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An Efficient Drowsiness Detection Scheme using Video Analysis

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Abstract: Road accidents caused due to drowsiness of the driver are quotidian. As per the World Health Organization global report, India has the highest number of road accidents, and about half or greater number are because of drowsy driving, and this has become a major issue. Real-time drowsiness detection models detect when the driver is feeling drowsy by monitoring behavioural aspects or by using physiological sensors. Though the use of bio-sensors gives more accurate results, they are intrusive and distract the driver. We have developed and implemented a behavioural-based drowsiness detection algorithm that monitors the movement of the face and closeness of eyes to detect and alert a drowsy driver. We successfully implemented our algorithm in Matlab-2020 software, where we took a live video from a webcam and processed each frame to classify it as either drowsy or not. We also tested on a dataset featuring live driving subjects and achieved 90% accuracy with 84% precision. If drowsiness is detected, a system audio alert is generated to alert the driver. In case eyes or face are not detected in a frame, we by default classified it as drowsy and produced the alert message because a false negative is more dangerous than a false positive, and thus attained a high recall of 98%.

Keywords: Drowsiness detection, Face movement detection, Eye closeness detection, Viola-Jones algorithm, SVM classifier

1. Introduction

Road traffic accidents claim the lives of a significant number of people in India. Highway traffic, overspeeding, mobile phone use while driving, drunk drivers, and driver drowsiness are all factors that contribute to road accidents. Overall, driver drowsiness is responsible for about half of these collisions. Drowsiness is described as a stage in between wakefulness and sleep [1]. As a result, a driver's sleepiness is a key factor in serious accidents that result in a significant number of fatalities per year [2]. From the previous decade, these deaths have risen dramatically around the world. According to statistics, traffic accidents are the ninth leading cause of death worldwide. Furthermore, statistics show that 10% of crashes are caused by excessive yawning, trouble holding eyes open for longer periods, and failure to maintain the required distance between the front and back vehicles, as well as failure to maintain adequate distance between the side dividers, and so on. The vast majority of them occur on highways, especially after long periods of driving. From 2009 to 2013, the National Highway Traffic Safety Administration (NHTSA) [3] reported over 72,000 police-reported collisions and an estimated 100,000 crashes caused by drowsy drivers, injuring over 41,000 people and killing over 800 people. Several people have recently experienced problems with driver drowsiness. According to research conducted in India, approximately 1.51 million people died in accidents in 2018 as a result of overspeeding vehicles and driver drowsiness [4]. Drowsiness has since become a leading cause of automobile accidents.

According to the World Health Organization's Global Report on Road Safety, India ranks first in the world for road accidents in 2018, accounting for 11% of all accidents worldwide. Drivers with sleep deprivation show moderate response time, misguided thinking of the circumstance, and absence of mindfulness and abilities that are of most extreme significance while driving. Dozing off while driving is just as dangerous and deadly as driving while inebriated. According to various reports, 1 out of every 10 drivers drives for 4-8 hours a day, 3 drivers drive for 8-12 hours per day, and the remaining 6 drivers drive for more than 12 hours per day [5]. Half of them admitted to feeling drowsy regularly, particularly on long drives. When a driver is drowsy, the risk of an accident increases by up to four times when compared to when the driver is alert.

Drowsiness can be defined by several factors. Sleepiness is manifested in people by a variety of gestures and physical appearances, such as the eyes closing and the driver's mouth opening and yawning, or the neck slanting, among others. The behavioural-based approach is examined in this paper using eye-tracking, eye flickering, face recognition, and head positioning. A camera and Matlab tools are used to detect drowsiness in real-time. As a software-based

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production, this technique is used.

2. Related Work

Over the recent years, it has been observed that drivers' sleepiness has solely been the momentous reason for road accidents and can prompt serious wounds, massive deaths, and financial misfortunes. Many researchers demonstrated the need for a dependable driver drowsiness identifying framework, which could caution the driver before an incident occurs. Various methods and theories have been proposed by experimentalists to identify drowsiness. They have tried to understand driver drowsiness by focusing on aspects that incorporate vehicle-based, physiological, behavioural measures, and so forth. A detailed review is discussed in this section which will give an understanding of the current frameworks, some of the issues related to them, and the improvements that should be done to make a strong framework. Some of the ideologies are as follows.

A scheme was proposed for drowsiness detection based on vehicle movement. This method mainly focused on considering the steering wheel position and its adjustments which is a most vital factor to keep the vehicle in the same lane without any deviation. Calculations were performed associating micro-adjustments of the steering and sleepiness which resulted in an efficiency of 86% in identifying drowsiness. In another case[6], users driving patterns in drowsy and fully active conditions in the system were compared by monitoring the path length among the automobile position and lane boundaries which were achieved by arranging a camera in the anterior region of the rear-view mirror, and finally, the deflection in the path were examined. Be that as it may, driving pattern identification depends on numerous elements like driving abilities, vehicle qualities, and road conditions.

The next class of techniques involves the assessment of the biological attributes of the users. It employs bioelectrical sensors, which include Electrocardiogram, Electroencephalogram, and Electrooculogram. The principal signals accounted for estimating the drowsiness of humans in [7] are theta, alpha, and delta frequencies. In [8], EEG signals form the basis for drowsiness detection. They control the electrical activity of the brain. The zero-crossing and energy distributions are computed and the instantaneous frequency and signal irregularities are extracted. The deep convolutional neural network architectures for extracting features from the images of the spectrograms obtained by EEG. Further, wavelet transforms with tunable Q-factor and long short-term memory networks were considered for subband decomposition and classification processes.

Another novel approach in [9] of EEG uses principal component analysis and PCANet deep learning model for preprocessing and feature extraction. The work reported in [10] focuses on implementing automated driver drowsiness along with an alarming system using signals obtained from electrooculography. An embedded system circuit consisting of a microcontroller on Arduino was prepared for signal procurement. Then supervised learning K-nearest neighbor was accounted for classification. All these strategies give the most precision that is over 90%. However, a significant disadvantage of all these types of frameworks is the intrusiveness which distracts the drivers because of the connection of too many sensors. Non-meddling strategies for biosignal estimation exist yet are less precise.

Likewise, speech recognition techniques can be employed to distinguish a sleepy or dozy voice in the vehicle [11]. The idea involves voice analysis of humans to understand their level of fatigue. The outcomes are at the same time approved through Electro encephalography (EEG) based estimations. A trial was done where the persons are approached to tell specific sentences at various levels. The responses were observed for the figuring of different boundaries like duration, unvoiced length, and reaction time. Also, Mel Frequency Cepstralor Coefficients (MFCC) are used in understanding the quietness, the voiced forms, as well as unvoiced forms, and these parts, are set apart utilizing a Gaussian Mixture Model (GMM). Nonetheless, a disadvantage is that these techniques are complicated. Furthermore, a framework was built which figures the driver's breathe changes by observing pulse rate [12]. This framework has downsides which include direct contact with the skin and may also disturb the driver's activities. With the help of a plethysmography belt, respiratory signals are procured and further the quality of these signals is maintained. It considers the respiratory rate variability for monitoring driver's alertness [13].

Researchers examined and conveyed their work by considering deep learning for drowsiness identification in brain-computer interfaces utilizing the fNIRS framework. The scientific technique for functional near-infrared spectroscopy with the end goal of practical neuroimaging. Both dorsolateral prefrontal cortices and prefrontalcortices were engaged in fNIRS activities. Deep networks were used in identifying both active and sleepy conditions. The testing was carried out with convolutional neural networks. It was used on colour map pictures to determine the best reasonable mediums for monitoring the functions in the brain [14].

In [15] authors have introduced a theory in which the person's gaze is analyzed utilizing various new profound deep-learning procedures based on convolutional neural networks and facial appearance. A deep learning algorithm is prepared to sort the gaze from a given face-recognized picture through a multi-GPU stage, and afterwards, its network parameters are moved to a GPU inside a computer that runs on Windows. However, this methodology is inadequate for the necessity of a large amount of information to prepare a network to coordinate and work well with an undeniable degree of precision.

In [16] experimentalists have taken just the status of iris for identification of dozy or sleepiness. They didn't consider the yawning identification or the head movement like lowering and that leads down to a framework with a greatly improved exactness. They introduced a system to analyze the gaze utilizing both eye signs and head signs. Likewise proposed a monocular camera framework and also a vigorous eye cue algorithm. They figured features of the eye that can be useful for data related to the driver's gaze. Likewise, they gathered naturalistic driving information and assessed the framework execution and performance.

Another interesting approach that addresses the importance of early reaction time of the drivers was considered in [17]. It emphasizes detecting drowsiness beforehand that gives users ample amount of time to respond. The sliding window mechanism was used for attaining a sequence of blink events. These features are trained to Hidden Markov Long Short-Term memory model to know the dynamic hierarchical structure that analyses blink in longer and shorter durations. In this methodology, blink features were taken into account. It can be improvised further by implementing it with other features.

In [18] the idea depends on facial component extraction through computer vision and the behaviours like yawning length, and eye movements. To measure sleepiness the eye aspect ratio for eye closure detection and mouth feature computations for yawn detection are taken as major parameters. The recognition is performed with a haar-based classifier. Results are generated by the recurrence of the eye flickers, and the suspicion that yawn count rises as the individual gets dozy. Drowsiness also depends on the total number of driving hours. Hence an innovative feature of the varying threshold of frames for mouth and eyes was implemented in [19].

Another technique [20] applies the EM-CNN model to analyze the state of eyes and mouth. For the detection of specific facial regions, feature points derived from multitask cascaded convolutional neural network are utilized. Both eye closure and percentage of mouth closure time are the parameters for the study. Its efficiency surpasses other convolutional neural network methods.

From the detailed review in the domain of drowsiness detection, it is identified that the design and development of an efficient passive drowsiness detection scheme capable of working in real-time will be accepted by the community due to its criticality. Based on this, we designed and implemented a new drowsiness detection scheme and it is detailed in the next section.

3. Proposed Scheme

This section discusses the proposed method to detect drowsiness. A behavioural-based approach that analyses the frontal features of the driver is followed. This method involves the detection of face, eyes, and head movement. It is implemented using Matlab software. The process begins by capturing the live video from the camera. This acts as initial input for the scheme. Further, an image is selected from the live streaming and a face detection procedure is performed on this captured frame. Face Detection is achieved using Viola-Jones Algorithm. In-built functions present in Matlab are used to invoke methods for face and eye detection.

The Viola-Jones Algorithm detects frontal faces from the frames that are converted from coloured to grayscale images. A learning algorithm is utilized implemented to detect faces. The captured snapshot is divided into a grid-like structure. Detection windows are used to recognize and evaluate haar-like features of the rectangles in the grid. The integral image is formed by summing up the terms of rectangular sub-regions. Then a cascading system is used for further processing. The first stage consists of the sub-regions passing through the best features and if it is evaluated to positive then the remaining features are considered in the later stages. Finally, if all the classifiers accept the image, the region is classified as a human face and the detection is shown.

The live capturing is continuous until the user exits the system. This is ensured as the driver can feel drowsy at any duration and hence continuous detection is mandatory. A loop operation is performed for this purpose. Initially, any random frame is considered. The snapshots are continuously captured followed by face and eye detection which creates a rectangular bounding box over the frame. The eye-detection method involves the following stages. The first step is to detect both left and right eyes and convert the captured frame to a grayscale image. If multiple faces are detected initial or the first row is considered. The second step involves the calculation of the box coordinates of both left and right eyes. The frame is then cropped based on the calculated resultant. The next stage involves checking whether the number of elements that store bounding box values is non-zero and if the result is positive then update the values otherwise change them with initial box coordinates. Finally, both the eyes are cropped and are further enlarged.

To analyze the eye movement a support vector machine (SVM) classifier is loaded. It is a supervised model in machine learning which used in classification problems. Identification of the candidate's eye region and classifying them based on the state of the eyes is possible through SVM. It uses hyperplanes to differentiate two or many classes. SVM attempts to form a decision boundary such that the separation between the two classes is maximum. Also, it is viable to perform a good and quick detection of eye operations since we can protect any false recognition through SVM. The next phase consists of extracting the histogram of oriented gradient (HOG) features for both eyes as shown in Figure 1 which results in a vector Figure 2 that is employed for further tracking and detection. The features predict the class labels for the left eye where the predictor data consists of the previously extracted features. A similar procedure is carried out for the right eye. The predicted data obtained is examined by checking whether both the eyes are fully open or not. Based on the result the eyes are classified into blinking or active state. If any of the predicted data is true then the corresponding eye is open and another eye is entitled as closed. This method results in the state of the eye along with data of each eye describing the openness or closeness.

If the eyes are neither in an active state nor in blinking state then an audio signal is generated prompting the user to open the eyes which are achieved by reading the string with the help of text to a speech synthesizer. This is also indicated by modifying the bounding box colour to red.

For the head movement detection, Euclidean distance between the frames is calculated continuously and is compared to a threshold value. This proposed method considers the threshold value of 5 which is obtained from the continuous experimental study. If the Euclidean distance is greater than this threshold value of 5 then display as moving. The box coordinates are updated and the frame is appended to the video player. This process of head movement detection, face and eye detection is carried out until the user exits the system. The threshold value is computed through the trial and error method. It may be noted that based on the sensitivity of the applications the threshold value can be fine-tuned.

We can observe in Figure 1 that for an open eye the HOG features align in a circular shape around the eye, whereas for an open eye they don't align. Figure 2 shows the common frequency patterns of HOG of an open eye and a closed eye. So using these HOG features we can use SVM classification to classify an eye image as either open or close.

4. Experimental Study and Result Analysis

The experimental study and result analysis are carried out on the live video footage obtained from the webcam of our laptops. The webcam video has uint8 RGB frames

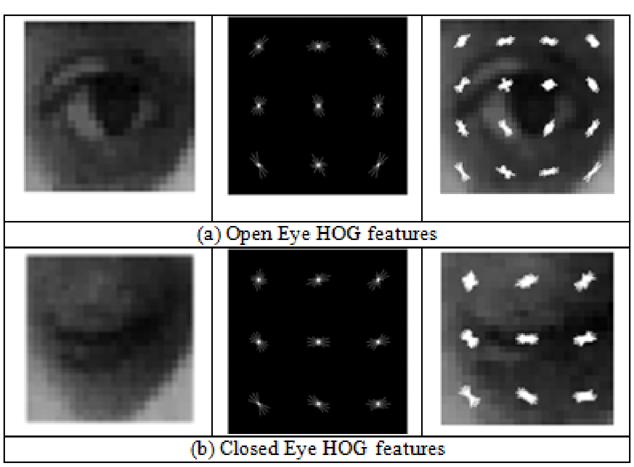


Figure 1. Eye states and their HOG features

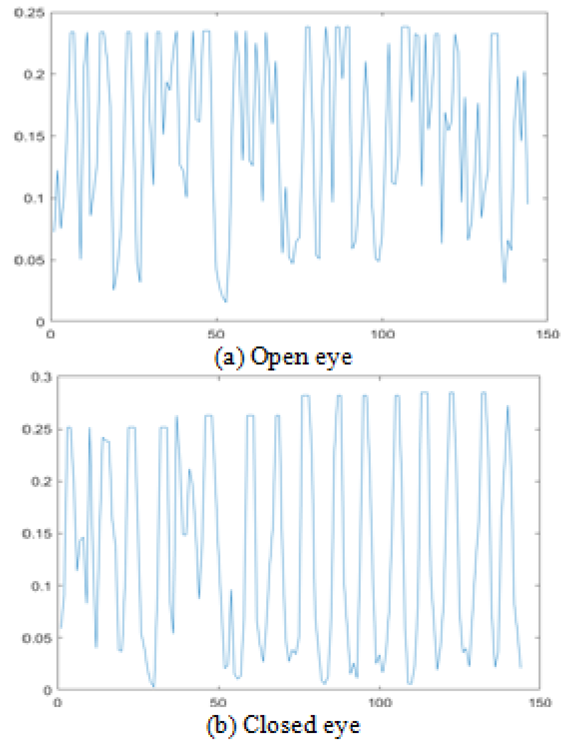


Figure 2. Plot of HOG feature

of resolution 640×360. We have implemented the code using Matlab R2020b software and captured the output video in '.avi' format. We took a live snapshot from the webcam and detected face movement and classified both eyes as open/close. A yellow rectangle is inserted around the face and eyes if they are detected. If face movement is detected, a message is displayed over the rectangle around the face, and also an audio output is given alerting the driver to come back to the static position. The state of each eye is displayed as an inserted text in the frame at the left top corner position. If both the eyes are detected as closed, then a system audio alert is given to wake up the driver from predicted drowsiness. A timestamp is inserted in every frame to concur the video continuation. Each frame is appended in a video displayer. A pause of 0.5 seconds is given at the end of each iteration to let the processing complete smoothly and since we don't need to analyze the footage at every instance. The frame rate of all videos is also reduced for the same reason.

Figure 3 and Figure 4 shows a few frames of input, the desired output, and the experimental output tested on 5 different persons in different states. In addition to the test on our live webcam video, we also tested our algorithm on a dataset featuring live driving subjects. This dataset is cited from [21]. The subjects in the dataset have driven a car for continuous hours and their behaviour was captured through a camera fixed in the car. Comparing the predicted output

Algorithm 1 Drowsiness Detection using video analysis

Input : Live Video Streaming through Webcam
Output : Audio Alert based on drowsiness detection

1: Setup and initialize webcam object cam, video displayer object *vp*, viola-jones face detector *fd* and eye detector *ed*.
2: Capture one frame and store the frame properties such as size, resolution, and use *fd* to get bounded box *bbox [x, y, width, height]* properties of initial face position.
3: Declare a global assembly for audio alert and instantiate object *ss* for speech synthesis and change to full volume.
4: while !(system is closed) do
5: Get *Frame* from *cam*
6: Detect face in Frame using viola-jones algorithm and store face position bounding values in *bbox2 [x, y, width, height]*.
7: If $((bbox(2) - bbox2(2))^2 + (bbox(1) - bbox2(1))^2)^{0.5} > 5$:
   1) display face is moving
   2) Give low volume sound alert
8: Update *bbox* = *bbox2*.
9: Crop face from *Frame*. Now calculate ROI for expected eye positions based on standard face ratios.
10: Crop each eye from *Frame* and store in *left* and *right*.
11: Perform parametrised viola-jones algorithm for eye detection in ROI to get exact eye positions in *Frame*. Crop these and store in same variables.
12: Extract HOG features from each eye image and feed it to the SVM classifier which will resturn a binary result for each eye in *Lresult, Rresult*. (where 1 means open and 0 means closed)
13: Initialise left message L, right message R, and drowsiness status D as *"left eye: closed"*, *"right eye: closed"* and *"Blinking"*. Set box color to yellow.
14: If *Lresult=1or Rresult=1*: set *D="awake"*
15: Else: Give full volume sound alert *"Please open your eyes"* and change box color to red.
16: If *Lresult=1*: set *L="left eye: open"*
17: If *Rresult=1*: set *R="right eye: open"*
18: Insert rectangle over face, eyes in *Frame* and add timestamp, messages *L, R, D*at top left of *Frame*.
19: Append *Frame* to the videoplayer object.
20: End of while in step 4.

to the actual output, the confusion matrix is calculated and shown in Table I and Table II. Table III shows the calculation of accuracy, precision, and recall of the existing scheme [19] and the proposed scheme.

The existing scheme discussed here detected drowsiness using yawn and eye closeness, whereas we have detected using face movement and eye closeness. However, face movement detection only works on video inputs as it measures the change in face position in consecutive frames. While the eye-closeness can be assessed on individual frames.

TABLE I. Confusion Matrix: Proposed scheme

No. of samples: 100	Positive	Negative
True	49	41
False	9	1

TABLE II. Confusion Matrix: Existing scheme [19]

No. of samples: 100	Positive	Negative
True	83	0
False	10	7

TABLE III. Comparison of Accuracy, Precision and Recall

Parameters	Proposed scheme	Existing approach [19]
Accuracy	0.90	0.83
Precision	0.84	0.89
Recall	0.98	0.92

5. Result Analysis

The proposed algorithm was implemented successfully and we have analyzed the efficiency of the scheme using various parameters. It accurately detected face, eyes, face horizontal and vertical movement, left eye, right eye, the closeness of left eye, the closeness of right eye, and inferred drowsiness state. Face movement was detected in all frames, including bright and dim lighting. Eye detection fails if the eyes are not fully visible in the frame, e.g. in the case of small frame spectacles. If drowsiness is detected, an audio alert is successfully given to alert the driver.

In case the eyes or face are not properly detected, as a safety precaution, we mark it as drowsiness detected because a false positive is tolerated, but a false negative is fatal. In a comparative study, we have chosen this dataset because it features real driving samples in contrast to any static simulation or webcam recording, which is apt for testing driver drowsiness detection algorithms. Our algorithm gained 90% accuracy with 84% precision and a recall of 98%. We want to highlight that a high recall implies a low False Negative classification which is intended.

The main parameter for testing drowsiness classifier is accuracy. The following papers have the corresponding accuracies: [6]-86%, [7]-89.5%,[8]-94.31%, [10]-91.5%, [13]-90%, [17]-80%, [18]-85%, [20]-93.6%.

False classifications are common when the face or eyes are not clearly visible in the frame due to misalignment or bad lighting or any aberrant obstructions.

The main advantage of our behavioural analysis approach is it has very little hardware requirement, and we can add any features through soft computing.

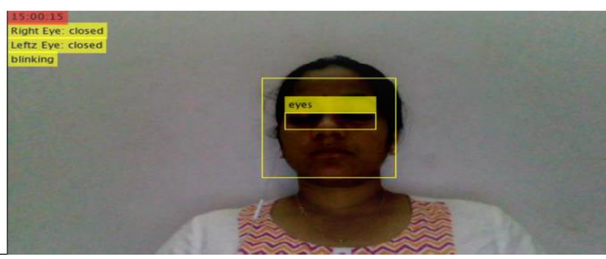
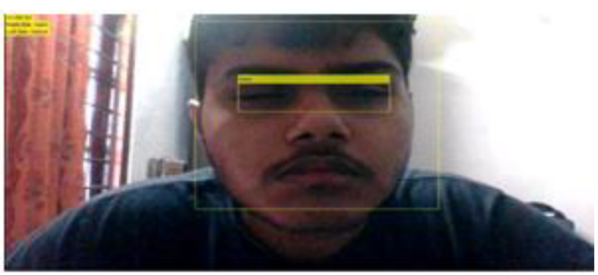
S.no	Frame	Desired Output	Experimental Output
i.		Face status: moving Right eye: open Left eye: open Drowsiness: No	Face status: moving Right eye: open Left eye: open Drowsiness: No Result: Accurate
ii.		Face status: Not moving Right eye: open Left eye: open Drowsiness: No	Face status: Not moving Right eye: open Left eye: open Drowsiness: No Result: Accurate
iii.		Face status: moving Right eye: closed Left eye: closed Drowsiness: Yes	Face status: moving Right eye: closed Left eye: closed Drowsiness: Yes Result: Accurate
iv.		Face status: Not moving Right eye: closed Left eye: closed Drowsiness: Yes	Face status: Not moving Right eye: closed Left eye: closed Drowsiness: Yes Result: Accurate
v.		Face status: Not moving Right eye: open Left eye: closed Drowsiness: No	Face status: Not moving Right eye: open Left eye: closed Drowsiness: No Result: Accurate

Figure 3. Sample results obtained during experimental study (without spectacle)

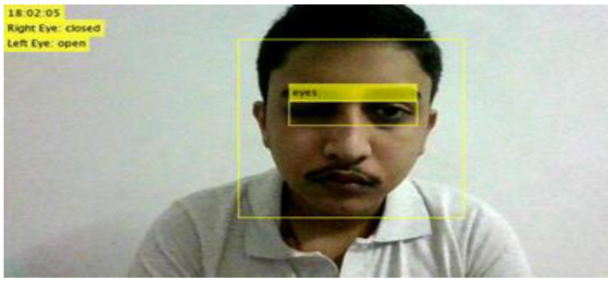
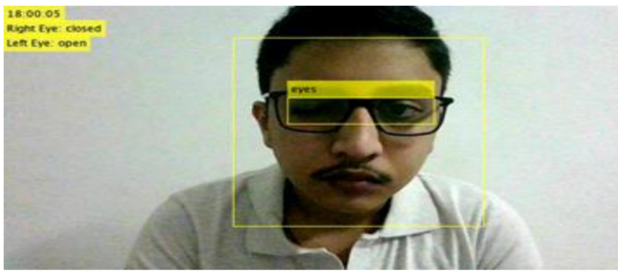
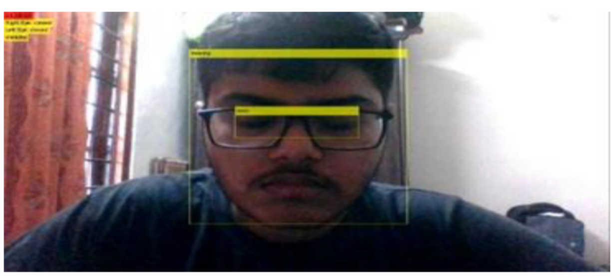
S.no	Frame	Desired Output	Experimental Output
vi.		Face status: Not moving Right eye: closed Left eye: open Drowsiness: No	Face status: Not moving Right eye: closed Left eye: open Drowsiness: No Result: Accurate
vii.	 **Person with big frame Spectacles**	Face status: Not moving Right eye: closed Left eye: open Drowsiness: No	Face status: Not moving Right eye: closed Left eye: open Drowsiness: No Result: Accurate
viii.	 **Person with small frame Spectacles**	Face Status: Not Moving Right Eye : open Left Eye : open Drowsiness : No	Face Status : Not moving Right Eye : Closed Left Eye : Closed Drowsiness : No Result : Not Accurate
ix.	 **Person with big frame Spectacles**	Face status: moving Right eye: closed Left eye: closed Drowsiness: Yes	Face status: moving Right eye: closed Left eye: closed Drowsiness: Yes Result : Accurate
x.		Face status: moving Right eye: closed Left eye: closed Drowsiness: No	Face status: Not moving Right eye: closed Left eye: closed Drowsiness: No Result: Accurate

Figure 4. Sample results obtained during experimental study (with spectacle)

6. Conclusion

We have introduced a drowsiness detection algorithm based on a behavioural-based approach and image processing. It monitors and detects any head movements and classifies each eye as open or closed. We have used the Viola-Jones algorithm for face detection and calculated a distance between positions of the face in consecutive frames; if this distance is greater than a threshold value, we infer that the face is moving. For eye monitoring, we utilized a pre-trained SVM classifier model to classify a cropped eye image as either closed or open. The status of both eyes, along with a timestamp, is inserted and displayed in the live frame. If any head movement is detected, a warning message is displayed on the screen and a low volume audio alert is given. If both eyes are detected as closed, then a full volume audio alert is given to alert the driver. We implemented our algorithm in Matlab software, where we did our experimental study on live webcam video and on a dataset featuring real driving subjects. Our recorded accuracy is 90%, with a precision of 84% and a high recall of 98%. We have analyzed our results and concluded that our algorithm accurately detects face movement in all scenarios, but it fails to detect eye closeness if the eyes are not fully visible in the video footage. We plan to overcome this drawback in our future works by using point tracking analysis combined with MaxBidirectionalError.

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