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Drowsiness Detection System Based on Machine Learning Using Eye State

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***Abstract*—Drowsiness is one of the major causes of driver-induced traffic accidents. The interactive systems developed to reduce road accidents by alerting drivers is called as Advanced Driver Assistance Systems (ADAS). The most important ADAS are Lane Departure Warning System, Front Collision Warning System and Driver Drowsiness Systems. In this study, an ADAS system based on eye state detection is presented to detect driver drowsiness. First, Viola-Jones algorithm approach is used to detect the face and eye areas in the proposed method. The detected eye region is classified as closed or open by making use of a machine learning method. Finally, the eye conditions are analyzed at time domain with PERcentage of eyelid CLOsure (PERCLOS) metric and drowsiness conditions are determined by Support Vector Machine (SVM), kNN and decision tree classifiers. The proposed methods tested on 7 real people and drowsiness states are detected at 99.77%, 94.35%, and 96.62% accuracy, respectively.**

Index Terms— **Driver Drowsiness, ADAS, Viola-Jones, PERCLOS, Machine learning.**

I. Introduction

DRIVERS' DROWSINESS is one of the major causes of road traffic accidents. According to many surveys 25-30% of road accidents are caused by drowsiness of the driver, and as a result, many lives are lost, many properties are damaged, and these numbers increase each day [1]. Drowsiness (also means sleepiness) is a situation where a person feels a need to fall asleep and is a situation of sleep-wake cycle [2].

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Recent survey by the National Highway Traffic Safety Administration (NHTSA) estimates that 56,000 of road accidents are caused by drowsy drivers annually in the U.S.A. resulting in 40,000 injuries and 1,550 fatalities [3]. It requires considerable amount of effort to develop an effective system that can detect drowsiness and take appropriate measures against road accidents. Some progress has been made in the construction of smart vehicles to prevent such accidents [4]. With increasing interest in intelligent vehicles, the development of robust and practical fatigue and drowsiness detection systems has gained utmost importance.

ADAS is part of the active safety systems that is designed to alert the drivers to help them avoid traffic accidents. The main objective is to contribute the reduction of traffic accidents by using newly developed technologies; that is, incorporating new systems for increasing vehicle security, and at the same time, decreasing the dangerous situations that may arise during driving due to human errors [5]. Many surveys show that ADAS can prevent up to 40% of road accidents depending on the ADAS type and the type of accident scenario [6].

Techniques used to detect driver drowsiness can generally be divided into three main categories. The first category includes methods based on evaluation of biomedical signals such as brain, muscle, and cardiovascular activity. Generally, these methods require electrodes that are attached to the body of the driver, which is mostly considered uncomfortable to the driver. The method belonging to the second category mainly evaluates driver performance by observing changes in vehicle side position, speed, steering wheel, and other Control Area Network (CAN) bus signals. The advantage of these approaches is that the signal is meaningful, and the acquisition of the signal is very easy. The third category approaches address the problem of finding drowsy drivers using computer vision techniques applied to the human face [7-9]. This category includes methods based on driver visual analysis using image processing techniques. These approaches are effective because drowsiness, driver's facial appearance and head/eye activity are taken into consideration in this case.

In this paper, Viola-Jones [10] algorithm is used for eye pair and face detection. The next step is an advanced and efficient approach of calculating PERcentage of eyelid CLOSure (PERCLOS) of the driver. PERCLOS means the proportion of time that the subject's eyes are closed over a specific period of time [11].

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The second section of this paper compares some works related to this study. In the third section, methods of face detection, eye pair detection and drowsiness detection of the driver is presented. Experimental results are presented in the fourth section. The last section concludes the paper.

II. RELATED WORK

Various studies have been done on driver drowsiness detection based on eye state. The performance of these studies varies based on methods used for detection of the eye pair.

In [12], iris-sclera pattern analysis method is used to detect the open eye. In the next stage, PERcentage of eyelid CLOsure (PERCLOS) metrics is utilized to determine the drowsiness state of the driver. The entire system is designed to be independent of any specific data sets for face or eye detection. The proposed system is evaluated using real-life images and videos. At the end of the experiments, an open-eye detection accuracy of 93% is achieved.

In another paper [13], eye tracking based approach for drowsiness detection is used. In this work, detected eye regions from Viola-Jones algorithm feed to PERCLOS method for successful detection of drowsiness of a driver. The method achieves an accuracy of 95%.

A binary SVM classifier with a linear kernel is used as classifier in [14]. Drowsiness detection is performed under different lighting conditions, and it is shown that this approach performs well in the challenging lighting conditions. This system achieves an overall accuracy of 94.58% in four test cases which is an impressive result.

In [15], a drowsiness detection method based on face and eye detection within a video input is proposed. PERCLOS is calculated based on the area of iris region. The experimental results suggest that this method can potentially detect drowsiness based on PERCLOS as it is found that when the driver is drowsy the PERCLOS value is lower (compared to PERCLOS value when the driver is alert). Better results are obtained when both iris regions (from left and right eyes) are used to measure PERCLOS values.

The proposed method in [16] benefits from face landmarks to estimate the user's eye aspect ratio, subsequently applying an optimized-SVM to classify the state feature. Then, a decision rule is adopted to determine whether the driver is drowsy or not.

III. PROPOSED METHOD

The proposed system is discussed in this section, where the driver drowsiness is detected. The flowchart of the proposed system is given in Figure 1.

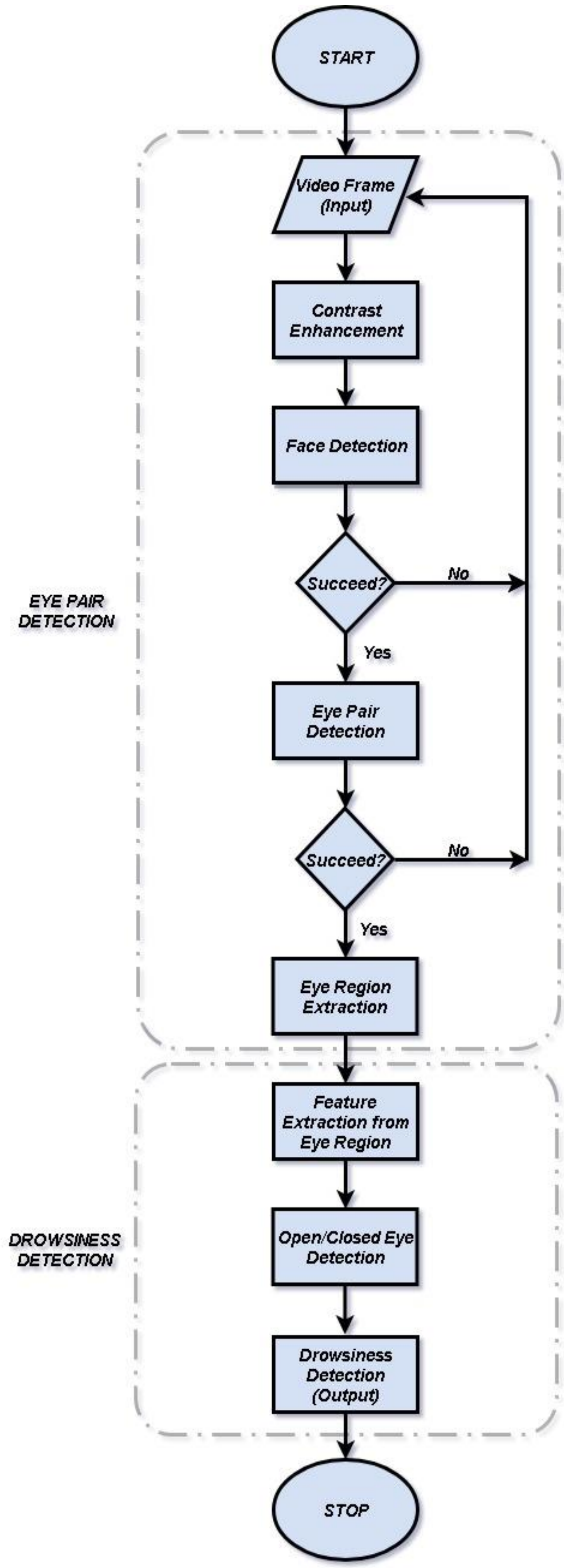


Fig.1. Flowchart of the proposed system

A. Pre-processing

In this paper the input videos are captured from 7 real people. The original-colored frames are shown in Figure 2. The lighting condition varies due to the outdoor environment. That is why the frames within the video needs to be pre-processed in order to enhance the images. Histogram stretching is applied to improve the contrast of low contrast images. Sample contrast-enhanced frames are shown Figure 3.

B. Face and Eye Detection

Viola-Jones algorithm is used for both face and eye pair detection since its efficiency in detection performance and relatively low computational load. Viola-Jones algorithm requires full view frontal faces to be able to operate. There are some operations which enable it to run in real-time that are integral image, Haar-like features [10], AdaBoost [17] and the cascade classifier. In Fig. 4, detected faces in the frames are shown and then in Figure 5 the detected eye region can be seen.

The Viola-Jones face detection method uses combinations of simple Haar-Like features to classify faces. Haar-like features are rectangular digital image features that get their name from their similarity to Haar wavelets. The value of a two-rectangle feature is the difference between the sum of the pixels within two rectangular regions. The regions have the same size and shape. A three-rectangle feature computes the sum within two outside rectangles subtracted from the sum in a center rectangle. Finally, a four-rectangle feature computes the difference between diagonal pairs of rectangles.

Integral image computation is a step of Viola-Jones method where input face image is converted into an integral image. This integral image is used for quick feature detection. The meaning of integral image is the outline of the pixel values in the original images. The integral image at location (x, y) contains the sum of the pixels above and to the left of (x, y) inclusive. The integral image computation can be performed in the equation given below:

$$ii(x,y) = \sum_{x'<x, y'<y} i(x', y') \qquad (1)$$

where each location of x and y in the integral image is the sum of pixel values in above and left location of x and y.

AdaBoost is a machine learning boosting method capable of finding a highly accurate hypothesis by combining many weak hypotheses each with average accuracy. The AdaBoost method is generally viewed as the first step straight into more practical boosting methods helps to select small features from the face that facilitates fast and easy computation. Unlike other methods, AdaBoost algorithm gives desired region of the object by discarding unnecessary background.

The Viola-Jones algorithm eliminates candidates quickly using a cascade of stages of cascade classifier. The cascade eliminates candidates by making stricter requirements in each stage with later stages being much more difficult for a candidate to pass. Candidates exit the cascade if they pass all stages or fail any stage. A face is detected if a candidate passes all stages. The cascade classifier consists of levels each containing a weak classifier. The responsibility of each level is to evaluate if a given sub-window is actually non-face or maybe a face. Typically, early levels are passed more frequently with later levels being more demanding.

Feature extraction is the process of reducing the size of data by identifying the distinguishing features of the problem. Feature can be shape, color, pattern, reflection, edge properties, etc. The performance will also increase as the selected features can be effectively separated from the others. In this study, Histogram Oriented Gradient (HOG) is used for feature extraction. The method is to obtain feature data by dividing a filter placed on the frames into overlapping blocks and summing the amplitudes of the pixels within each block in an orientation histogram and all the histogram entries are used as the feature vector to describe the object.

C. Eye State Detection

The blinking of the eyes is detected using Support Vector Machines (SVM) in the proposed method. SVM classifier is one of the most powerful classification techniques used for eye state detection. By distinguishing the features of closed and open eye pairs from each other in the most appropriate way, the detection of eye state is provided. In Figure 6, some detected eye states in the example frames are shown.

D. Driver Drowsiness Detection

Driver drowsiness detection is decided using the PERCLOS metric on three levels as shown in Table 1. The SVM, kNN, decision tree classifiers are used for decision of the drowsiness state.

PERCLOS is the rate of eye closure calculated at specific time intervals. That is, the ratio of the number of closed eyes in the number of frames over the selected period to the total number of frames in the period. PERCLOS (2) is calculated as: N_t is the number of frames in a period; N_a is the number of frames in which the eye is open.

$$PERCLOS = \frac{N_t - N_a}{N_t} \times 100\ \% \qquad (2)$$

Finally, SVM, kNN, decision trees and machine learning methods are used to determine driver drowsiness.

TABLE I
DRIVER DROWSINESS DETECTION

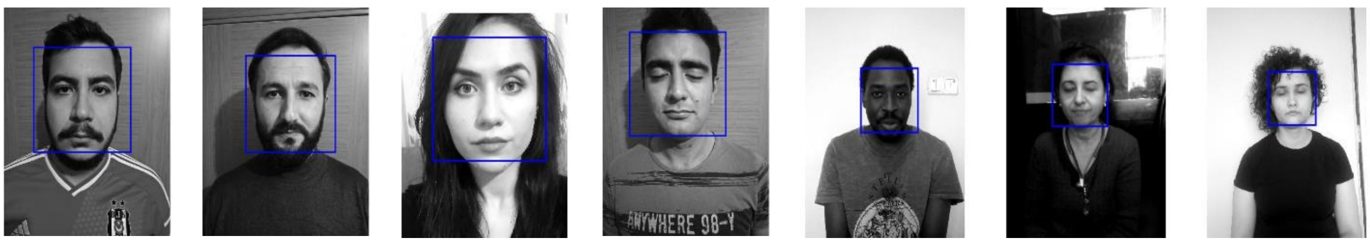
PERCLOS	Levels	Explanation
0.0-0.15	No warning	Awake and vigilant
0.15-0.30	Warning	Distracted
0.30 and above	Danger	Drowsy

(a) (b) (c) (d) (e) (f) (g)

Fig. 2. Sample colored frames from each video

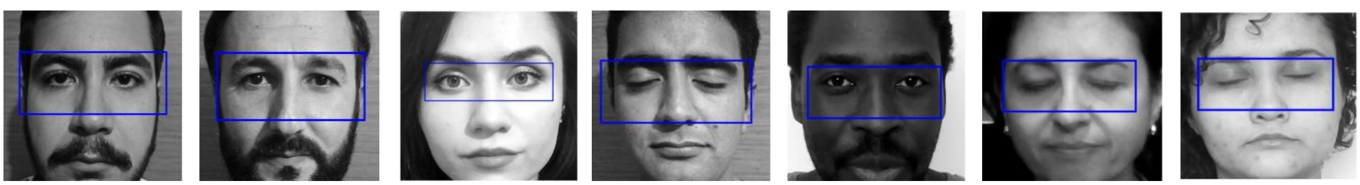
(a) (b) (c) (d) (e) (f) (g)

Fig. 3. Sample contrast-enhanced grayscale frames from each video



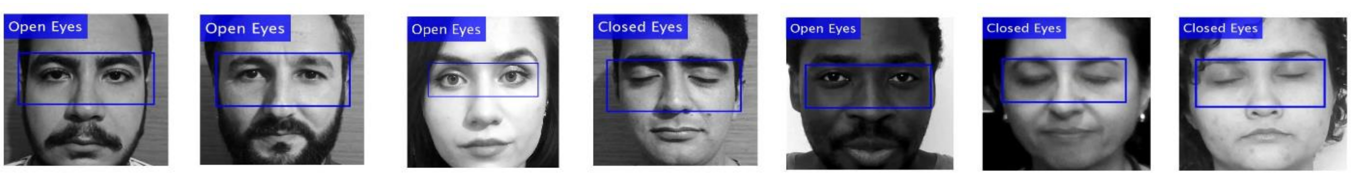
(a) (b) (c) (d) (e) (f) (g)

Fig. 4. Detected faces from each video



(a) (b) (c) (d) (e) (f) (g)

Fig. 5. Detected eyes from each video



(a) (b) (c) (d) (e) (f) (g)

Fig. 6. Eye state detection from each video sample

IV. EXPERIMENTAL RESULTS

The dataset of the study consists of 7 videos with a total of 19,156 frames. The proposed approach is executed on an Intel Core i5 processor with 2.50 GHz processor and 6 GB RAM memory with 1.5fps processing speed in MATLAB implementation.

The performance of the experiment is assessed with accuracy, precision and recall criteria. Related equations for these criteria are given in (3), (4) and (5). In these equations, TN is the number of correct estimates for which a sample is negative; FP, the number of false estimates that a sample is positive; FN indicates that an estimate is negative, and TP is the number of accurate estimates that a case is positive [18].

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \tag{3}$$

$$\text{Precision} = \frac{TP}{TP + FN} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FP} \tag{5}$$

For the proposed method, the equations in (3), (4) and (5) are computed by frame and video-based performances. Frame-based performance is the performance of eye condition detection and is shown in Table 3. In Table 3, closed eyes are represented by 0 and open eyes by 1. Video-based performance is the result of driver fatigue detection. Video-based performance results are the results obtained by classifying the PERCLOS values calculated from 10 to 100 window sizes (ws) in each video. ws is also N_t in (2). Video based average performance of SVM, kNN, decision tree classifiers is given in Table 4.

Figure 7 shows the eye state examination of Figure 6(e). The vertical axis represents the closed and open eyes detection results for each frame in the horizontal axis with the numbers 0 and 1, respectively. With the value ws is 100, the PERCLOS value is calculated as 0.15 in the time period shown in the graph. Thus, it is concluded that the driver is distracted.

The drowsiness results according to Table 1, classified by SVM, kNN, decision tree classifiers respectively, are shown in Figure 8 for Figure 6 (e). The eye state classification results 0, 1, 2 in the graphs represent that the driver according to Table 1 is awake and vigilant, distracted, drowsy, respectively.

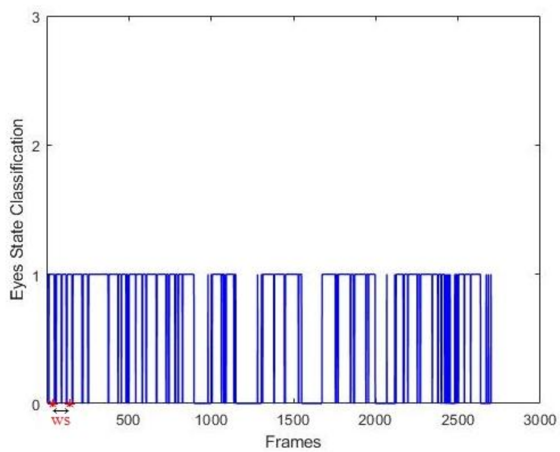


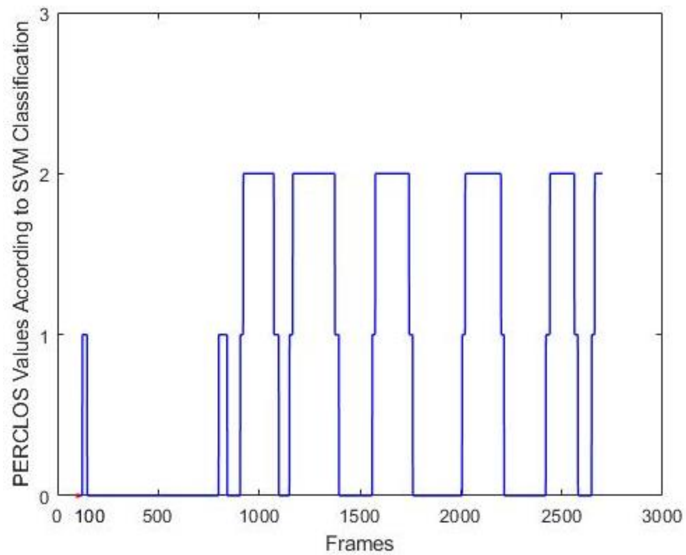
Fig. 7. Temporal representation of the eye state from Figure 6(e)

TABLE II
FRAME BASED PERFORMANCE EVALUATION

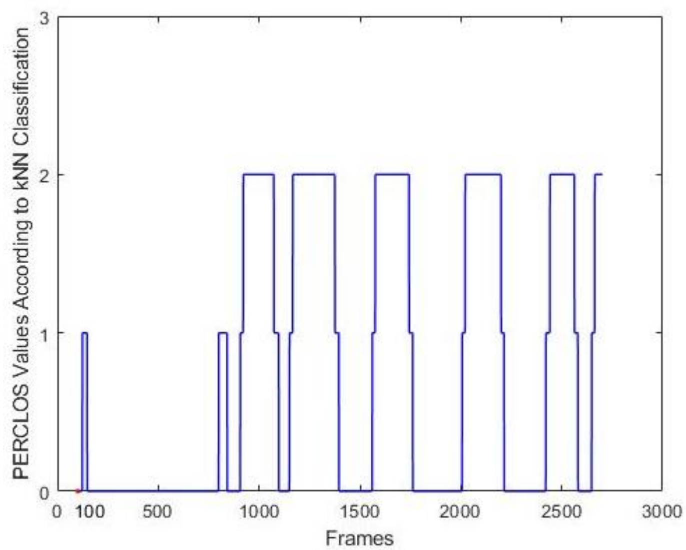
	V1	V2	V3	V4	V5	V6	V7	All
ACC	0.98	0.91	0.97	0.89	0.98	0.92	0.99	0.98
PRE 0	0.98	0.92	0.97	0.91	0.99	0.88	0.99	0.98
PRE 1	0.98	0.91	0.96	0.89	0.97	0.94	0.99	0.98
REC 0	0.93	0.79	0.95	0.74	0.94	0.82	0.99	0.92
REC 1	0.99	0.97	0.98	0.96	0.99	0.96	0.99	0.99

TABLE III
VIDEO BASED PERFORMANCE EVALUATION

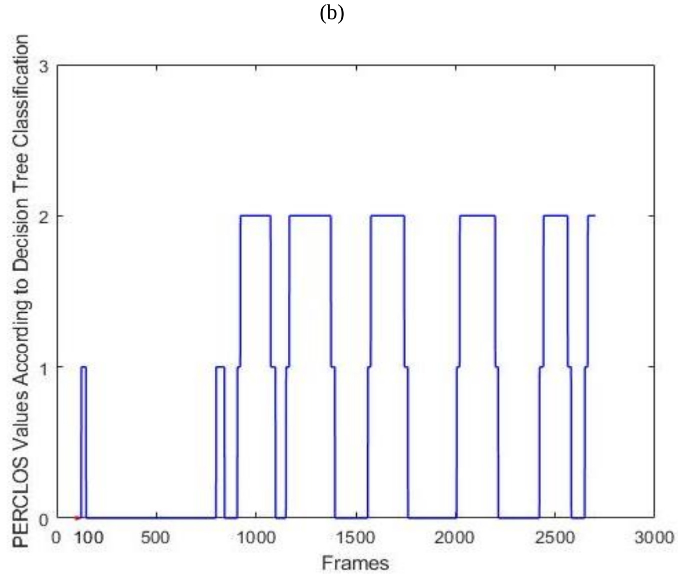
Window Size	SVM	kNN	Decision Tree
10	1.000	0.976	0.973
20	1.000	0.945	0.959
30	0.997	0.914	0.950
40	0.998	0.912	0.955
50	0.998	0.912	0.944
60	0.994	0.903	0.949
70	0.996	0.914	0.948
80	0.995	0.928	0.951
90	0.997	0.939	0.955
100	0.998	0.944	0.959



(a)



(b)



(c)

Fig. 8. Temporal representation of PERCLOS using classifiers from Figure 6(e) (a) SVM (b) kNN (c) Decision Tree

V. Conclusion

In this study, driver drowsiness is determined using the physical changes of the driver. Forming data set is the most important step for the proposed method. In order to make the algorithm more robust, a wider dataset has been created. A total of 7 different people's videos are used to form the dataset which includes 18.125 frames in total. Then Viola Jones algorithm is used to detect the face and eye pairs. The drowsiness of the driver is determined by taking into account the closed and open eyes detected by the PERCLOS approach. In addition, SVM, kNN and decision tree classification methods are used to for eye state and driver drowsiness detection. In this study, it has been observed that illumination intensity changes, head movements, head rotation, iris movements and body shakes can affect the detection of eye condition.

In the future, individuals wearing eyeglasses will be included in the study and dark environment images will be used by using NIR camera. The study will also be strengthened with hybrid methods and finally the output will be implemented on an embedded system.

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