Drowsiness Detection for Drivers

ABSTRACT:

The emphasis of the project is mainly on proposing a new method of Drowsiness Detection that can be implemented in real life. It has an important application of alerting drivers when they fall asleep so as to avoid accidents. The speciality of this project is that along with the drowsiness detection, it can alarm the driver using sound effects. The existing models use various techniques such as yawning detection; artificial neural network, steering motions, vehicular based motions etc. These various models do give a fair chance of predicting whether the driver is sleepy or not but it does not guarantee that the prediction has 100% accuracy. This work completes the existing models of drowsiness detection by changing the aspect ratio of the eyes and also an added feature of sound which will alert the driver. Our safety is the first priority during the trip. A driver error can lead to serious physical injuries, deaths and significant economic losses. Nowadays there are many systems available on the market like navigation systems, various sensors, etc. to make the driver easy work There are several reasons especially human errors that cause traffic accidents. Reports say that there is a huge increase in road accidents in our country from the last years. The main reason that occurs from Road accidents are drowsiness of driver while driving. It is a necessary step to come with a Efficient technique to detect drowsiness of a driver when he falls sleepy. This could save many accidents from occurring.

INTRODUCTION:

Drowsiness is a process in which a level of consciousness is reduced due to lack of sleep or tiredness and can cause the driver to sleep peacefully. When the driver suffers from drowsiness, he loses control of the car, so he could suddenly deviate from the road and hit an obstacle or a car to overturn. There is an increase in the number of traffic accidents due to a driver. The level of mitigation of vigilance has become a serious problem for the society. Some of these accidents are the result of the driver's medical conditions. However, most of these accidents are related to driver fatigue and drowsiness of a driver The automobile accidents associated with driver fatigue are more likely to be serious, leading to serious injuries and deaths. It is estimated that 30% of all road accidents was caused by drowsiness. It was demonstrated that Driving performance gets worse with the increase drowsiness with resulting shocks that constitute more than 20% of all car accidents. Traditionally transportation system is no longer sufficient. Considering the available statistics to us, the problem needs to be solved as soon as possible.

The main objective of this project is the design and implementation of a system capable of detecting driver sleepiness, particularly those diagnosed at the right time to alert. This will prevent many accidents and save countless human lives and reduce the high cost of damage caused by accidents.

This project uses the concept of eyes where it would calculate the aspect ratio of the eye and accordingly predict whether the driver has fallen asleep or not. It would alert the driver after detecting.

LITERATURE SURVEY:

There are various techniques to detect whether the driver has fallen asleep or not. Some of the existing models are as follows:

1. YAWNING BASED DETECTION:

Yawning is one of the symptoms of fatigue. It is assumed that the yawn is shaped with a large vertical mouth opening. The gaping mouth is bigger in yawning than talking. Using the tracking of the face and then of the mouth tracing one can detect yawning. They detect yawning based on the opening speed of the mouth and the amount of changes in the mouth contour area. When the system detects the yawn, the alarm is activated. Instead of using a single technique to detect the drowsiness of driver, some researchers combined different vision-based imaging techniques to improve performance.

2. ARTIFICIAL NEURAL NETWORK BASED DETECTION:

In this approach they use neurons to detect driver's drowsiness. Only a neuron is not always very precise and the result of this is not good compared to more than one neuron. Some researchers are carrying on Investigations in the field of driver sensing detection using an artificial neural network. Fatigued people show certain visual behaviors that they are easily observable by changes in facial features such as eyes, head and face. Visual behaviors that normally reflect a person's fatigue level include eyelid movement, look, head movement and facial expression. To use these visual cues, they created an artificial neural network to detect drowsiness. They tested the samples and got 96% result.

3. EEG BASED TECHNIQUE:

In this technique it is mandatory to wear an electrode helmet from drivers while driving. This helmet has several electrode sensors that position in the right place and get brain data. The researchers used the characteristic of the EEG signal in sleepy driving. A method based on power spectrum analysis and the Fast ICA algorithm. It has been proposed to determine the degree of fatigue in a driving simulation system, the EEG signals of the subjects were captured by the NT-9200 instrument in two states, one state He was sober and the other was sleepy.The multi-channel signals were analysed with FastICA algorithm, to remove ocular electric, my electric and power frequency interferences.The experimental results show that the method presented in this document can be used to determine the degree of drowsiness of the EEG signal effectively.

4. VEHICULAR BASED METHODS:

Another approach to measure driver's drowsiness involves vehicle-based measurements. In most of these cases, these measurements are determined in a simulated way environment by placing sensors on various vehicles components, such as steering wheel and acceleration pedal; The signals sent by the sensors are analyzed which determines the level of drowsiness. Some researchers have found that lack of sleep may result in greater variability in driving speed However, the two most commonly the measures based on the vehicles used are the steering wheel movement and standard deviation of the rail position.

5. STEERING WHEEL MOVEMENT BASED TECHNIQUE:

The SWM is measured using a steering angle sensor and is a measure based on the vehicle widely used to detect the level of driver's drowsiness. The behavior of the driver address is measured using an angular sensor mounted in the direction column. When the driver is sleepy, the number of micro registrations on the steering wheel reduces compared to normal driving. Fair Clough and Graham have discovered that the private drivers have made fewer investments in the wheel of normal drivers to eliminate the lane effect changes, the researchers considered only a small address. Wheel movements (between 0.5 ° and 5 °), are required to adjust the lateral position inside the lane. Therefore, based on small SWMs, it is possible to determine the driver's drowsiness and then provide an alert of sleepy drivers if necessary. In a simulated environment, Light side winds that pushed the car to the right side of the roads have been added along a curved path to create variations in the lateral position force drivers to perform a corrective SWM car manufacturers, like Nissan, BMW, Volvo, Renault, etc. they have adopted SWM but it works In very limited situations. This is because they can work reliably only in particular environments and they are much more dependent on the geometric characteristics of the path and, to a lesser extent, the kinetic vehicle characteristics.

6. STANDARD DEVIATION OF LANE POSITION (SLDP):

The SDLP is another measure by which the driver's level of drowsiness can be assessed in a simulated. In the environment, the software itself provides the SDLP and, in the case of field experiments, the lane position is monitored by an external camera. He conducted an experiment to derive numerical statistics based on SDLP and found that with increasing KSS evaluations, SDLPs (meters) also increased. For example, the KSS scores of 1, 5, 8, and 9 corresponded to the SDLP measurements of 0.19, 0.26, 0.36, and 0.47, respectively. The SDLP was calculated based on an average of 20 participants; However, with some driver, the SDLP did not exceed 0.25 m, even for a KSS score of 9. In the previous experiment, A significant difference is observed in the correlation analysis from one subject to another: another limitation of SDLP is that it depends only on external factors, such as road signs, climatic conditions and lighting. In summary, many studies have established that vehicle-based measures are an inadequate indicator of the risk of performance failure due to somnolence. Furthermore, vehicle-based metrics are not specific drowsiness. The SDLP can also be caused by any kind of compromised driving, including driving under the influence of alcohol or other drugs, especially depressants.

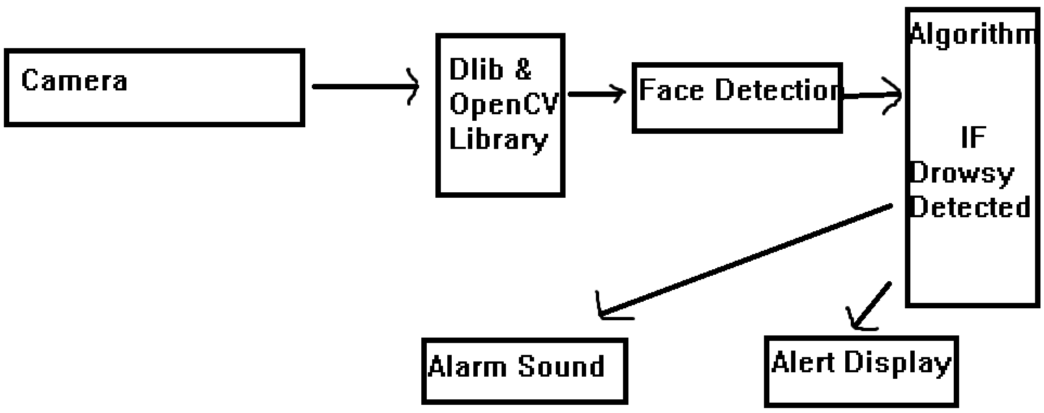
7. SUBJECTVE MEASURES:

Subjective measures the assess the level of drowsiness. They are based on the personal estimation of the driver and many tools were used to translate this assessment into a measure of driver's drowsiness. The scale is the Karolinska Sleepiness Scale (KSS), a nine point point Scale that has verbal anchors for each step. Hu et al. measured the KSS ratings of the drivers every 5 minutes and used it as a reference to the EoG signal collected Some researchers compared self-determined ones. KSS, which was recorded every 2 minutes during the driving task, with the variation of the rail position (VLP) and found that these measures did not agree. Ingre et al. determined a relationship between the eye the duration of the flashing and the KSS collected every 5 minutes during the task of driving. The researchers determined it Departures of the main lane, high duration of the eye flashing and the physiological signs related to somnolence are prevalent for KSS classifications between 5 and 9. However, the subjective qualification does not completely coincide with the vehicle, physiological and behavioral measures. Because the level of drowsiness is measured approximately every 5 minutes, sudden changes cannot be detected using the subjective measures. Another limitation to the use of subjective evaluations is this self-intrusion warns the driver, therefore reducing your level of drowsiness. Furthermore, it is difficult get drowsy comments from a driver in a real guide situation. Therefore, while subjective evaluations are useful in to cause drowsiness in a simulated environment, the remaining measures may be more suitable for detection of drowsiness in a real environment.

PROPOSED SYSTEM:

The objective of the proposed system is to detect whether the driver has fallen asleep or not. The project is implemented using Python Software. It uses the concept of image processing and its applications such as OpenCV and dlib.

The playsound library is used for importing the sound function and plays the sound when the driver needs to be alerted. The dlib library is used to detect the human face and then the predictor function is used for retrieving the co-ordinates. The facial landmarks for the eyes are used to get the co-ordinates of the left and right eye. The eye aspect ratio is calculated according to the Euclidean formula and the ratio is calculated according to the formula.



The program starts and with it the Video Stream starts. The frame of the Video Stream is converted to Grayscale image and the dlib function is called to detect the human face and place the landmarks accordingly to get the co-ordinates of both the eyes. Calculating the eye aspect ratio, if the ratio is less than the aspect ratio, then a counter is increased and if the counter increases a specific value, it means that the driver has fallen asleep and then the play sound function is called to alert the driver.

Module 1: Sound Alarm Function

```
defsound_alarm(path):
	playsound.playsound(path)
```

Module 2: Eye Aspect Ratio Function

```
defeye_aspect_ratio(eye):
	A = dist.euclidean(eye[1], eye[5])
	B = dist.euclidean(eye[2], eye[4])
	C = dist.euclidean(eye[0], eye[3])
	ear = (A + B) / (2.0 * C)
	return ear
```

Module 3: Argument Parser

```
ap = argparse.ArgumentParser()
ap.add_argument("-p", "--shape-predictor", required=True,
	help="path to facial landmark predictor")
ap.add_argument("-a", "--alarm", type=str, default="",
	help="path alarm .WAV file")
ap.add_argument("-w", "--webcam", type=int, default=0,
	help="index of webcam on system")
args = vars(ap.parse_args())
```

Module 4: Dlib's face detector and facial landmark predictor:

```
detector = dlib.get_frontal_face_detector()
predictor = dlib.shape_predictor(args["shape_predictor"])
```

Module 5: Calculating the index of the facial landmarks of eyes

```
(lStart, lEnd) = face_utils.FACIAL_LANDMARKS_IDXS["left_eye"]

(rStart, rEnd) = face_utils.FACIAL_LANDMARKS_IDXS["right_eye"]
```

Module 6: Video Stream

```
vs = VideoStream(src=args["webcam"]).start()

time.sleep(1.0)
```

Module 7: Grayscale Conversion

```
frame = vs.read()

frame = imutils.resize(frame, width=450)

gray = cv2.cvtColor(frame, cv2.COLOR_BGR2GRAY)

rects = detector(gray, 0)
```

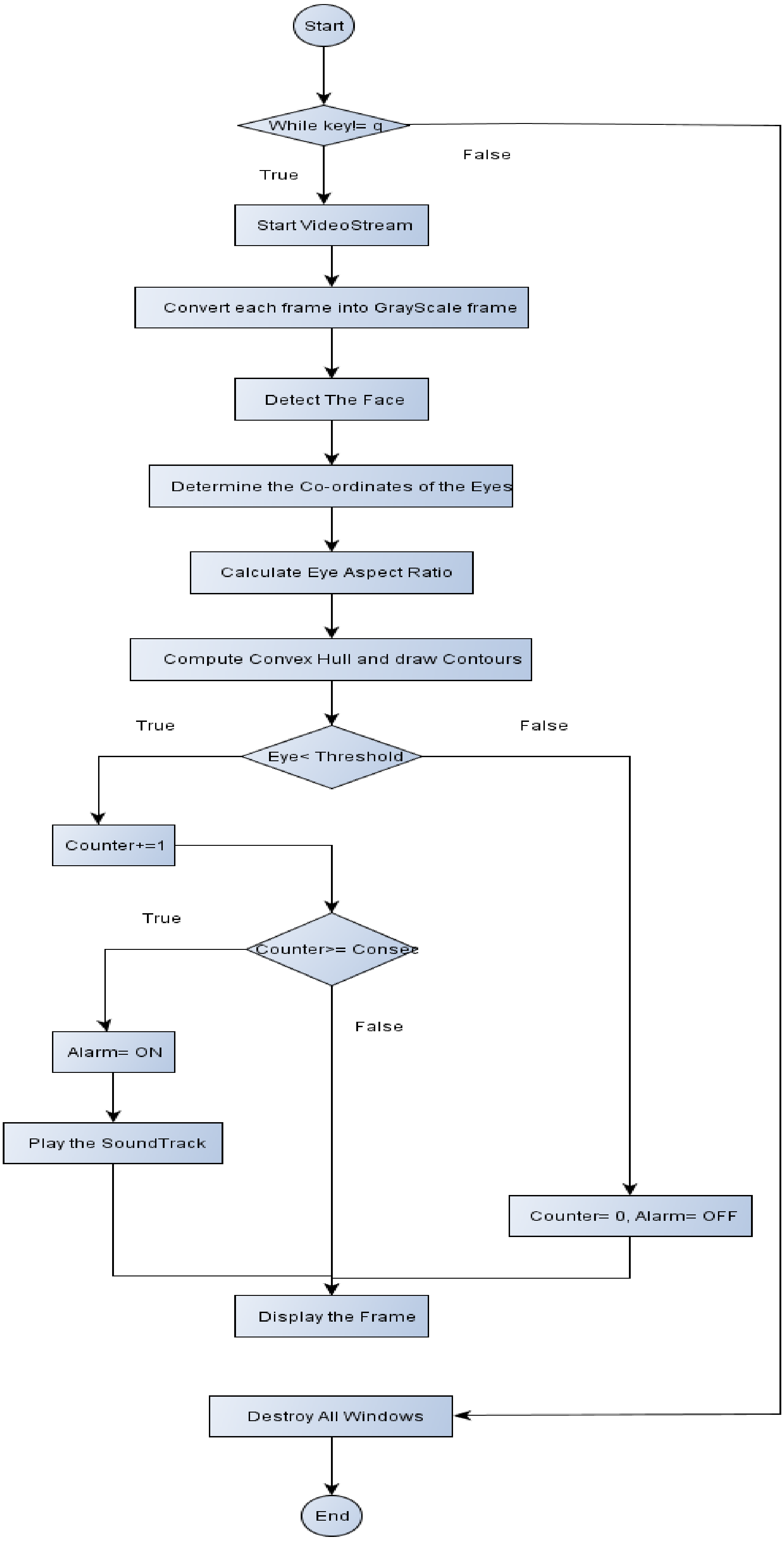
Module 8: Co-ordinates ofEye and Eye Aspect Ratio

```
leftEye = shape[lStart:lEnd]

rightEye = shape[rStart:rEnd]

leftEAR = eye_aspect_ratio(leftEye)

rightEAR = eye_aspect_ratio(rightEye)
```

Module 9: Computation of Convex Hull and Contours

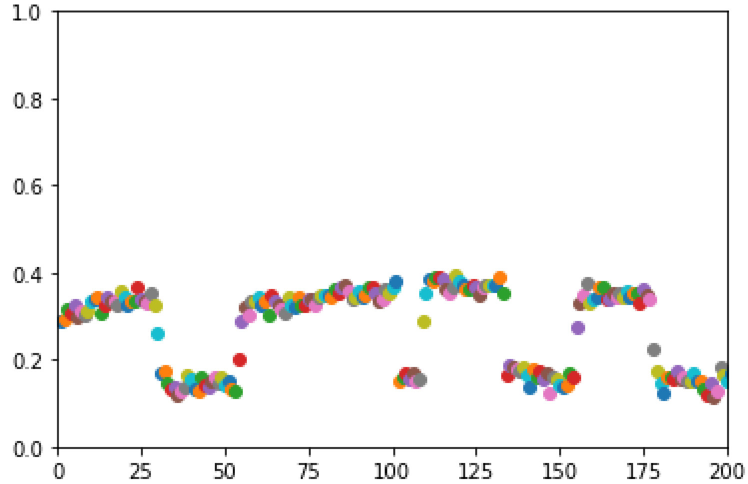
```
leftEyeHull = cv2.convexHull(leftEye)

rightEyeHull = cv2.convexHull(rightEye)

cv2.drawContours(frame, [leftEyeHull], -1, (0, 255, 0), 1)

cv2.drawContours(frame, [rightEyeHull], -1, (0, 255, 0), 1)
```

ALGORITHM AND FLOWCHART OF THE PROCESS:

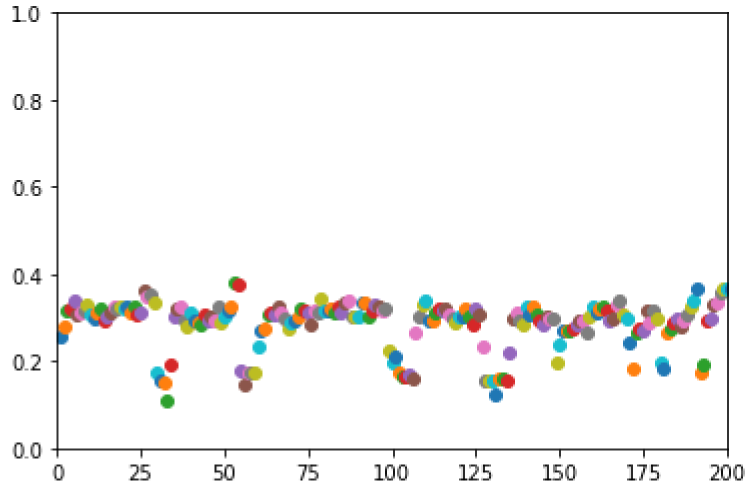


EXPERIMENT RESULTS AND DISCUSSION:

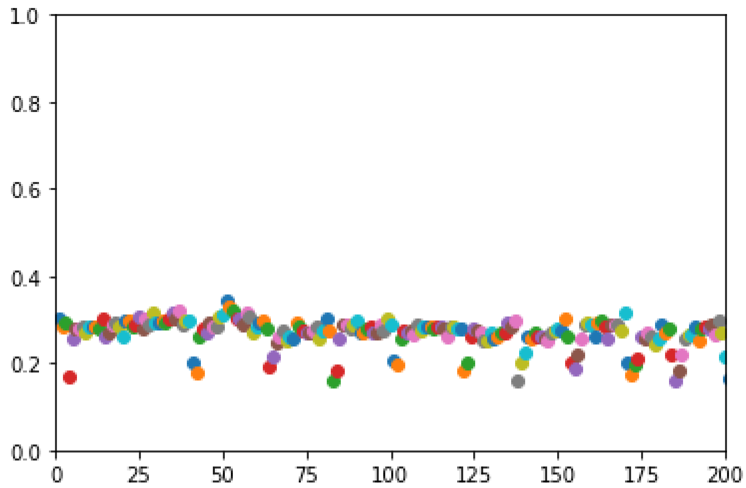
EAR ratio graph with frames. The below figure has sudden drops in the EAR, that indicates the closed eyes.



The below figure has drop with respect to the casual blinks of eyes.



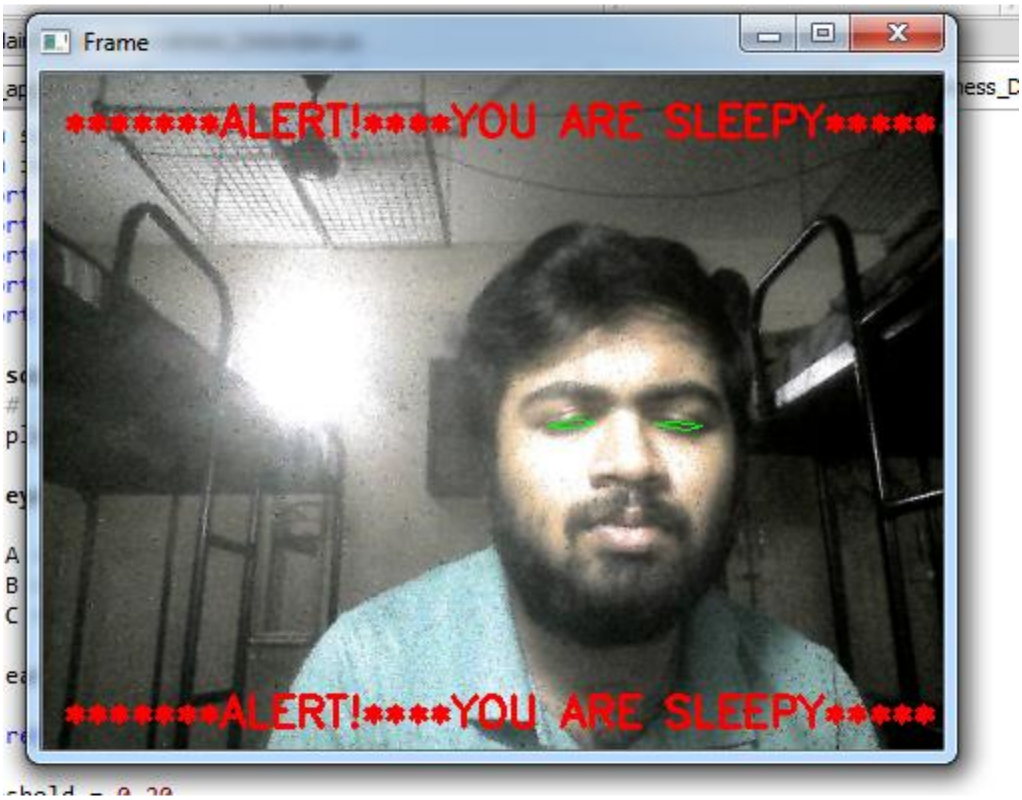
The below figure shows the drops with respect to the fast blinking of eyes.



So, from above results we can conclude that the Threshold for the Drowsiness detection should be 0.2 . Keeping this threshold value, we will be asure that the eyes are definitely closed during that period.

OUTPUT when eyes are open:

OUTPUT when eyes remain closed for more than the threshold number of frames:



Also works when person wears glasses:

PERFORMANCE EVALUATION AND COMPARISON WITH EXISTING ALGORITHMS:

The current method uses the trainer method to judge the drowsiness. In the current method the face samples are fed to the trainer model, so that it can detect the face. Then again separate models to be created for both closed and open eyes. But in our Algorithm, we are using 68-landmarks model to detect any face. Also with this same model we get the position of eyes. Using the distances between various landmarks on face, we calculate EAR. So, our algorithm is universal and can be used for any person. Also it does not require training data. Algorithm being very simple, it is easy to understand as well.

CONCLUSION:

The proposed system in this analysis provides accurate detection of driver fatigue. The analysis and design of driver drowsiness detection system is presented. The proposed system is used to avoid various road accidents caused by drowsy driving and it can also help drivers to stay awake when driving by giving a warning when the driver is sleepy. And also this system used for security purpose of a driver. During the monitoring, the system is able to decide if the eyes are opened or closed.

When the eyes have been closed for too long, a warning signal is issued. Image processing achieves highly accurate and reliable detection of drowsiness. Codes being in python can be embedded into microcontrollers and independent devices for mass production.

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