Accidents caused by falling asleep are probably dangerous. Due to the greater speeds and delayed reaction times involved in drowsy driving collisions, there is a high morbidity and death rate. Nonetheless, most of these collisions are caused by drowsy or fatigued drivers. Fatalities and serious injuries from car accidents are more likely to occur when a motorist is fatigued. The non-invasive and affordable approaches of detecting driving tiredness based on driver behaviour have recently attracted a lot of study interest. Yet, facial recognition and tiredness evaluation technology in complex situations and challenging environments could limit the performance of algorithms.

When the surroundings shift, PERCLOS is applied on a mask to acquire the motorist's face and assess their driving condition. Experiments demonstrate that the approach performs well under ideal circumstances. However, the construction of the mask has an impact on the method's ability to generalise. Viola and Jones' cascade facial detection system uses a Haar-like characteristic and an Adaboost to develop a transmitted classification that works well in identifying faces. Drivers loose complete control over the vehicle, when they fall asleep. So, there is a need to design a intelligent vehicle system using Machine Learning, Deep learning techniques and integrate IOT technology. Therefore, we propose a mechanism to alert the driver regrading the condition of drowsiness or daydreaming.

Our contributions are summarized in three folds as:

- ✓ A novel convolutional neural network and haarcascade classifier-based network was proposed to identify a driver's face, which significantly improves efficiency.
- ✓ In order to determine if a driver's eyes are either open or shut, we add a new option based on the Davis King library (Dlib) toolkit.
- ✓ Many tests are performed to demonstrate the effectiveness of the EAR in various drivers and the considerable improvements in accuracy and speed of the suggested method.
- ✓ To show the efficacy of the proposed hybrid algorithm, we deployed our model on Raspberry Pi to detect drivers' drowsiness in near real-time.

2. RELATED WORK

Traffic accidents were mainly caused by drivers' drowsiness. So, there is a need to develop a system which can monitor and detect drowsiness in near real-time. In [1] the detection of eye states was developed by combining haarcascade with circular hough transform. So, the haarcascade classifiers initially detects the drivers face and then eyes and classify open and closed eyes. To detect the circular shape of eyes detected they applied circular hough transform.

Su Hong et al. [2] proposed a Partially Least-Squared Regression-Based Hybrid Theory for Predicting a rise in drowsiness. They suggested an innovative way of modelling driver fatigue using various eyelid movement characteristics utilizing a data fusion approach referred to as partial least squares regression in order to tackle the problem of strong coupled interactions between eyelid shift includes and anticipate a likelihood of drowsiness. The established model's prediction accuracy and resilience are validated, demonstrating that it offers a novel method of combining many parameters to improve our capacity to recognise and anticipate the state of sleepiness. We can train classifier networks that are more precise and effective using frameworks. Although this study is two years old, more lightweight frameworks have since been developed, allowing us to examine better algorithms. However, some improvement can be done utilising more complex networks like CNN.

In [3] they developed sleppness detection system based on steering wheel angular velocity and adopted time series analysis. Initially under fatigue state steering behavior was analyzed, then temporal detection window was determined. Finally, data series of steering angular velocity was choosen as detection feature and validated their designed model on real data. In [4] a Yawn detection system was proposed for monitoring the driver's drowsiness by applying Spatio-variational descriptors and they tested their network on YawDD and MiraclHB datasets.

He H et al. [5] proposed a two stage CNN network for detecting drivers' fatigue in real-time. They cascaded two stage CNN, in which one stage CNN is used during detection phase and other stage CNN is used for classification phase. The proposed network was also implemented on Raspberry Pi in real-time to show their network robustness. In [6] a sleppness detection system was designed as mobile device application referred as "Percentage of Eye Closure" (PERCLOS) determined by using mobile camera. They used wearable sensors and adopted Support Vector Machine (SVM) on test data and achieved 98.3% classification accuracy.

To monitor both drivers' drowsiness and distraction levels a vision based embedded system was proposed [7]. In order to reduce the car accidents an alert system was proposed by first detect drivers face, then detect eyes using facial landmarks and finally calculate EAR to detremine the driver's drowsiness level. Deng W et al. [8] proposed a DriCare network for determing the drivers' fatigue situaution. They designed a new detection system for facial regions based on 68 keypoints, and uses facial regions to determine the state of the driver. They also adopted new face-tracking system in-order to improve the tracking accuracy.

In their vehicles, Volvo incorporates a feature referred to as "Driver Alert Control" [9]. This technology compares a segment of road with the markings on the side of the roadway using a camera to detect movements of the driver's steering wheel. The car warns the driver if it does not follow the road evenly. Nevertheless, the device is not meant to assess driver weariness. Volvo has admitted that they attempt to infer driver weariness indirectly from steering wheel movements rather than directly taking it into account. It is said that sometimes, despite driver weariness, driving performance is unaffected. As a result, there could be false negatives, where no alarm is sent to the driver, and it is the driver's responsibility to make sure that they properly stored.

Jabbar Rateb et al. [10] proposed real-time drivers drowsiness detection using deep learning approach and implemented on android applications and achieved 81% accuracy. The mechanism of detecting is then rigorously verified by metrics like an erroneous positive and erroneous negative on several individuals and assemblages of people from various origins, peer groups, sections, etc. This study plans to carry out further real-world experiments in the years ahead to gather extra information for evaluation and improve predictions by developing a more dependable and superior algorithmic structure. This method's drawbacks include its high sensitivity to noise around the sensors. For instance, the environment must be entirely silent when the subject is conducting the EEG experiment. The noise will obstruct the sensors' ability to track brain activity.

Arunasalam M et al. [11] proposed a real-time drowsiness detection system using Arduino. They developed a hardware system which provides drivers drowsiness detection, trigger alarm for driver's drowsiness, controls speed of the vehicle for higher drowsiness and also forwards a message of driver's location details. In [12] a drowsiness eye detection system was proposed by haarcascade classifier and combination of contour, blur and canny functions. In order to detect face area and eyes haarcascade classifier [13] was applied and to detect the drivers' eyes opening or closing a combination of contour, blur and canny functions were applied. In [14] a multi-task cascaded CNN was proposed to detect drivers fatigue state automatically. They employed "face detection and feature point location" and extracted feature points from region of interest. They adopted CNN to detect the eye and mouth status from the region of interest and they achieved 93.6% detection accuracy.

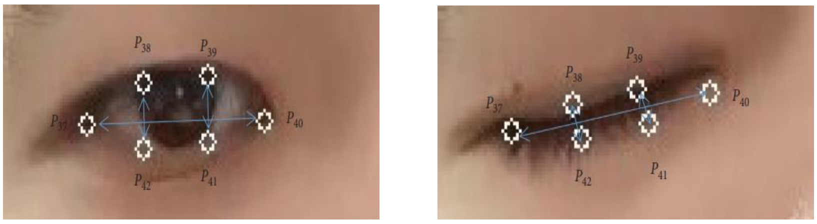
Cheng Long et al. [15] employed CNN to detect the face of driver and open-source library to extract fatigue feature map from ech video frame using facial keypoints. To obtain final fatigue feature map they employed LSTM and their network has achieved 93% accuracy only. In [16] a deep facial anlysis network based on deep learning was proposed for driver's fatigue detection system using 24 facial features. They also trained a facial keypoint network using both local binary patterns and AdaBoost classifiers. Atlast, they adopted fuzzy logic to deduce drivers fatigue state. To analyze and anticipate drivers' drowsiness Ed-Doughmi et al. [17] proposed Recurrent Neural Network (RNN) over a video sequence of drivers face frames. They proposed 3D-CNN multi-layer-based architecture to detect drivers' drowsiness and achieved 92% accuracy. A hybrid model [19] was constructed by integration of CNN and Bi-LSTM for driver's drowsiness detection. A drowsiness detection was implemented by using wavelet packet transform [20]. They carried out analysis by considering time-domain features on EEG channels. The features selection was utilized to detect drivers' detection and achieved an accuracy of 94.45%. Even the degree of driver's drowsiness level can also be detected by using psychological signals [21-22] such as EEG, ECG, EOG, PDA and EMG and apply various ML, DL and multimodal fusion [23] techniques.

3. PROPOSED SYSTEM

The method that is being proposed works by detecting yawns and eyes. The term Eye Aspect Ratio (EAR) refers to the proportions of the eye region, this is usually used for assessing the time and rate of blinking of the both left and right eyes as well as in tiredness calculations detection. There has not been any information about using EAR to diagnose facial paralysis objectively. In this work, the variation in binocular eye movements of individuals with facial paralysis was measured by variations in EAR. In the movement picture series, EAR was used to define the positional variations of the visual landmarks of paralysed facial patients. Figure 1. shows eye state diagram. The expression for EAR is given as:

$$\mathrm{EAR}=\frac{||P2-P6||+||P3-P5||}{2||P1-P4||} \tag{1}$$

According to research, a person's conduct and face can both indicate how sleepy they are. We adopted Viola Jones's cascade of classifiers method [13] for faces and is used to analyse the photos and determine tiredness based on mouth position. The photos and a set of image data for mouth and yawning were compared. Figure 2. shows mouth state diagram.



(a). Eye opened will have more EAR. (b). Eye closed will have less EAR.

Figure1. Eye state diagram.

$$\text{Mouth\_Map} = (c_r)^2 * \left((c_r)^2 - \frac{\eta \times c_r}{c_b}\right)^2 \tag{2}$$

$$\eta = 0.95\,\frac{\frac{1}{n}\sum \mathbf{1}_{(x,y)} cr(x,y)^2}{\frac{1}{n}\sum_{(x,y)}(c_r(x,y)/c_b(x,y))} \tag{3}$$

During yawning, some people would cover their mouth with their hand. Although yawning is an indication of tiredness and fatigue, it makes it difficult to capture decent photographs if a person is doing it are some illustrations of the yawning detection techniques employed in the study.

(a). Mouth opened will have more EAR. (b). Mouth closed will have less EAR.

Figure 2. Mouth state diagram.

Initially, a model based on CNN was proposed with four layers for convolution, three layers that pool data, then two thick layers. Next, the model is trained with several configurations to produce the best results. Our model has undergone several modifications to make it as compact as possible. Figure 3. shows the layers used in our proposed CNN.

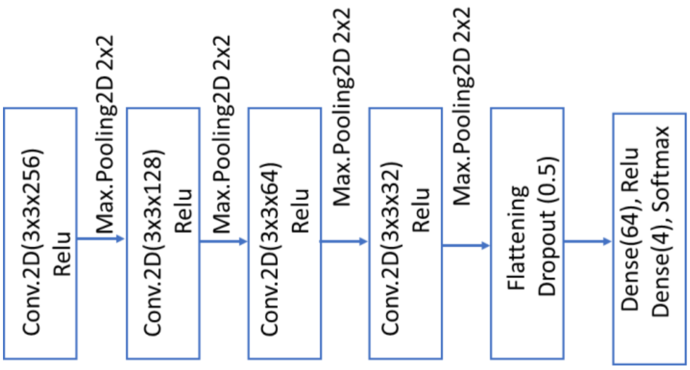


Figure 3. shows the CNN used in our proposed system.

First, the OpenCV library is used to input the video feed from a camera. Facial landmark detection utilising the Dlib's API is performed on every clip frame captured. The detached face's both eyes will subsequently be separated and they will be fed to the trained model. A queue is used to hold the predicted eye condition for each eye image in a frame and then utilised to evaluate utilising. Evaluate whether the driver is drowsy by taking a proportion of the (PERCLOS) measurement. This is a typical model for detecting drowsiness that was constructed and trained from scratch on the MLR dataset. Figure 4. shows the proposed system architecture.

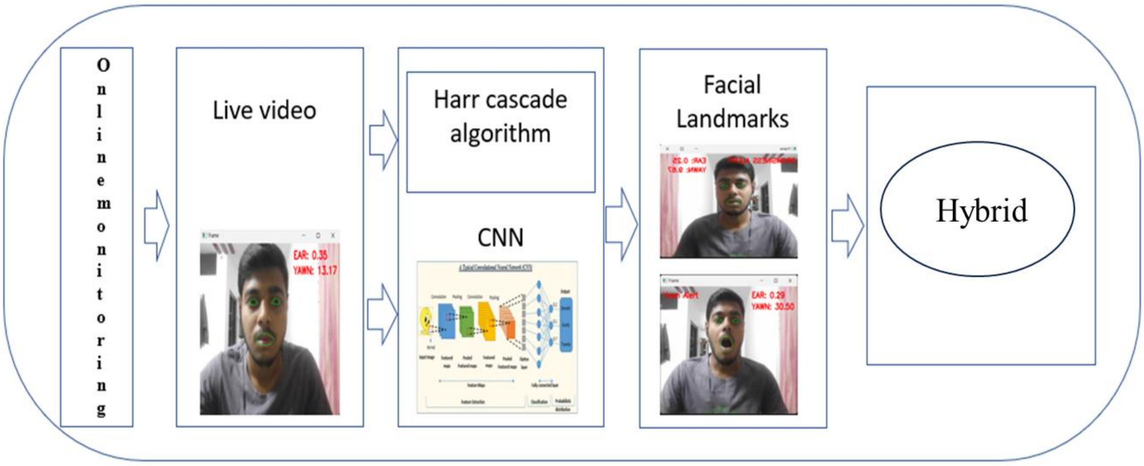


Figure 4. Proposed hybrid algorithm using Haarcascade+CNN networks and DLIB library.

Initially the system is configured and feed with live stream video. Now the sequence of video frames was extracted and step and step process of detecting drivers' drowsiness was shown in Figure 5. In our hybrid algorithm the various steps carried out are video processing, face detection, eye detection, yawn detection. Based on the drowsiness level i.e EAR < 0.25, an alarm will be generated by our system.

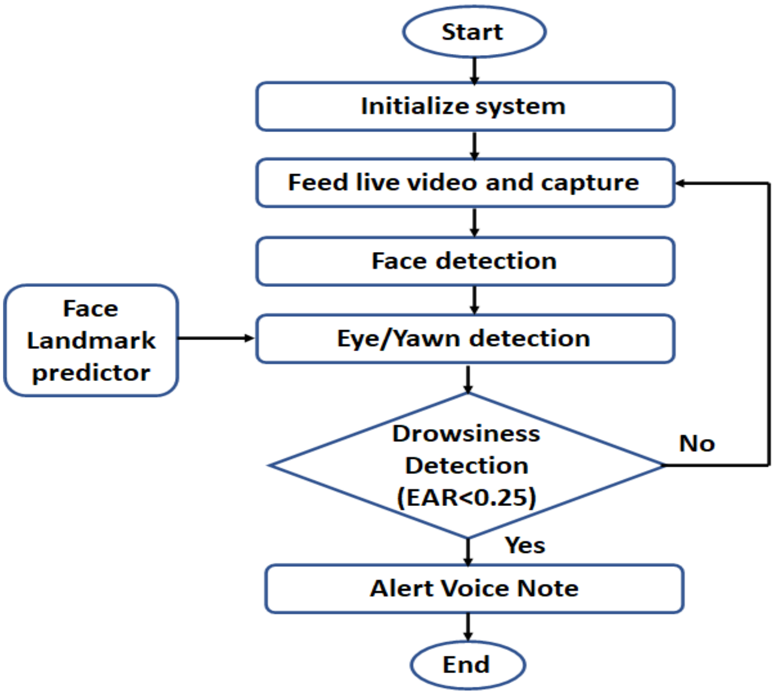


Figure 5. Flowchart of our proposed system. Our system pipeline starts with liv e video feeding, then performs face detection followed by eye/yawn detection and finally verifies EAR<0.25, if satisfied then generates an alert voice if not it ignores and captures next frame.

This method employs the OpenCV package to receive a 640 × 360-pixel video feed via a camera. Then each is sampled and image converted to grayscale from an ongoing video feed. The data is then sent into the extractor of features, which utilizes Dlib's API to recognize and predict landmarks of the face in every image.

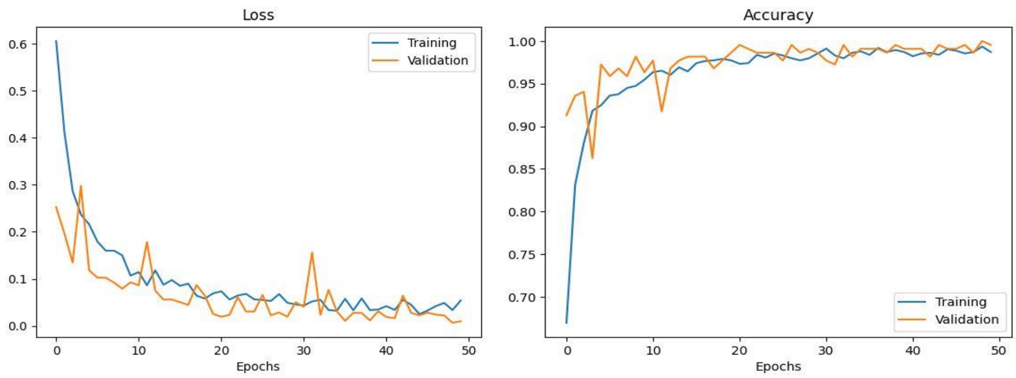
The eye extractor then crops a rectangle eye piece from the live input frame once the feature extractor has extracted all of the face landmarks. Additionally, it pre-processes the extracted eye image to the necessary sizes before feeding it to the eye classifier. Jitter and frame losses occurred during analysis because the technique was initially used to analyse a single threaded python program. When running in a single thread, our code took approximately 200-220 milliseconds to analyse a frame. As a result, multi-threading enhanced the model's performance to 170-195 ms for frame analysis.

Ultimately, it is processing and analysing each eye state categorization into a queue for the purpose to compute PERCLOS and if the PERCLOS amount exceeds the Threshold Value, assume that the driver is fatigued. Instead of utilizing a discrete frame-by-frame technique, this method estimates the PERCLOS value periodically for the 2-second window screen to lose the smallest amount of data.

4. RESULTS AND DISCUSSION

In our experimental setup, we used Google Colab which runs on Tesla V100 Gpu, CPU Intel Core i5-8300H, main frequency 2.3GHz, 16GB memory. Our hybrid network for trained for 50 epochs and was implemented using Tensorflow, OpenCV, Dlib toolkit. We adopted Adam as our optimizer solution and network was trained on YawDD dataset [18]. This dataset was captured under static environment from a group of volunteers which are of different ages, colour and category. They collected dataset only on three types of actions such as talking/singing, normal driving and yawning. We adopted 100 videos of short duration and which includes 50 men and 50 women. We used 5156 images which includes drowsy and non-drowsy. Our proposed model used 4125 images for training and 1031 images for testing.

The images below illustrate the model that was trained in action, featuring closed eyelids and yarn representing the trustworthy ratings of the model's identifications for a certain category at a specific point in time. Figure 6. (a) and (b) shows the training and validation loss and accuracy curves of our proposed algorithm. From Fig.6. (a) it is seen clearly that loss was almost zero and became stable after 35 epochs. At the sametime validation loss was 0.05 after 20 epochs. Similarly, the model training and validation accuracy was almost saturated after 40 epochs. These results clearly shows that our model achieves minimal loss during the training and validation of Yawn dataset.



(a) (b)

Figure.6 Training and Validation loss and accuracy curves.

Table.1 shows the comparison of various algorithms while detecting drivers' drowsiness level using various performance metrics. We compared our hybrid algorithm with several esisting algorithms such as Adaboost, Haarcascade, LSTM, RCNN, MTCNN+DLIB, and MTCNN+LSTM. To be fair all the existing algorithms were retrained and tested on YawDD dataset. We compared our model with several existing algorithms only in terms of drowsy and non-drowsy scenarios. We integrate our proposed model using machine learning and deep learning techniques. Our network was developed by integrating Haarcascade + CNN algorithms along with DLIB library and thus formed a hybrid network to detect drivers' drowsiness. We calculated various performance metrics such as precision, recall, F_1 score, accuracy and speed as shown in Table.1. Overall, it is clearly seen that our model obtained better results in terms of precison, recall, F_1 score and accuracy metrics. It is observed that our model achieves +15.6, +8.12, +12.05 and +8.3 higher precision, recall, F_1 score and accuracy than compared to MTCNN+LSTM model. It is clearly observed from Table.1, our model runtime for frame is 53.8 milliseconds and whereas the runtime of MTCNN+LSTM model is 65.2 millisceonds. But the only remark is our model speed fails to achieve higher speed than compared to MTCNN+LSTM model.

Table 1. Comparision of proposed algorithm with several existing algorithms.

Algorithm	Precision	Recall	F1-score	% Accuracy	Speed/ms-f-1
Adaboost	85.4	92.14	88.63	92.1	58.6
Haarcascade	96.7	97.23	96.96	97.4	58.6
LSTM	81.5	88.76	84.97	92.1	48.2
RCNN	81.8	88.84	85.17	92.3	54.4
MTCNN+DLIB	70.4	83.52	76.4	85.6	51.3
MTCNN+LSTM	81.6	89.77	85.49	90.2	65.2
Proposed	97.2	97.89	97.54	98.5	53.8

From the above it is clear that we achieved higher detection accuracy and comparable speed while detecting drivers' drowsiness in near real-time.

5. CONCLUSION

According to the test dataset findings and actual testing under an assortment of lighting and occlusion circumstances, we find that the suggested approaches for treating sleepiness recognition as a personal identification task is both feasible and accurate. Furthermore, this technology will function immediately on almost all Android devices, and edge devices making it incredibly accessible.

Expanding the drowsy database and integrating photos to enable the algorithm to identify sleepiness in low-light settings is one important enhancement that may be made in the years to come. This might be advantageous for drowsiness-related incidents, which are more likely to occur when riding at twilight. Additionally, we focused on yawning in the algorithm we developed to increase the accuracy and dependability of the sleepiness detection system. Therefore, our proposed hybrid algorithm i.e., CNN+Haarcascade+DLIB achieved 98.5% detection accuracy and runs with 53.8ms detection speed. When our model was implemented on Raspberry Pi it runs with 11 frames per second (FPS). However, when the proposed hybrid algorithm was implemented on Raspberry Pi in real-time it is working at very speed, as it runs with a 1.2GHz clock frequency.

Conflicts of Interest: The authors declare that there are no conflicts of interests regarding the publication of this paper.

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