7th Annual International Conference on Arab Women in Computing
In Conjunction with 2nd Forum of Women in Research

Machine Learning-assisted Driver Drowsiness Detection System

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ABSTRACT

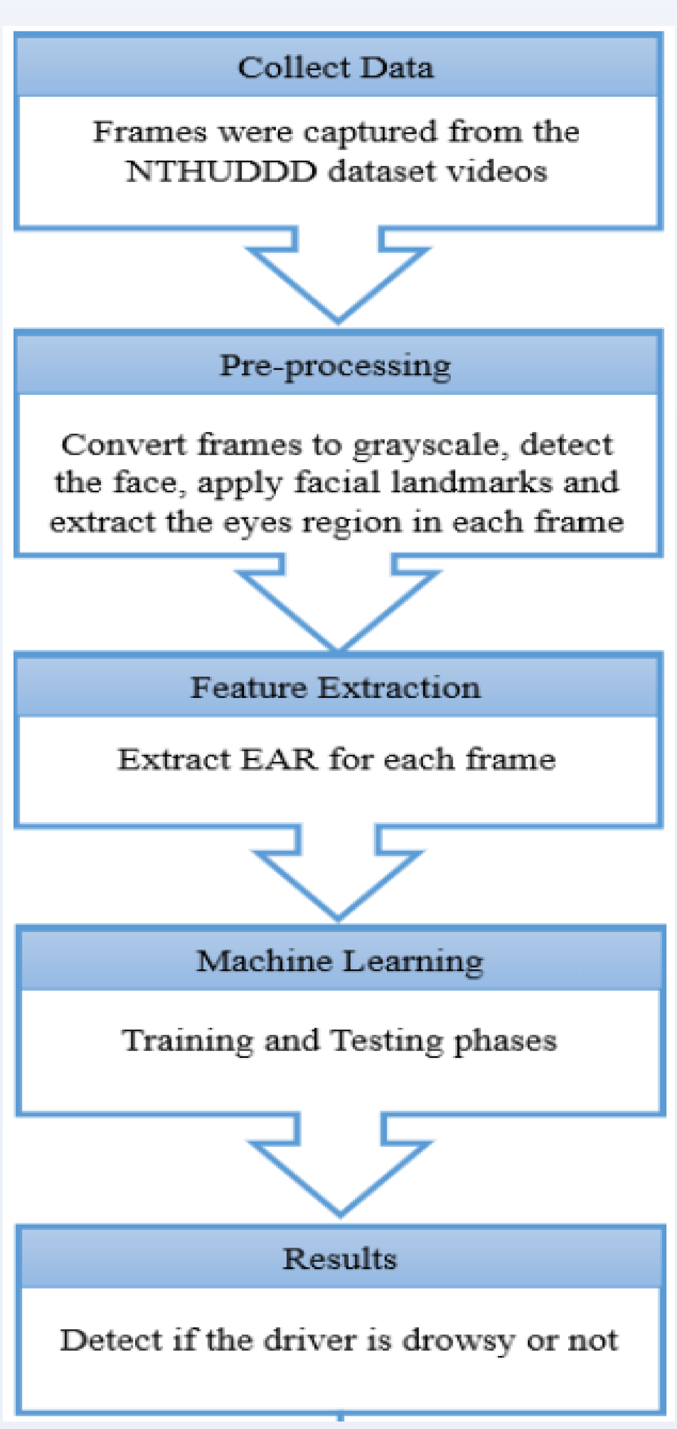
Drowsiness is a major cause of accidents and can affect road safety significantly. Many fatal accidents can be prevented if drowsy drivers are warned at the right time. A variety of drowsiness detection systems exist nowadays. Such systems monitor the driver's state and initiate an alarm if drowsiness signs were detected. This paper proposes a real-time visual-based drowsiness detection system that detects drowsiness by extracting an eye feature called the Eye Aspect Ratio (EAR). By using videos from a public dataset, the face region in each frame is localized. Then, by applying a facial landmarks detector, the eye region is detected and extracted as the region of interest. After that, the EAR for each frame is extracted, analyzed, and recorded. Finally, three different classifiers were used to raise the detection accuracy, namely, linear support vector machine (SVM), random forest (RF), and sequential neural network (NN). Subsequently, the extracted data are classified, resulting in an evaluation of the driver's eye state, either open or closed. If an eye closure was detected for a period of time, an alarm will be initiated to alert the drowsy driver. The findings of this study show that the RF achieved the best performance compared to linear SVM and sequential NN classifiers.

OBJECTIVES

Our project aims to implement a real-time driver drowsiness detection system. If drowsiness is detected, an alarm will rise, alerting the driver and ensuring the driver's safety and the others on the road.

- Drowsiness will be detected based on a visual feature that will be extracted from the driver's eyes called Eye Aspect Ratio
- SVM, RF, and Sequential NN classifiers will be used to classify if the eyes state.

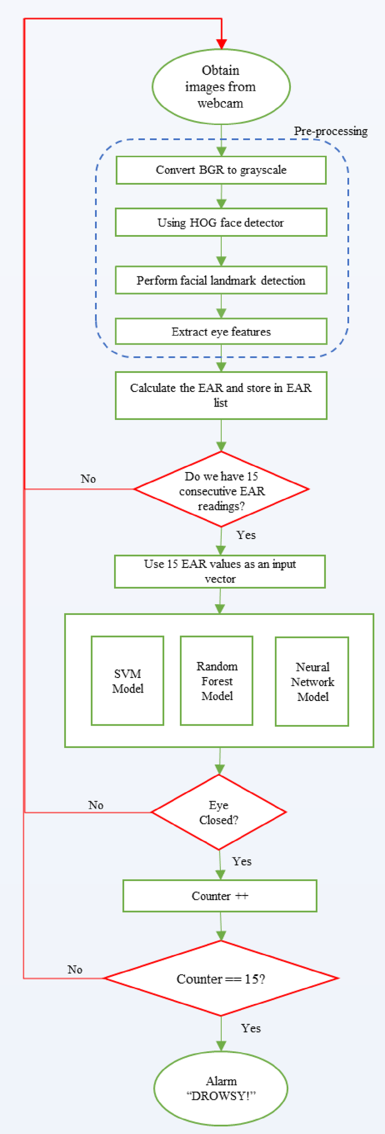
To achieve this objective, we divided the project into five stages, as illustrated below.



METHODOLOGY

- System Design

The proposed system for detecting driver's drowsiness is defined as observed in the figure below. The proposed driver drowsiness detection system is composed of five main steps. Step one, capture the video and extract frames from it. In step two pre-processing is applied. First, each frame is converted from BGR image to Grayscale image. Then, face detection is applied to detect the driver's face within the frame using dlib's Histogram of Oriented Gradients face detector. Lastly, in pre-processing, the "shape_predictor_68_face_landmarks" dlib module is used to get the facial landmarks and extract the eye region. In step three, the EAR is calculated for each frame and stored in a list. Step four, when the first 15 EAR values are stored in the list, the system starts inputting a 15-length input vector to the trained model. Then the input data will be classified as open or closed eyes. In the last step, if closed eyes were detected more than fifteen consecutive times, which is equivalent to 1 sec, then the driver will be classified as drowsy, and an alarm will sound.



- Design specifications

In this project, our modelling is based on a metric called Eye Aspect Ratio. The EAR depends on the computation of the distance ratio between previously specified facial landmarks of the driver's eyes. It reflects the eye's openness degree allowing us to detect the initial signs of drowsiness. A very low EAR value means that the eye is closed.

Eyeblink is a quick closing and reopening of the eye. Each person has a slightly different blinking pattern. It mainly differs in the closing and opening speed, blink duration, and the degree to which the eye is closed. Normal eye blink lasts approximately 100 to 400 msec. In order to detect the different blinks for each person and since one EAR value per frame will not recognize the eye blinks correctly, we propose to train a classifier that uses a large temporal window of frames as an input. For every 30 f/s videos, we computed the EAR of the N-th frame, along with the EAR for N-7 and N+7 frames. Then, by concatenating these EARs, a 15-dimensional feature vector is formed for each frame. This vector is then used as an input to the three classifiers.

Linear SVM, RF, and sequential NN classifiers were used to train our models. Those three classifiers were chosen because the RF classifier is mostly used for binary classifications, which is the case with our data. Moreover, the linear SVM classifier is a common classifier used in many other drowsiness detection studies; thus, it was used to test our data. Finally, the sequential NN classifier was used to apply deep learning to test if the model will produce higher results.

Overall, all of the classifiers were used to classify the driver's eyes as open or closed. Generally, eye closures that excess 500 msec indicate entering a drowsy state. However, since blink duration differs from one person to another, we decided to set the drowsiness threshold to 1 second, which is equivalent to getting fifteen consecutive predictions of closed eyes. Thus, if fifteen consecutive predictions were labeled "closed eye," an alarm will raise, indicating that the driver is drowsy.

RESULTS

In order to test the proposed system, the videos of three subjects from the NTHUDDD testing dataset were used. The frames were extracted, pre-processed, and the EAR feature was extracted as explained earlier. Then, the collected data were fed to each of the three trained models. Finally, the confusion matrix and three metrics were used to evaluate the testing and training results that were acquired. Table 1 lists the results of the DDD system that were acquired using testing and training data.

Referring to Table 1, the results indicate that the RF model has shown the best performance compared to the linear SVM and Sequential NN models. Looking at the training results, it can be seen that the RF model has scored 100% at every metric. Simultaneously, in the testing results, the RF model has given the accuracy of 99% with a 96% and 99% sensitivity and specificity, respectively. As for the sequential NN model, it showed the second-best performance after the RF model. This model has shown 97% at all the metrics. As for the testing results, 97% accuracy, 96% sensitivity, and 97% specificity were acquired. In terms of the linear SVM, we have found that it showed the lowest results compared to the other two models. The linear SVM model gave an accuracy of 96% in the training results, while in testing, it gave 95% only. With regard to sensitivity and specificity, this model gave 97% and 95% respectively in both training and testing.

Table 1: Results of the drowsiness detection system using training and testing data.

Model \ Metric	Accuracy	Sensitivity	Specificity
Training			
Linear SVM	0.96	0.97	0.95
RF	1.00	1.00	1.00
Sequential NN	0.97	0.97	0.97
Testing			
Linear SVM	0.95	0.97	0.95
RF	0.99	0.96	0.99
Sequential NN	0.97	0.96	0.97

From the aforementioned, it can be realized that the overall results demonstrated high accuracy in detecting eye openness. That led to developing a system that is capable of identifying long eye closures from blinking. The experiments and tests done on this system agree with previous research work that used the EAR feature to indicate drowsiness. In addition, our results have shown higher accuracy than 90% accuracy. Furthermore, it succeeded in detecting the driver's face while wearing a mask.

CONCLUSION

It should be noted that the proposed driver drowsiness detection system has some limitations. Since only the EAR is used as a drowsiness indicator, false alarms might rise when the driver is laughing or yawning. Moreover, the performance of the HOG detector can deteriorate in some scenarios. This includes having more subjects in the video frame and intensity changes during the drive.

In future work, to overcome these limitations, we found that different adaptions and improvements have been left for the future to be applied in the field of drowsiness detection. The following ideas can be implemented:

- Widen the region of interest of the system by including the mouth and head movements. Thus, the system will achieve more accurate results when it comes to classifying drowsiness.
- A specially equipped camera can be added to adapt to the intensity changes and sustain the main object detection.
- Adding external strobe light to alert the other road users and drivers.
- Attaching a buzzer to the driver's seat. Whenever drowsiness occurs, the buzzer is set high and helps in alerting the drowsy driver.

This paper presented a real-time visual-based drowsiness detection system. The proposed system used a webcam to apply real-time drowsiness detection. To overcome the challenge of false detection of the closed eyes, ML was applied in the final stage. If drowsiness is detected, an alarm is initiated to alert the driver. Following the training stage, the three models were tested, where the RF model showed the highest performance with 99% accuracy. While human lives conservation is a universal matter, the car accident caused by drowsy drivers poses one of the main threats to road users' lives. The improvements of drowsy detection systems keep rising over time. Many world communities believe that such an engineering solution could prevent the loss of lives, resources, and safety. Thus, we hope that our driver drowsiness detection system will contribute to this field.

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ACKNOWLEDGMENT

We want to express our special thanks and gratitude to Dr. Ali Alnoman, Dr. Mohammed Awad, the American University of Ras Al Khaimah and all the people who have supported us to complete the research work directly or indirectly.