COMPRESSION OF CASCADE ALGORITHM FOR DROWSING DETECTION

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Abstract:

People nowadays are always on the go, therefore they don't have time to squander when they go by car. However, drivers no longer have to worry about being up all night long. This results in traffic accidents, thus we implemented sleepiness detection technology using machine learning language to avoid these sorts of mishaps. With this equipment, we can identify the driver's face and locate the three most prominent features—the eyes, nose, and mouth—as we drive. A sleepy warning may be shown on the screen if any of the three landmarks' aspect ratios are found to be greater than or equal to certain threshold values. In this case, we use the HAAR Cascade method for face identification; to locate landmarks, it uses a supporting cascade file that includes information about the mouth, nose, and eyes.

1. INTRODUCTION

Languages specialised for machine learning provide AI developers easy-to-use library resources. Because of this, it can execute simple ways to meet our needs. Without attaching sensors to drivers, we can detect driver drowsiness in this system, which falls under physiological based technologies [1-7]. However, this approach can be costly and increase system size compared to vehicle based techniques, which involve attaching sensors to both drivers and vehicles. For driver rosiness detection, this is not the way to go. We can safely identify driver sleepiness and tell them not to sleep by observing their visual behaviours. First, we may locate face detection [8]by utilising HAAR cascade help files and recognising facial landmarks on photos; this is accomplished by just attaché the web camera alone, which is less expensive; and then, we take input photographs from the camera. Once it has located landmarks, it may use threshold values to execute visual behaviours such as calculating the eye aspect ratio, mouth open aspect ratio, and nose length aspect ratio.

If the yawning and head bending threshold values are greater than 0.6 and less than 0.7, respectively, and the eye aspect ratio is also greater than 1.2, the system will generate drowsy alerts; if the ratios for the mouth and nose are negative, it will generate drowsy alerts and activate the driver. In this case, we can identify sleepy drivers visually, which reduces system size and costs, eliminating the need for sensors.

2.LITERATURE REVIEW

A driver fatigue detection system that makes use of eye tracking was presented by C. Y. Chenet al. [9]. In this case, we use a colour camera to identify the skin tone, convert the picture to grayscale so that it's completely devoid of colour, and then use a cunning edge detection method to pinpoint the eye frames. The system can detect eyes, compute the white points of edges every twenty frames, and sound an alert if it detects driver drowsiness, ensuring safe driving.
J. Mellor et al.[10] presented a method for non-intrusive sleepiness detection using support vector machine classification. This approach uses a training dataset with fixed values for the nose, mouth, and eyes as well as a goal column value, such as a yes/no sleepiness status, as its basis. To begin, the app launches a colour camera, which can then scan images, recognise facial landmarks, get three threshold values, and forecast whether or not the user is sleepy. After this, the app may notify the user that it has performed non-intrusive sleepiness detection. Even when the driver is wearing eyeglasses, the authors C. W. Chang et al.[11] were able to develop a system for detecting sleepy drivers in video frames by identifying facial landmarks. Wearing eyewear to recognise face landmarks was not possible in earlier systems. Because of this, it would not be able to detect tiredness in drivers fully, but it can detect it with 95% accuracy whether the driver is wearing or not wearing glasses.
A technique for detecting whether drivers are sleepy was developed and implemented by A. S. Baquhaizel et al. [12]. In this article, we see a demonstration of eye detection and identification.Computing the horizontal averages in the face landmark (i.e., after obtaining the eyes), we can then find the face landmark and use that information to identify the eyes. If the driver's eyes are open or closed, the system can tell thanks to changes in the eye landmark, and if they're not, it will sound an alarm to notify them. A method for detecting lethargy in the eyes was created by J. N. Borole et al. [13]. This method is able to recognise facial landmarks using images captured by a camera and a cascade network model file. It finds the driver's eyes first, begins counting the amount of time per blinks, compares that number to the adaptive threshold value indicated earlier, and prevents accidents by sending an alarm message to the driver to keep from dozing off.

3. SYSTEM IMPLEMENTATION

3.1 System Model

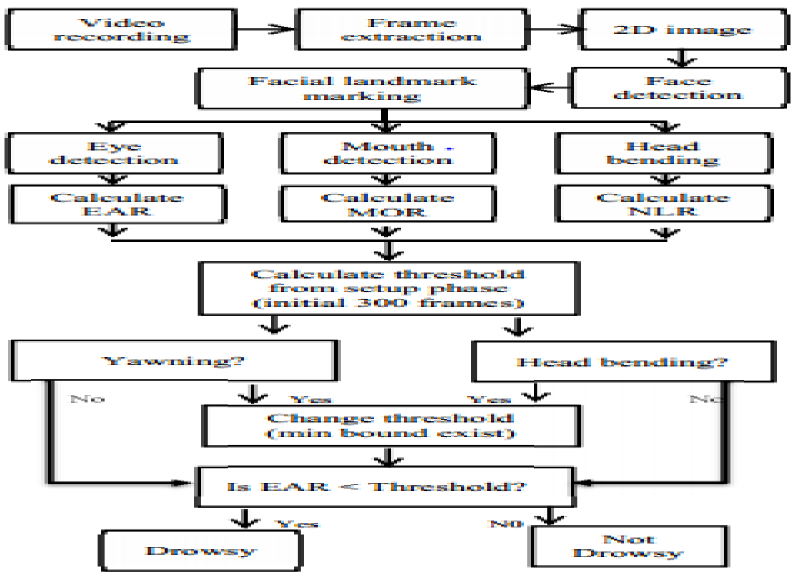

Figure.1 System Architecture

As shown in Figure.1, the webcam can run for a few seconds to read the extracted frames, and then it can generate an image. Using this image, it can detect faces, such as the eyes, mouth, and head. It does this by comparing three ratios, and if any of the thresholds match, it can generate a drowsy alert to warn the driver not to sleep.

3.2 Drowsy Detection with Visual Behavior

In this module driver can start web camera and he should be sit straight of camera for few seconds because reading face features as frames. Once completion of framings then continuously it can read driver face images and detect first face with help of Haar cascade file as well as they can marking facial landmarks with help of shape_predictor_68_face_landmarks.dat file. Once finishing of facial land marking which is shown on figure.2 then they start to calculate the eyes, mouth and nose length threshold values if it is any threshold values exceeded the adaptive threshold value then it can generate drowsy alert to driver on screen.

$$EAR = \frac{(p_2 - p_6) + (p_3 - p_5)}{2(p_4 - p_1)}$$

The below formulas can be use calculating ratios:Eye Aspect Ratio:

Mouth Opening Ratio:

$$MOR = \frac{(p_{15} - p_{23}) + (p_{16} - p_{22}) + (p_{17} - p_{21})}{3(p_{19} - p_{13})}$$

Nose Length Ratio:

$$NLR = \frac{nose\ length(\mathrm{p}_{28} - \mathrm{p}_{25})}{average\ nose\ length}$$

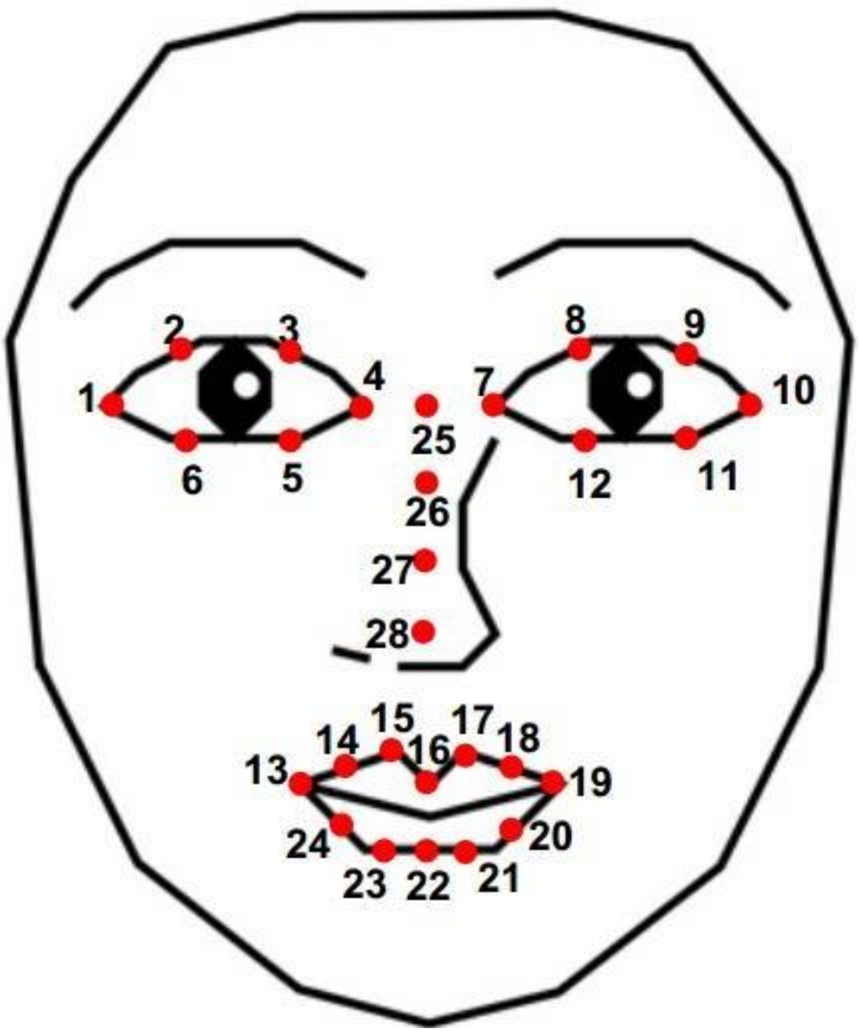

Figure.2. facial landmark points

Table I: Drowsy driver landmark points of Facial

Parts	Landmark Points
Mouth	[13-24]
Right eye	[1-6]
Left eye	[7-12]
Nose	[25-28]

Table II: Adaptive ratio values or threshold values

EAR from setup phase (average of 150 maximum values out of 300 frames)	0.34
Threshold=EAR- offset	0.34-.045=0.295
At Yawning,(MOR> 0.6)	Threshold=Threshold +0.002 *Max bound exist
At Head Bending, (NLR<0.7 OR NLR >1.2)	Threshold=Threshold +0.001 *Max bound exist

3.2 Drowsy Detection with Machine Learning

Bayesian Classifier: For the purpose of driver drowsiness detection, this system may use the naïve bayes algorithm [15]. In order to forecast the occurrence of diseases, this method employs the Bayes rule. Text classifications make heavy use of this approach, which is both quick and predictable, and which computes the posterior probability of events in conjunction with other events. The sklearn.naive_bayes package is being imported by this MultinomialNB classifier.

SVM: Because of its usefulness in classification, the support vector machine classifier [16] deserves a lot of attention. As an initial step in feature classification, support vector machines (SVMs) may create borders between classes and then use support vectors—the classes that are geographically closest to the hyper plane line—to divide them. In this case, the system may develop a training model to identify driver sleepiness by separating the hyper plane with positive and negative data, selecting the closest support vectors, and so on.

KNN:

In contrast to other machine learning classifiers, the K-nearest neighbour classifier[14] uses the Euclidean distance formula to determine how far apart two points are. During prediction, this classifier determines the distance between each record and returns or stores that distance. Then, starting with the most recent record, it can return a predicted output value based on how closely the distance is to all of the distances. This value serves as our drowsiness detection output. Another module from sklearn.neighbors, KNeighborsClassifier, has to be imported.

FLDA:

One way to decrease the number of dimensions is by using Linear Discriminant Analysis (LDA) [17]. Dimensionality reduction strategies, as the name suggests, aim to minimise the number of variables (or dimensions) in a dataset while preserving as much information as feasible. The linear decision-boundary classifier that is trained using Bayes' rule and fitted with class conditional densities. The model assumes that all classes have the same covariance matrix and fits a Gaussian density to each class. We are able to identify driver sleepiness via the use of machine learning algorithms. When it comes to detecting driver sleepiness, the K-NNclassifier outperforms all other classifiers with a 97% success rate.

EXPREMENTAL RESULTS

3.3 System Testing Results:

Figure.3 Detection of facial landmarks

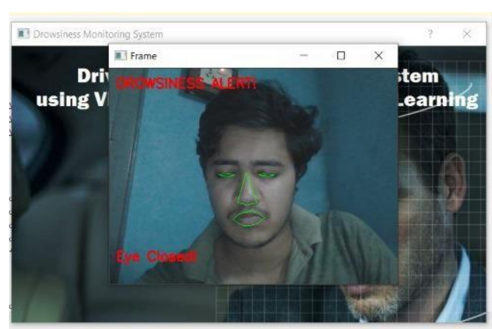

Figure.4 Drowsy Detection due to Eye closed

Figure.5 Drowsy Detection due to Yawning

Figure.6 Drowsy Detection due to Head Bending

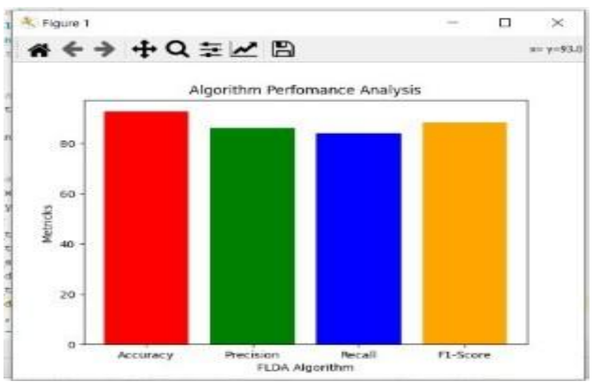

Figure.7 FLDA algorithm performance analysis

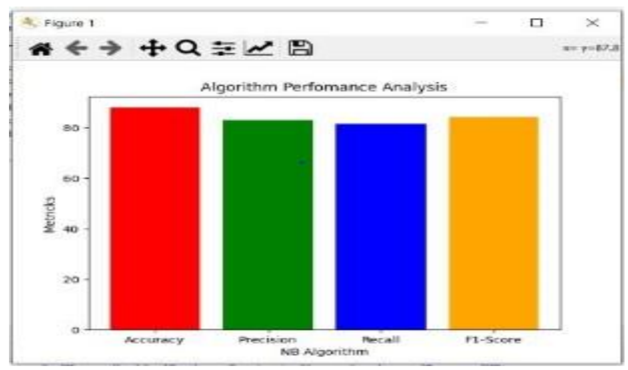

Figure.8 Bayesian algorithm performance analysis

3.4 EVALUATIONS

Table.2 Classification Metrics of Classifiers

Algorithm	Accuracy	Precision	Recall	F1_score
FLDA	0.93	0.86	0.84	0.88
Bayesian	0.88	0.83	0.81	0.84
SVM	0.95	0.90	0.88	0.93
KNN	0.97	0.89	0.90	0.94

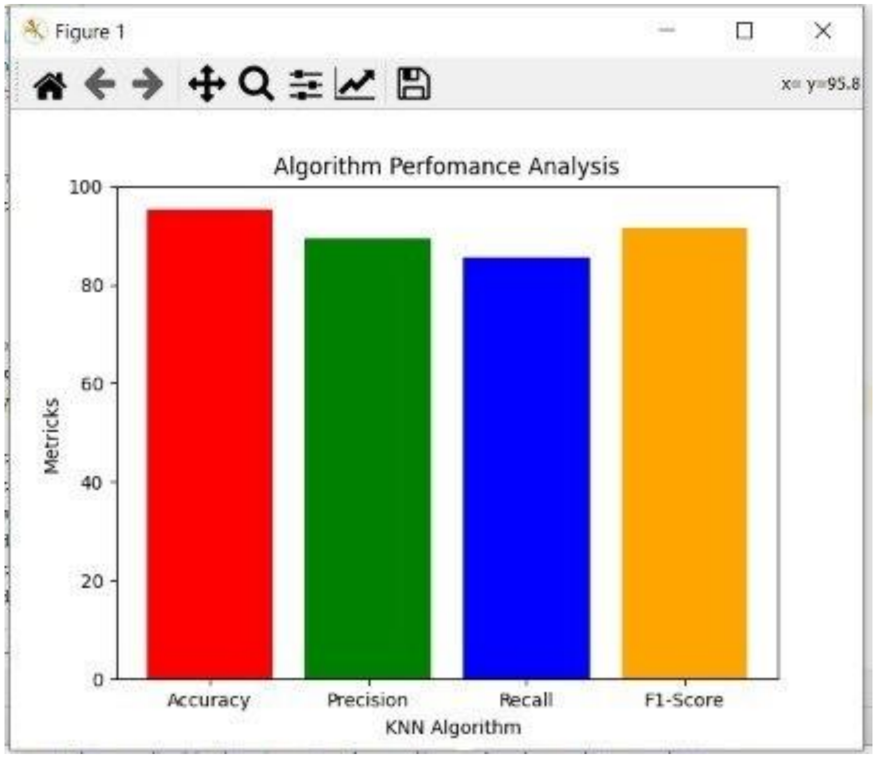

Figure.9 KNN algorithm performance analysis

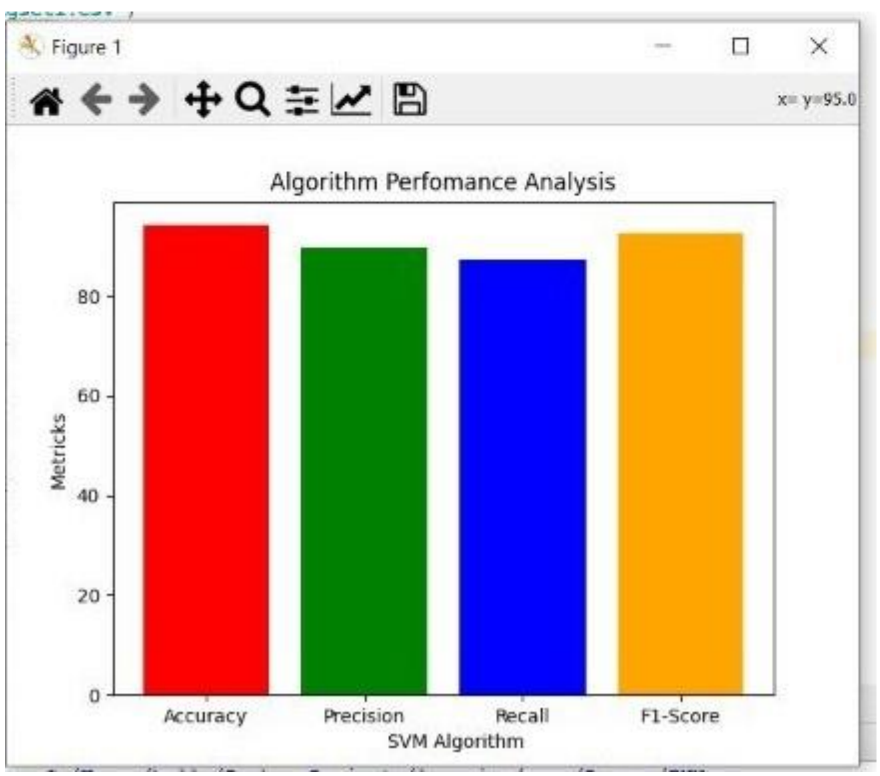

Figure.10 SVM algorithm performance analysis

4. CONCLUSION

In this system we can get accurately detect driver drowsiness with help of three aspect ratios which is getting from visual behaviors methods as well as we are implemented machine learning technique NB, SVM, KNN and FLDA classifier for predicting drowsy status like normal, yawing, head bending, eye closing with help of training dataset. The KNN classifier given 97% accuracy with compares remaining algorithms. So that previous methods like physical or vehicle methods are giving very less detecting driver drowsy results if it is compare with current system.

5. REFENENCES

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