ACCIDENT PRONE SITUATION PREDICTION OF A VEHICLE USING MACHINE LEARNING APPROACHES

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Abstract **With the advent of cutting-edge technology in automobiles, they have become the first choice for commute across the world. While this made transport by road more convenient, it also gave rise to a fatal problem,
i.e., car accidents. In this paper, a method is proposed that helps in predicting the probability that analyses the factors found to influence car accidents the most. Using a set of features extracted by building a system for the same purpose, it first predicts the possibility of accident in a binary form. These results attest our method as a valuable tool for a number of people such as car drivers, automobile safety designers and companies etc.**

Keywords: Machine Learning, Model accuracy, Logistic Regression, F1 Score, Support Vector Machine, Target variable.

1. Introduction

Increase in the number of deaths due to road accidents every year sheerly due to negligence or emotional behavior of drivers has become a major problem in India. People driving late at nights, especially truck drivers, due to reasons such as fatigue, lethargy, long work hours and sleepiness, often lose control on the road and cause accidents which may or may not be fatal to the passengers but surely results in loss. The best way to avoid these kinds of fatal circumstances should be to avoid driving at all when not feeling up to the task.

Thus, the project proposes a model that is able to warn the driver whether the car cabin is prone to accidents or not. This will be achieved by measuring various characteristics of the moving car such as:
[1] Drowsiness state through the eyes (percentage of eye closure)
[2] Drowsiness state through the mouth (yawning) of the driver .
[3] Pulse detection of the driver to gauge his/her stress level.

The main aim of the project is to predict the possibility of accident based on these characteristics according to their respective thresholds in the form of discrete values. We have collected more than 2000 instance of data from the real time observation and checked the accidents prone probability on that dataset with the help of machine learning algorithm.

The accuracy of machine learning models, based on these values shall help us in evaluating the features that must be present in an accident prevention system inside a car cabin.

2. Literature Review

In [11Poh *et al.* (2010)], the authors proposed an automated novel approach that extracts visual features from the data with the help of deep learning model, i.e., convolutional neural networks. The inputs and the learnt weights help in driver drowsiness detection. Each frame of the data uses a soft-max classifier to classify the driver as drowsy and non-drowsy.

In [Alioua *et al.* (2014)], the authors proposed a SVM and circular Hough transform (CHT) based driver fatigue using mouth detection and feature extraction to identify if the driver is yawning or not and classify the drivers' states into drowsy and non-drowsy.

In [Abtahi *et al.* (2011)], the author uses the drivers' yawn to detect if the driver is fatigued or not in two phases, the first being the yawn detection independent of mouth detection, i.e., through the hole in the face and secondly, the largest hole in the face is selected as the candidate for a yawn.

In [Rosén and Sander (2009)], the authors proposed calibration of a person's heart rate using a mobile phone's camera. This is done with the help of a fingertip in an optimal position on the smartphone's camera by detecting the differences in the colour signals of the skin segment.

In [Zhao *et al.* (1964]], authors proposed a deep learning algorithm to detect and estimate head pose with the help of raw images. This algorithm helps in differentiating the head pose between safe and distracted in case of automobile drive with the help of SF3D dataset. This differentiation is carried out on each frame of a video that displays an automobile driver driving and aids in concluding a head pose that is safe for driving as a precedent and corresponding values as threshold values.

According to [Ruikar (2013)], 77.5% of Indian car accidents occur due to driver behavior such as fatigue, distraction and drunkenness. 41% fatalities are due to over-speeding in India [4] and a reported number of 86,241 deaths and 2,71,851 injured people were resulted due to over-speeding in India due to over-speeding of automobiles according to the NCRB 2019 Report.

With the help of such data available, the aim of this paper to predict the accuracy of the model that includes in its study the factors responsible for car accidents by machine learning and deep learning methods.

3. Data and Techniques

3.1 Data procurement and Processing

Owing to the novelty of our work, limited datasets were available in the field of accident detection using researched features, so we extracted the features that will be focussed in this study by using certain programmed detection techniques. Over 2,000 instances of all such features were calculated by simulating an automobile cabin environment and obtaining the value of all features for 4 different drivers, 1 male and 4 female test subjects. All data collection and processing procedures described in this work were implemented in Python by the authors. These features may be stated as follows:

1. EYE ASPECT RATIO: Contains the values of percentage of eye-opened of the driver.

2. MOUTH OPEN RATIO: Contains the values of mouth opened and duration of mouth opened of the driver.

3. PULSE_VAL: Contains the pulse value of the driver.

Apart from the values stated above, the dataset also contains the following values of the following features:

(1) EAR_THRESHOLD: Contains the values of whether or not the measured eye aspect ratio of the driver has crossed the threshold (0 for negative and 1 for positive).

Eye aspect ratio is an important factor on detecting drowsiness of driver through his or her face detection. Eye aspect ratio is calculated by using landmark model of machine learning. When the subject's eye is open, the value of EAR is fixed but as soon as the subject's eye is closed, the value drops to 0. In this way eye aspect ratio is useful to detect drowsiness or sleepiness of driver. There is a specific formula that we are using to calculate eye aspect ratio that is given below:

$$EAR = \frac{|p1-p5|+|p2-p4|}{2|p0-p3|}$$

(1) where, p1, p2, p3, p4, p5, p6 are landmark points on drivers face detected by camera.

(a) (b)

Fig 1. Illustration of points estimation: (a) Distance of points for an open eye, and (b) Distance of points for a closed eye

According to [Rosebrock (2017)] and [Singh *et al.* (2018)], the EAR threshold value is 0.30 but we have taken 0.35, in order to increase the credibility of the values. If value of 'EYE ASPECT RATIO' is greater than 0.35, then model will consider driver as in active state and value of 'EAR_THRESHOLD' remains zero and as soon as the value goes less than 0.35 then the model will consider driver to becoming inactive and value of 'EAR_THRESHOLD' will turn out to be 1.

Here we can understand from graph the importance and working of EAR in drowsiness detection technique.

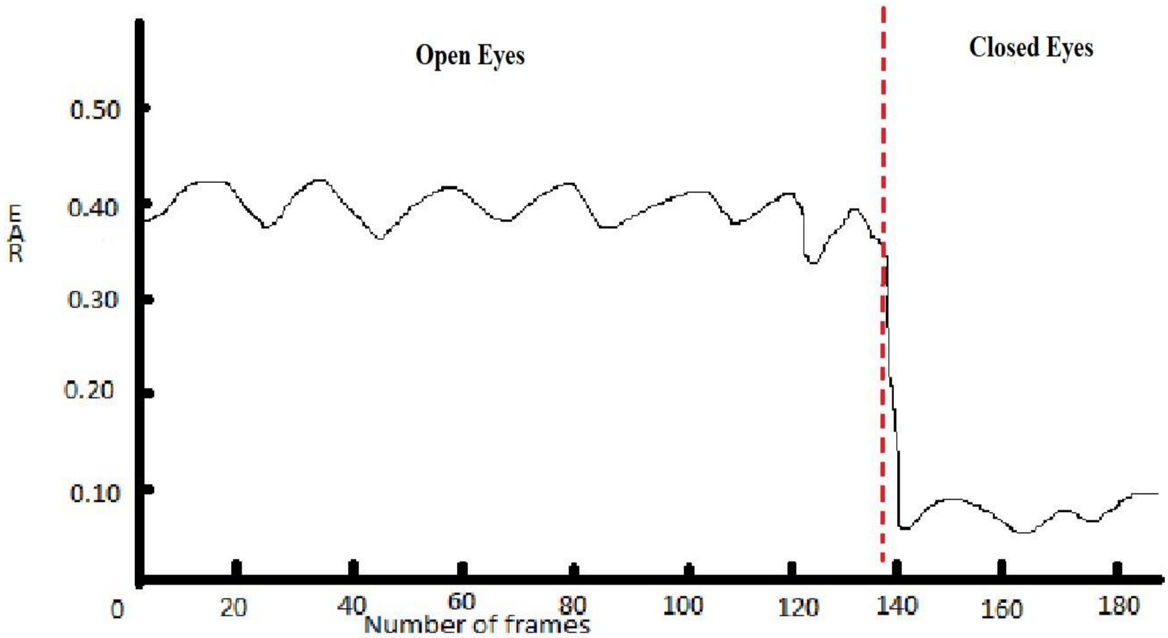

Fig 2. Graph depicting flow of EAR value in open and closed eyes

Here we can see that when eye is open the graph is constantly going straight and value of EAR suddenly goes down when eye is going to close.

(2) YAWN_THRESHOLD: Contains the values indicating whether or not the driver is yawning.

Yawn is a sign of getting drowsy if a person is getting sleepy there is high possibility to get yawn [Zilli *et al.* (2010)]. That is why we are using this factor in our dataset to train our model to detect accurate situation of driver. Yawn can be detected by using the same method of detecting the eye aspect ratio that is landmarks detection. Yawn will be detected by calculating MAR that is Mouth Aspect Ratio. After predicting the landmarks, only the mouth landmarks are required to calculate Mouth Aspect Ratio (MAR) to predict if the driver is drowsy or not.

$$\text{Mouth Aspect Ratio}=|p1-p2| \qquad (2)$$

We are calculating Mouth aspect ratio (MAR) by measuring distance between upper lip and lower lips, as shown in the Fig. 3 [Varma *et al.* (2012)].

(a) (b)

Fig 3. Illustration of points estimation: (a) Distance of points for an open mouth, and (b) Distance of points for a closed mouth

Here if the distance between and lower lips is less than 20 the value of 'YAWN_THRESHOLD' will remain zero and if the distance between upper lip and lower lip is greater than 20 then the value of 'YAWN_THRESHOLD' turns out to be 1.

(3) PULSE_THRESHOLD: Contains the values indicating whether or not the driver's pulse is unsuitable (0 for negative and 1 for positive).

According to [Wei e*t al.* (2012]] non-contact, long-term monitoring human heart rate is of great importance and provides a method, namely, Photo plethysmography (PPG) can provide a means of heart rate measurement by detecting blood volume pulse (BVP) in human face. Heart rate means the number of beats per minute. We use Haar feature and cascade classifier to detect heart rate of driver from face recognition. According to [Dwivedi *et al.* (2014)], the threshold value is 12 bpm. We have applied threshold value for heart rate range if the value of heart rate is less than 90 then the value of 'PULSE_VAL' remains 0 and if the value of heart rate is greater than 90 then the 'PULSE_VAL' value will become 1.

According to [Nadrag *et al.* (2018)], during blood circulation in the body, the pumping of blood causes variations in the colour of skin, that go unnoticed by human eyes but it can be detected with the help of a camera. The most suitable place to perform this is the forehead of the subject and the size of the rectangle depends on the space

3.2 Calculating target variable

The target variable of our dataset, i.e., 'RESULT_ACCIDENT' stores the possibility of accident occurrence given a certain value of the forestated features. The value of the target variable is calculated with the help of the following algorithm:

1. Observe the value of EAR_THRESHOLD and compare it with the real time EAR.
2. Observe the value of PULSE_THRESHOLD and compare it with the real time PUlSE_VAL
3. Observe the value of YAWN_THRESHOLD compare it with the real time MOR.
4. Note down the above three compared values in terms of 0 and 1 to calculate our target variable.
5. Lastly, RESULT_ACCIDENT=1 if any of the values observed above result in 1, otherwise 0.

3.3 Prediction Module

With the help of Scikit learn library, we were able to fit the prediction models to our dataset. We executed a binary classification task, where the featured values result in accident if the threshold values of the features are exceeded according to the algorithm, otherwise it results in no accident.

In this paper, we tested 4 machine learning models, namely Logistic Regression, Support Vector Machine, K Nearest Neighbours and Naïve Bayes. We compared the accuracy and F1 Scores of all these models as fitted on the dataset to obtain the model that has the highest accuracy for our dataset. 75% of the dataset values were used for training while remaining of the dataset values were used for testing.

3.4Algorithms

We have collected more than 2000 instance of data from the real time observation and checked the accidents prone probability on that dataset with the help of machine learning algorithm.

	A	B	C	D
1	EAR	YAWN	PULSE	OUTPUT
2	0.327041067	11.83333333	90.6	1
3	0.37783564	11.83333333	50.4	0
4	0.371883446	11.83333333	50.4	0
5	0.323330447	11.83333333	50.6	0
6	0.290491256	11.16666667	80.6	1
7	0.275938417	11.16666667	50.4	1
8	0.285858262	11.33333333	50.4	1
9	0.289394785	11.33333333	50.6	1
10	0.293331849	11.33333333	50.6	1
11	0.302386225	11.66666667	50.4	0

4. Experiments and Results

For the prediction experiments, each machine learning model computed accuracy and F1 Sore of the dataset with the help of confusion matrix. The best obtained result (Accuracy=0.98) is 13 percent points higher than K-Nearest Neighbour algorithm. The results can be observed from Table 1. Logistic Regression is very close to nearly perfect, as can be seen from the table.

S. no.	Model	Accuracy	F1 Score	Precision	Recall
1.	Logistic Regression	0.988235	[0.98936, 0.98684]	0.98	0.98
2.	Support Vector Machine	0.977763	[0.97789, 0.97452]	0.96	0.97
3.	Naïve Bayes	0.87431	[0.87550, 0.88122]	0.79	0.78
4.	K-Nearest Neighbour	0.862745	[0.88095, 0.83796]	0.84	0.93

Table 1. Comparison of different machine learning models

5. Conclusions

The proposed method works on stating a number of values according to the researched count of factors that are greatly responsible for car accidents all over the world, and especially in India. With the help of dataset created, we built a formula that helps us in establishing the discrete binary values of the possibility of an accident. This novel dataset has been very helpful in predicting the accuracy of the approach that we began working with, i.e., the factors that contribute to road accidents. According to previous data available as well as the results obtained from our predictions, we successfully established the relationship between the factors that we started with and the target variable. The benefits of this paper are:

(1) A dataset that contains all the fatal threshold of features that cause car accidents.

(2) An insight into the driver activities that heavily influence car accidents.

(3) A convenient initial point to build accident prevention and driver alert systems.

6. Future Work

The paper focuses on all important points that are required to make concerned parties aware of the situations inside a car cabin that may or may not lead to accident. Improvisations can be done by increasing the number of factors that influence car accidents, testing on a larger number of people and testing in highways as they usually are the witnesses to road accidents.

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