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Drowsiness Driving Detection, Prediction and Warning Drowsiness Detection

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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, mouth detection and heart rate variability, 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, mouth opening/closing, and electrocardiogram [5]. Drowsiness detection includes monitoring of face, eye movements [6]. Techniques such as degree of mouth opening and eye opening ratio in a given time have been used to detect fatigue [7]. The video acquisition was carried out using a surveillance camera strategically placed to detect the level of fatigue of a driver and give an alert after ocular detection [1]. Facial landmarks were used in the calculation of the eye closure ratio [3].The level of fatigue, as well as other variables such as time have been studied [8].

In the proposed system, the driver drowsiness detection method consists of four components, as shown in Fig. 2. Three inputs were used for drowsiness detection. The first entry was Face identification where the eyes were detected. The next step was the identification of oral yawns or not using Euclidean algorithm. Thirdly, Heart rate (HR) was obtained from the rhythm sensor. Lastly, the combination of the three inputs helped to detect the driver's sleepiness.

The layout of this article is noted. Part II presents related works. Part III, Drowsiness Detection Architectural Solution and Flowchart. Analysis of research results, part IV. Part V concludes the article.

II. RELATED WORK

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. Data training was done in multiple layers and the system relied heavily on mouth categorization. Performance metrics were used to see if the output model was useful among them F1-Score.

In [3] the development of a frivolous and synchronized method for the discovery of drowsiness was initiated. The images from the video capture targeted the faces of the drivers along the detection path. The targeted facial points were identified, including eye operations, through predefined procedures. Empirical results demonstrated an 84% modeling success using Random Forest. Reference [4] studied how to practically classify the awake positions of the driver, mainly somewhat drowsy, amalgamating vehicle data, reactions as well as sensory pointers with contemplation, the execution of these identifications in the recognition system. The driver's level of drowsiness was calculated from the act of driving,

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physiological indications in addition to the driver's behavior. The system successfully predicted drowsy driving using a data set accumulated over ten seconds. In [5], a mobile driver drowsiness measurement solution was used. Development limited the electrocardiogram (ECG) to a custom printed circuit board (PCB) layout. The PCB was installed and used a two-channel solution.

In [6], an automatic appearance was used to recognize driver fatigue. A camera tracked the driver's eye to predict drowsiness. The driver was awakened by a signal each time he fell asleep. The system took care of detecting eyes in a specific segment of the face. After failing twenty frames, it indicated that one is sleeping. In [7], a convolutional neural network that notices targeted eyes next to mouth features was implemented. For the discovery of fatigue, they used the proportion of the eyes as well as the functioning of the mouth. Reference [8] used occasion-related variables to predict driver fatigue, such as uninterrupted driving time, uninterrupted rest, and nap before driving. The physical involvement allowed the researcher to obtain the truth about the driver's attitude through special indications of fatigue reactions.

In [9], the artificial neural networks that were applied were very much concerned with sleepiness identification as well as predicted decay time. The models used data which was obtained from the driver. Reference [10] took the opportunity to study the levels of connection which include attitude, motor reactions and the way of holding the steering wheel. The source of the data was from the eye study. Vehicle protection and sanctuary with the involuntary automobile method mainly based on the independent region have been used [11]. A vision-based approach was implemented in this study. In [12], the designed system identified the behavior of a drowsy driver and warned him with an audible signal. The driver was monitored and eye aspect ratio was calculated, and the distance of the lips determined the state of the mouth.

This work analyzed the eyes condition and gave an alert before an accident [13]. In [14], the study aimed to caution lazy drivers while driving. Head tilt and eye flicker were made to decide driver fatigue. Driver gaze information was used to determine eye status and whenever closed eyes were detected, an alarm was triggered [15]. Haar's library store detected wanted portions on the driver's face. In [17] deep learning detects drowsiness at the wheel by studying eye movements. Reference [18] physically describes a non-intrusive driving stupor prediction system.

A study was performed on the driver appearance when a car started to maneuver [19]. In [20], driver fatigue was detected including drowsiness, eye iris and closing. A driver's alertness was detected using video processing and a wavelet network to identify drowsiness [21]. The input constraint of the proportion of eyes closed was used to detect drowsy driving [22]. Differences in driver fingerprints have been taken into account in the prediction of drowsy driving [23]. Radar technology has been used to identify drowsy and non-drowsy driving [24]. In [25], grip strength was used on the steering wheel to detect drowsy driving.

Driving drowsiness prediction was applied using pedal and steering wheel data [26]. In [27] filter and wrapper facet selection was implemented in this study. Data obtained from steering wheel tilt has been used to predict drowsy driving [28]. Reference [29] performed multilevel distribution and emotion analysis to detect drowsy driving. Different signal fusion methods have been used for fatigue detection while driving [30].

III. DROWSINESS DETECTION ARCHITECTURAL SOLUTION and FLOW CHART

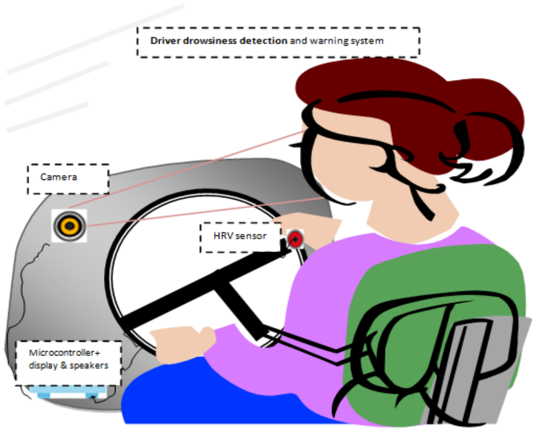

Fig. 1: Drowsiness detection architecture

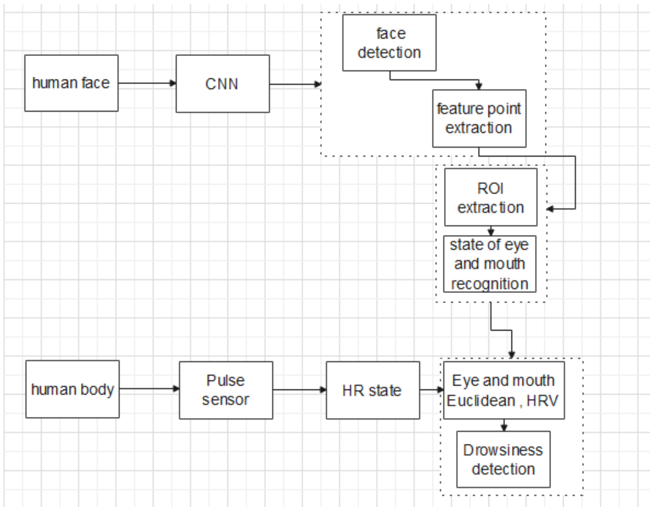

Fig. 2: Drowsiness detection flow chart

A. *Face Detection*

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 mouth, 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 mouth region of interest and the facial border is represented by the numbers 1 to 27.

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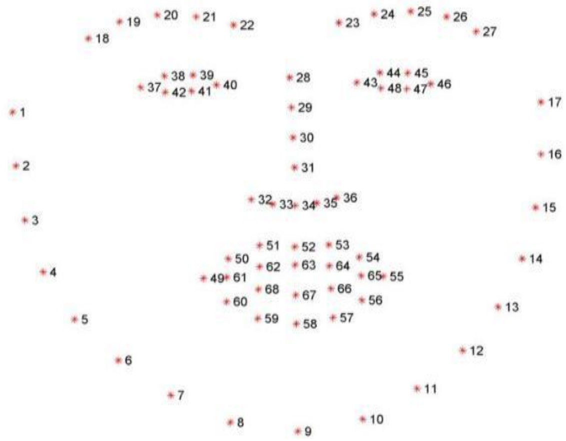

Fig. 3: Facial landmark

B. 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.

C. The Mouth Detection

The determination of the state of the mouth 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 mouth was open for a time greater than or equal to (>=6) six seconds.

D. 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.

E. 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, mouth 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. ANALYSIS OF RESEARCH RESULTS

To deploy and test the system some of the components used include:

- A laptop fitted with camera, speakers, monitor
- pulse sensor,
- Arduino UNO microcontroller,

Additional requirements as noted in [6];

- 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 mouth. The eye training used 335 images and the mouth used 305 images. The model managed to identify the eyes and mouths of different people. The training was performed using open and closed eyes as well as opened and closed mouth. Some of the images used in the dataset model are shown in Figs. 4 and 5.

Fig. 4: Closed mouths

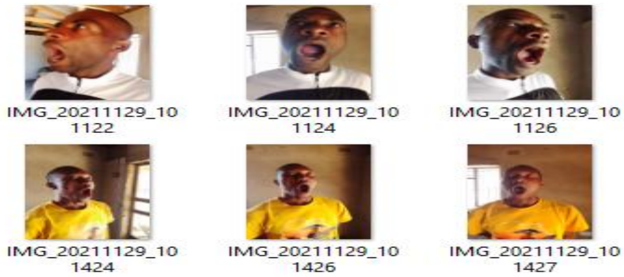

Fig. 5: Yawning mouth

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

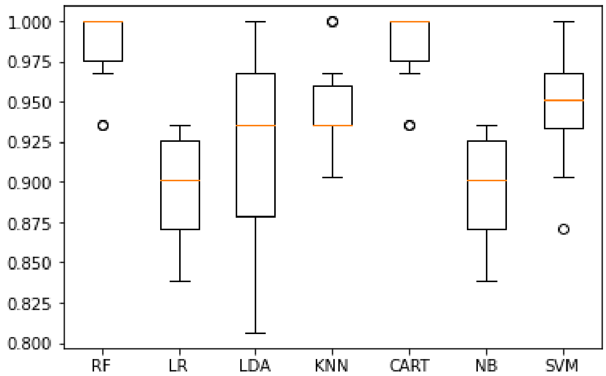

Fig. 6: Machine learning algorithms comparison for eyes

The above fig. 4.6 shows the box and whisker plot of the machine learning algorithms used for eye classification.

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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%.

	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	38
1	1.00	1.00	1.00	39
Macro avg	1.00	1.00	1.00	77
Weighted avg	1.00	1.00	1.00	77

Table 2: Eyes Accuracy Rate

RF	**LR**	**LDA**	**KNN**	**CART**	**NB**	**SVM**
1.00	0.96	0.96	0.98	1.00	0.96	1.00

Table 3: Mouth Classification

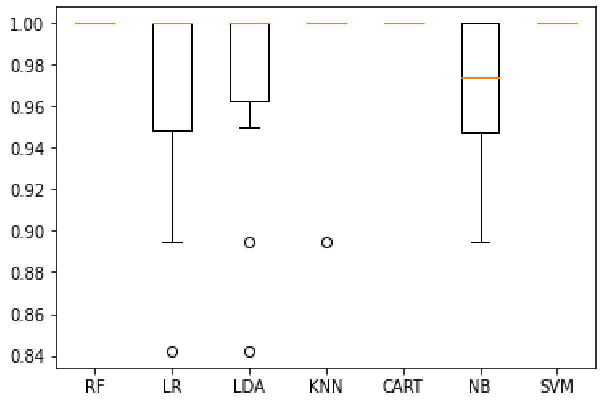

Fig. 7: Machine learning algorithms comparison for mouth

The above fig. 4.7 shows the box and whisker plot of machine learning algorithms used for mouth classification. All the algorithms yielded 100% on mouth classification except for NB which had a 97% result.

	Precision	Recall	F1-score	Support
0	1.00	1.00	1.00	33
1	1.00	1.00	1.00	15
Macro avg	1.00	1.00	1.00	48
Weighted avg	1.00	1.00	1.00	48

Table 4: Mouth Accuracy Rate

From Table 1, the RF and CART classifiers had the highest score of 0.98. K-NN and SVM obtained scores of 0.94 while LDA reached 0.91; LR and Naïve Bayes (NB) obtained 0.89.The model evaluation acquired 100% on Precision, Recall and F1-Score as shown in Tables 2 and 4 above. System experimentation was performed after connecting all system components to an Arduino UNO microcontroller. The mechanism includes a laptop with speakers and a web camera. The output of the system tests is shown in the figs. below.

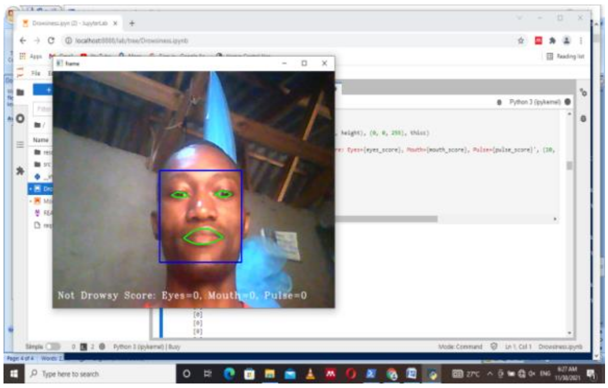

Fig. 8: Normal state

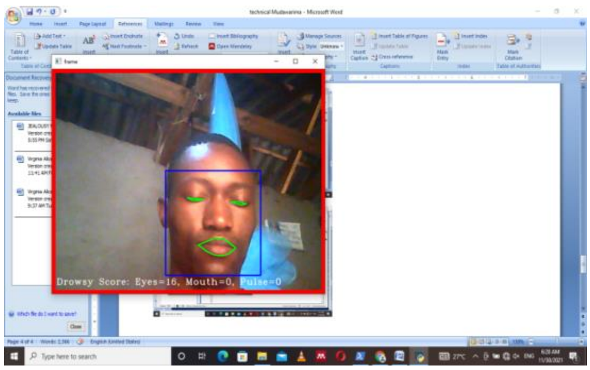

Fig. 9: Drowsy state, eyes closed

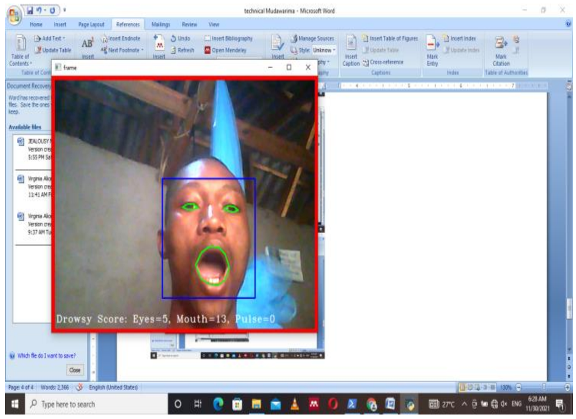

Fig. 10: Drowsy state, yawning

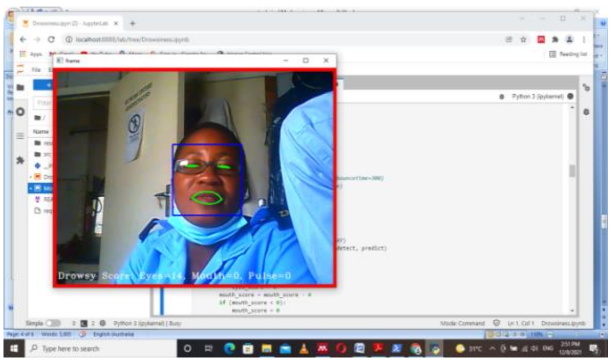

Fig. 11: Eyes closed detected with glasses

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Different participants were used in the experimentation process; Fig. 8 highlighted a normal driver without any drowsiness. When a driver's eyes closed for a consecutive number of seconds, greater than six, or the mouth yawned for a period greater than six seconds, drowsiness recognition was completed as shown in the corresponding Figs. 9 and 10. The method succeeded in discovering the condition of the eyes of the driver wearing glasses as shown in Fig 11.

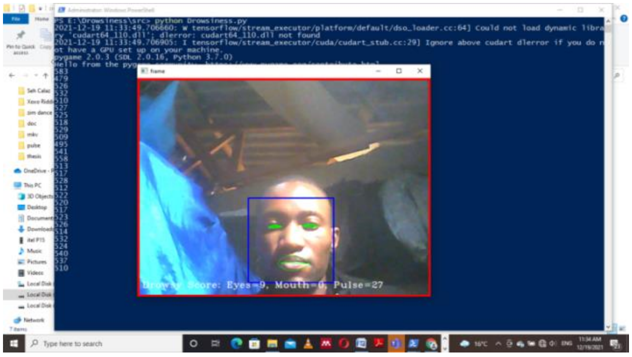

Fig. 1: Pulse rate drowsy detection

The detection was made in real time while checking the camera and pulse sensor of an Arduino microcontroller (UNO). Pin 0 inputted the signal which was printed on IDE port COM5. Python code was used to read the result. The individuals' normal pulse ranged between 45 and 100 BPM and any lower and upper indicated drowsiness. Fig. 12 showed the detected pulse values. This highlighted that a combination of behavioral and physiological approaches helped improve drowsiness detection with high-precision output.

V. CONCLUSION AND FUTURE WORK

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, mouth furthermore pulse rate 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.

The following are considered advantages of the study:

- The accomplishment of the system was less costly and realizable.
- The resources were available from both local and on the internet in terms of coding purposes.
- Participants volunteered to partake in the experimentation process.
- Fair results were obtained as anticipated.

The limitations of the study:

- The small dataset used could not give enough weighty results.
- Only a few people were used on the experimentation part hence cannot offer a concrete conclusion on the causes of drowsiness.
- It was difficult to infuse pulse rate results and behavioural results to give a solid conclusion.

The following can be explored in future studies to deal with drowsiness driving matters:

- To change experimental design setup and gather more details concerning drowsiness driving.
- Make use of other technologies existing which detect alcohol and drug abuse by drivers and alert law enforcers using GSM location.
- If resources permit there is a need to assess the driver behaviour in real-time and record proceedings on score sheets, anonymity must always be considered.
- Inclusion of a variety of drivers from rural and city in the revise.
- A hybrid approach that includes behavioural, vehicle-based and physiological approaches need to be used so that all the performances would give a well predictable outcome in detecting drowsiness.

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