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Driver Sleep and Drowsiness Detection Using Machine Learning

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Abstract: Human drowsiness or fatigue required various approaches to be detected before or during the driving process. Nowadays, many people have managed to acquire personal vehicles which they use to travel around different regions. Arriving alive and on time is a crucial goal for all drivers en route. Drowsiness can be caused by long driving and lack of adequate rest. Several metrics proven to detect drowsy driving include eye detection and heart rate variability. Driving behavior like lane departure, use of indicators, braking and steering handle could also be used. The objective of this work is to develop drowsiness detection, a prediction system that integrates eye detection, which is the behavioral and physiological approach. The system should keep track of the driver's behavior and concentration while driving and give a voice warning or alarm whenever drowsiness is detected.

Keywords: Drowsy driving; fatigue; lane position, prediction, detection

I.INTRODUCTION

Detection of drowsy driving will have an impact on reducing road accidents. The system may also find application in industries by verifying the suitability of workers, especially those who work with hazardous objects 24/7, healthcare institutes, and safety-sensitive deployments. Whenever a person falls asleep, he or she may experience fatigue and find it difficult to stay focused [1]. Today, most professions require long-term focus to achieve intended goals. Drivers of heavy vehicles generally travel long distances without resting and are highly prone to drowsiness or fatigue while driving [2]. Therefore, it is necessary to monitor the work process as the behavior of humans may change due to the time and workload involved. At some point, a worker should be made aware of his or her state of alertness and advised to take a break whenever tired to avoid injury or the production of poor products /services. Drowsy driving claims several victims every day. In [3], sleeping while driving contributed to several road accidents. There is a need for early detection methods to minimize drowsy driving accidents [4]. Several authors have done a great job of detecting and alerting drivers during their driving time. A review of other studies highlighted that drowsy driving can affect driving performance, attitude parameters and physiological catalogs [4]. Different approaches can be used to detect drowsy driving, including steering wheel angle, eye blinking pattern, eye opening/closing, and electrocardiogram [5].

II. LITERATURE SURVEY

This work is closely related to real-time video streaming and image processing typically applied on cable television cyber surveillance monitoring systems. Studies on drowsiness systems are discussed. Routine review of driver collision avoidance technologies that continuously checked the length of eye blinks was presented [1].The method detects the blinking of the eyes via a standard webcam installed precisely in front of the driver's seat and detects the eyes according to a particular EAR (Eye Aspect Ratio).In [2], any analysis was carried out to see factors relating to tiredness.

III. APPLICATIONS

Fig. 1: Drowsiness detection architecture

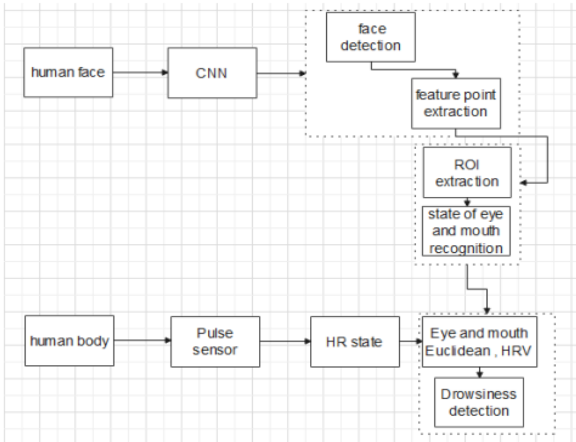

Fig. 2: Drowsiness detection flow chart

The psychoanalysis of face images is completed by the use of a shape predictor containing 68 face landmarks [6].

Feature point 68 was used to extract the ROI which included the eyes and the eye, as shown in Fig. 3. The numbers marked from 37 to 48 indicated the region of interest of the right and left eye. The numbers 49 to 68 show the eye region of interest and the facial border is represented by the numbers 1 to 27.

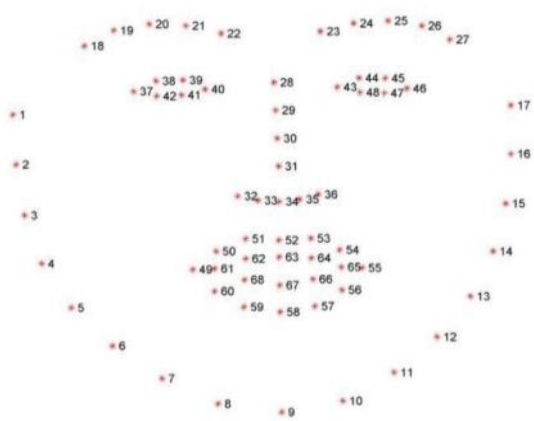
Fig. 3: Facial landmark

The Eye Detection

A generalized threshold measure was used with the help of health experts to determine when drowsiness is reached by eye opening and the time spent closing. If the eyes are closed for six seconds or more without blinking (>=6), one is assumed to be drowsy.

The Eye Detection

The determination of the state of the eye has been defined to help in the detection of driver drowsiness. When a driver feels sleepy, he or she yawns, so it was necessary to include the data in this research. Yawning was determined when the eye was open for a time greater than or equal to (>=6) six seconds.

The Pulse Rate Detection

A pulse sensor collected data of heartbeats per given second. Expert knowledge was included in the training of the model so that when the pulse is checked in the real world, it gives the same results. As a result, a reliable output was guaranteed. An ordinary pulse in adults ranges from fifty to eighty beats per minute.

Drowsiness status

When entering into fatigued situations, drivers usually yawn, lose consciousness and are unhurried in their reactions [7]. The system used data detected from the eyes, eye and pulse sensor. These three inputs could give driver status if he/she is alert or drowsy. When one of the three gives a high level of drowsiness, it automatically indicates that the driver is feeling drowsy. Usually, a drowsy driver would feel drowsy, yawn, and pulse rate would change accordingly

IV. PROPOSED SYSTEM

The proposed system used the k-NN method for driver state classification. To the best of our knowledge, it is not previously studied in the context of a camera-based driver drowsiness detection using blink features. Existing k-NN-based approaches include the steering behavior , EEG measures or facial features. The work of investigates the feasibility of a drowsiness classification system based on blink features gathered with an EOG. The author achieved a promising classification accuracy, indicating the potential of a k-NN classifier in combination with blink-based features. The k-NN model requires a set of suitable features as basis for the classification, especially when a high-dimensional feature space is available. According to the ”curse of dimensionality” phenomenon, the available data becomes sparse as the number of possible configurations grows. Thus, one aim of this work is to identify a suitable set of meaningful features. The feature selection techniques mainly used in this work are wrapper methods. Wrapper methods select feature subsets according to their predictive value in the actual classification process. Therefore, this method is capable of considering dependencies between the feature subset and the classifier as it directly assesses the classification performance.

Python software: is a construed, universal rationale programming language.

- Dlib: used to generate additional multifaceted software plus solving numerous real instance-based tribulations.
- OpenCV: a store of various indoctrination functions principally used for genuine-time processor apparition programs.

CNN was used for model training. Two sets were used in the dataset, for the eye and eye. The eye training used 335 images and the eye used 305 images. The model managed to identify the eyes and eyes of different people. The training was performed using open and closed eyes as well as opened and closed eye. Some of the images used in the dataset model are shown.

A number of machine learning algorithms used included Random Forest (RF), Linear Regression (LR), and K-Nearest Neighbor (KNN). These are shown in the tables' 1 and 3 Below

RF	LR	LDA	KNN	CART	NB	SVM
0.98	0.89	0.91	0.94	0.98	0.89	0.94

Table 1: Eye Classification

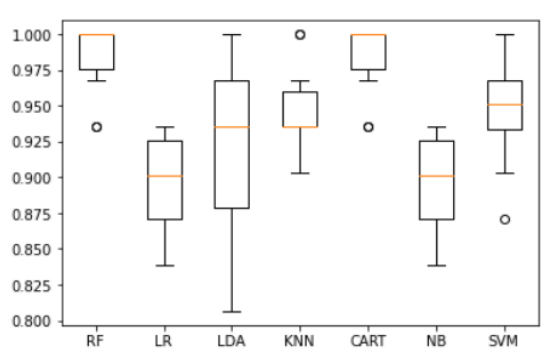

Fig. 6: Machine learning algorithms comparison for eyes

Random Forest and Classification and Regression Trees (CART) have a high rate of classification of 100%. Support Vector Machine (SVM) have 95% classification rate followed by Linear Discriminant Analysis (LDA) and KNN with 93%.LR and Naïve Bayes (NB) obtained the least classification rate of 90%.

Advantages of Proposed System

- The system is more effective since it presents k-Nearest Neighbor (k-NN) algorithm is used to classify the driver's state of drowsiness based on the eye closure and head movement characteristics.
- The system is accurate since it is implemented Sequential Floating Feature Selection method.

Algorithm

```
#Importing OpenCV Library for basic image processing functions
import cv2
# Numpy for array related functions
import numpy as np
# Dlib for deep learning-based Modules and face landmark detection
import dlib
#face_utils for basic operations of conversion
from imutils import face_utils
  cv2.imshow("Result of detector", face_frame)
  key = cv2.waitKey(1)
  if key == 27:
      break
```

Application Modules

The first step in the process of developing a camera based classification system is to define the state of drowsiness in terms of observable measures. Especially the eyelid movements as drowsiness indicators were studied through the decades. The authors of introduced the PERCLOS measure which denotes the proportion of time in a defined interval for which the eyes are more than 80% closed. The work of 28] hints that the blink behavior in general is an observable indicator for drowsiness. Besides the PERCLOS, other blink-related features can be extracted from an eyelid movement signal . Most of these features exhibit an altered behavior with an increasing drowsiness.

Data Collection

We recorded about 134 hours of material during three driving simulator studies, with the objective to obtain data that reflect the interactions between the eyelid closure and the drowsiness. Therefore, a camera facing the driver is set up to detect and track the eyelid movements. It is placed on the steering wheel column and is equipped with infrared illumination for robust eye and head tracking.

The camera provides several signals related to the driver's head position, gaze direction and eyelid closure. Among them, four signals are of interest for this work, including the eye closure and the eyelid confidence for the blink feature extraction and the roll and pitch angle of the head rotations. For the eye closure, the maximal distance Ld between the provided in.

Feature Extraction and Analysis

Proposed a robust technique to detect blinks and derive blink features based on the eye closure signal. Utilizing this method, a list of 35 blink features build the base of this work. They can be grouped into eleven categories, depending on which domain they stem from: frequency, time, amplitude, velocity, amplitude-velocity ratio, percentage, blink (form), eyelid, head movement, symmetry and the PERCLOS1. With regard to the signal processing and feature extraction, it has to be taken into consideration that drowsiness does not occur suddenly but rather has a slow progression. A sophisticated driver drowsiness classifier is supposed to handle interindividual differences properly and achieve high classification accuracies on all subjects equally. Yet, differences between the individuals blinking behavior can be tremendous. To cope with that, a baselining of the features is introduced by defining the first 10min of each experiment as a representation of the awake state for each subject. This underlies the assumption that the subject is still moderately awake when starting the experiment. Drivers who started the experiment in an already drowsy state are at a high risk of injecting invalid data into the underlying dataset and thus distort the model. Therefore, these subjects are excluded in advance from the dataset

V.RESULT

CNN was used for model training. Two sets were used in the dataset, for the eye and eye. The eye training used 335 images and the eye used 305 images. The model managed to identify the eyes and eyes of different people. The training was performed using open and closed eyes as well as opened and closed eyes.

VI.CONCLUSION

After obtaining results from the previous parts, the following can be concluded from the study:

- Detection of the eye can be done at easy using Dlib from python software
- CNN classifier RF and CART yielded almost 100% accuracy, training model.
- Drowsiness is linked to sleeplessness, and the influence of alcohol and drugs.
- Eyes can help out in detecting drowsiness.
- When one is in a drowsy state, he/she may close the eyes for consecutive times which lead to crashes, convoyed by some yawning at a specified hiatus.
- The average pulse rate of a person ranges from 45 up to 100 BPM and when one is drowsy the pulse can either rise or fall to below normal depending on the causal effect.
- A driver needs concentration so that accidents may be avoided on the road when one feels drowsy taking enough rest is essential

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