Design of Driver Drowsiness Recognition System Using Correlation Between Principal Components

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***Abstract*: A drowsiness detection system employing correlation between principal component analysis (CPCA) is the subject of this work. This work falls into the supervised machine learning category. This system has three basic steps: it uses CPCA to automatically detect a human drowsiness image, extracts various eye features, and uses Correlation between Principal Components to identify the Least Mean Square Error for eye detection. For effective and reliable drowsiness detection and annotation, the eye features of the drowsiness state image are measured using PCA, and correlation is used to detect it. This work presents a Supervised ML-based method that is significantly faster and can be run on low-computing capable processors. The primary drawback of the previous work was that detection was slow because unsupervised learning required more time on low-computing processors. This work discovered an optimized procedure with higher accuracy and a higher response rate, as well as an efficient throughput and detection rate.**

***Keywords*: Least Mean square Error, Correlation, Principal Component Analysis, Supervised ML, Drowsiness, Signal Noise Ratio**

I. INTRODUCTION

Eye closing, head nodding, or brain activity is real-time drowsiness behaviours that indicate fatigue. As a result, to monitor drowsiness, we can either take into account physical changes such as sagging posture, driver's head leaning, and eyes open or closed, or we can measure changes in physiological signals like brain waves, heart rate, and eye blinking.

[7] employs sequential floating forward selection (SFFS) Drowsiness identification, which is currently the best method for detecting drowsiness; however, it requires a significant amount of computation and also takes a significant amount of time to detect just one eye. eye detection is carried out using a PDF of 8x8 chunks of drowsiness [7], which requires a significant amount of computation. Conventional procedures [6] of drowsiness detection are based on eye blink and EAR based measurement only where no ML was involved, those methods are less accurate to identifies the drowsiness condition because methods used in [6] works same for every test case and there is no adaption of driver behavior. Another issue with the currently available method is that it was designed to detect drowsiness in just one eye at a time, while the currently available method necessitates two separate tests for two different eyes. [5] uses ML and ECG based drowsiness detection However, even when considering these advances, the disparities between naturalistic data and simulator-based acquisitions are still a relevant challenge and causes non-real time detection. As in this application real-time detection is prime requirement and these methods fails to achieve that. One other significant hurdle to the reliability of developed products in real-life conditions is the high variability of behavioural patterns across drivers. [4] Provides a Drowsiness Identification Procedure based on the Deep learning procedure, which is slower than other base works considered in this work, however their method can identify multiple Drowsiness in non-real-time. [3] study aimed to detect both severe and slight drowsiness without personalization. To detect slight drowsiness, they introduced the posture-related index. As posture is maintained by the central nervous system, the effects of drowsiness on the nervous system is expected to appear in postural change. their method can be used as general system, but it needed addition sensors installation in vehicle and improve cost of the system.

[2] uses Convolutional Neural Network Classification and Spatiotemporal Image Encoding of EEG Signals for Cross-Subject Zero Calibration Driver Drowsiness Detection, this method uses Deep learning hence this work will have more accuracy but a complex computer like processing system will be needed at the vehicle to detect drowsiness in real time, another issue is the installation of extra sensors apart from camera for ECG signals reading make this system non-general system. [1] uses hybrid machine learning and modified SVM classifier, [1] has very good accuracy of driver drowsiness detection and needed computer like systems to implement at vehicle which significantly improve the cost of the system.

This work proposed CPCA which is a supervised ML based solution which can be installed in low computational computer like Raspberry-pi and Node-MCU, which reduce the cost of system, Supervised ML needed less computational time hance it can achieve real time requirement of the system. proposes solution is a general system with easy installation and can be implement any existing vehicle, low cost. Accuracy of drowsiness detection is also good in proposed work.

II. METHODOLOGY

In their paper titled "Rapid Object Detection using a Boosted Cascade of Simple Features," Paul Viola and Michael Jones propose an efficient method for object detection called "Drowsiness Detection" that makes use of Haar feature-based cascade classifiers. A cascade function is trained from a lot of positive and negative images in this machine learning-based method. To train the classifier at first, the algorithm needs a lot of positive images—pictures of faces—and negative images—pictures without faces. They

resemble our convolutional kernel in every way. A cascaded Adaboost classifier is a strong classifier made up of several weak classifiers combined into one. The Adaboost algorithm is used to train each weak classifier. The Drowsiness region can be found if a candidate sample goes through the cascaded Adaboost classifier. While non-drowsiness samples can be rejected, almost all drowsiness samples can pass.

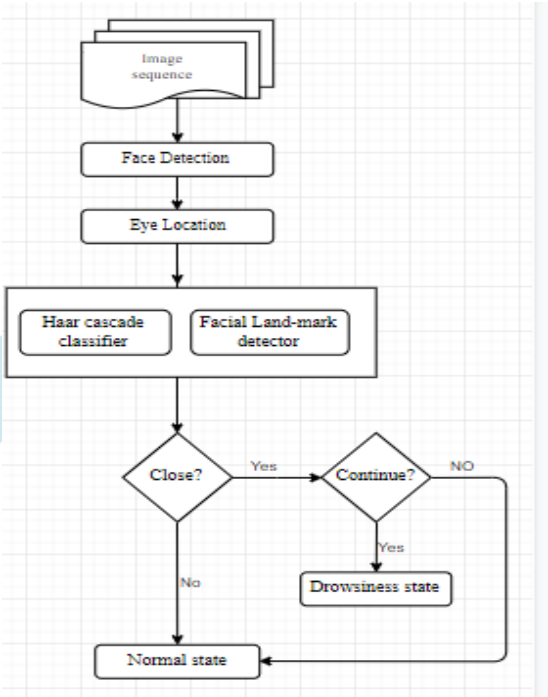

Fig.1: Flowchart of system

Figure 2 shows modeling diagram of proposed work where four stages are shown, once driver start the application system in vehicle, camera starts taking pictures and after each 0.1 sec it capture next image. Next it keeps tracking drowsiness state in captured image using proposed CPCA method, if drowsiness detected than systems generate alert message as well as generate audio signals to keep driver conscious.

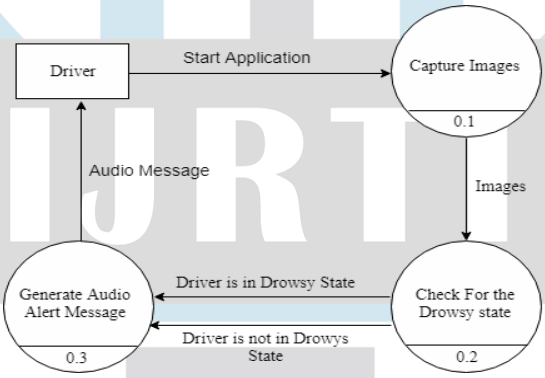

Fig 2 Drowsy state level-I

Figure 3 below shows the modeling diagram level-II, the modeling diagram is explained in table 1 below.

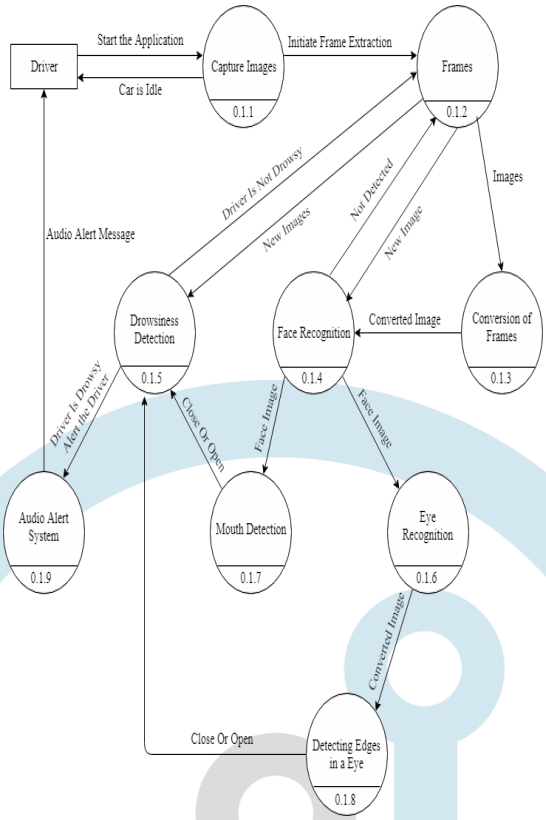

Fig 3 Drowsy state level 2

TABLE 1 STATE DIAGRAM FOR DROWSINESS DETECTION

Current state	**Next state**	**Input conditions to change state**
Driver	Capture Images	Start of application
Capture Images	Driver	Car is Idle
Capture Images	Frames	After every 0.1 sec. when new image captures
Frames	Conversion of frames	when conversion needed
Frames	Face Recognition	when conversion not needed
Frames	Drowsiness Detection	when eyes and mouth is already detected
Conversion of frames	Face Recognition	Modified image
Face Recognition	Eye Recognition	always
Eye Recognition	Eye edge detection	always
Eye edge detction	Drowsiness Detection	open and close detection
Face Recognition	Mouth detection	always
Mouth detection	Drowsiness Detection	open or close
Drowsiness Detection	Frames	when no drowsiness detected
Drowsiness Detection	Audio Alert Systems	when drowsiness detected
Audio Alert Systems	Driver	Audio Alert message

Additionally, the warning will be manually disabled as opposed to automatically. To accomplish this, a de-activation dialogue will be created with a straightforward mathematical operation that, if answered correctly, will remove the warning. Additionally, if the driver appears to be drowsy, they may respond incorrectly to the conversation. Using a time-domain graph, we can assess this. A warning message in the form of text and sound is sent if all three input variables indicate fatigue at once. This will provide an immediate sign of drowsiness or exhaustion, which can be used as a record of the driver's performance.

Concerns regarding the initial CPCA proposal to calculate the Eye aspect ratio (EAR). For each database set, the principal components are calculated, and the CPCA analysis, or correlation of PCA, between the database face and capture drowsiness, is used for detection. The person's name is written in the top left corner of the rectangle that was annotated with the recognized drowsiness highlighted in red.

III. ALGORITHM

Let the captured image is I and its RGB components are R, G and B. Image quality enhancement done by two different stages first HSV stretching and second is Median filtering. MAX is the maximal value in R, G, and B of all pixels in the image, and MIN is the minimal one.

$$H=\begin{cases} \text{Undefine} & \text{if MAX} = \text{Min} \\ 60X\frac{G-B}{MAX-MIN}+0 & \text{if MAX} = \text{R and G} \geq \text{B} \\ 60X\frac{G-B}{MAX-MIN}+360 & \text{if MAX} = \text{R and G} < \text{B} \\ 60X\frac{B-R}{MAX-MIN}+120 & \text{if MAX} = \text{G} \\ 60X\frac{R-G}{MAX-MIN}+240 & \text{if MAX} = \text{B} \end{cases} \quad \dots(1)$$

$$S=\begin{cases} 0 & \text{if MAX} = 0 \\ 1-\frac{MIN}{MAX} & \text{otherwise} \end{cases} \quad \dots.(2)$$

$$V = \{MAX \;..(3)$$

$$I_a = \text{concate}(H, S, V) \dots.(4)$$

Let P is one 3x3 chunk of I_a and operations shown in equations (5) and (6) also consider the operation on Eq. (5 and (6) as $P_{mod} = f(P)$

$$P_{new} = \text{sort}(P) \;..(5)$$

$$P_{2,2} = P_{new_{2,2}} \dots(6)$$

The filtered Image is give by eq (7)

$$I_{mod} = \bigvee_{i=1}^{i=i+3} \bigvee_{j=1}^{j=j+3} f(I) \;\dots(7)$$

The covariance matrix of an image is given by eq (8)

$$\text{CovImg} = I_{mod_{ij}} * I_{mod_{ij}}{}^{T\ 3} \dots.(8)$$

A PCA may be characterized from the data of p variables for n individuals, as indicated in table 1.

By definition, the first principal component is the linear combination of variables

$$X_1, X_2, X_3, \dots.X_N \;\dots.(9)$$

that is,

$$Z_1 = I_{mod_{11}}X_1 + I_{mod_{12}}X_2 + I_{mod_{13}}X_3 + \cdots + I_{mod_{1N}}X_N \;..(10)$$

The second principal component

$$Z_2 = I_{mod_{21}}X_1 + I_{mod_{22}}X_2 + I_{mod_{23}}X_3 + \cdots + I_{mod_{2N}}X_N \;..(11)$$

and so forth. If there are p variables, then there are at most p principal components, always calculated according to expressions similar to expressions (10) or (11).

The results of a PCA, that is, the principal components Z_N are obtained from an analysis that consists in finding the eigenvalues of a sample covariance matrix. The covariance matrix is symmetrical and has the form:

$$C = \begin{bmatrix} C_{11} & C_{12} & .. & C_{1N} \\ C_{21} & C_{22} & .. & C_{2N} \\ .. & .. & .. & .. \\ C_{N1} & C_{N2} & .. & C_{NN} \end{bmatrix} \;..(12)$$

in which the elements C_{ij}, positioned along the primary diagonal, are the variances of $X_i(\mathrm{var}(X_i))$ and the C_{ij}'s of the secondary diagonal represent the covariance between the variables $X_iX_j(\mathrm{var}(X_i, X_j))$.

Eye Aspect Ratio Calculation: For every video frame, the eye landmarks are detected. The eye aspect ratio (EAR) between the height and width of the eye is computed.

$$\mathrm{EAR} = \frac{\|p_2 - p_6\| + \|p_3 - p_5\|}{\|p_1 - p_4\|} \quad \ldots (12)$$

where the two-dimensional landmark locations shown in Fig. 1 are p1..., p6. When an eye is closed, the EAR approaches zero while remaining mostly constant when the eye is open. It is a person and head pose insensitive in part. The open eye's aspect ratio is completely invariant to uniform image scaling and face plane rotation, with only a small variation between individuals. The EAR of both eyes is averaged because eye blinking occurs simultaneously in both eyes.

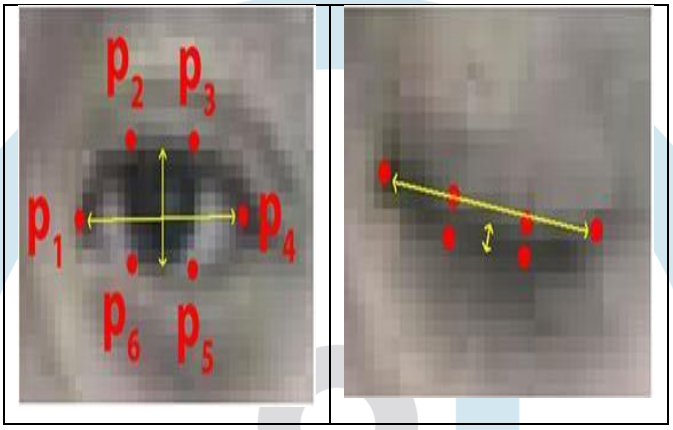

Fig. 4 Open and closed eyes with landmarks p(i) automatically detected.

The eye aspect ratio EAR in Eq. (12) is plotted for several frames of a video sequence.

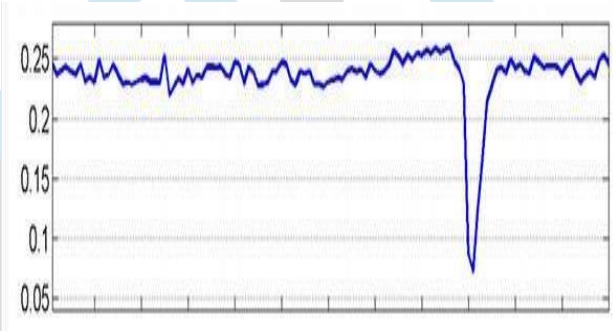

Fig. 5 EAR for a single blink

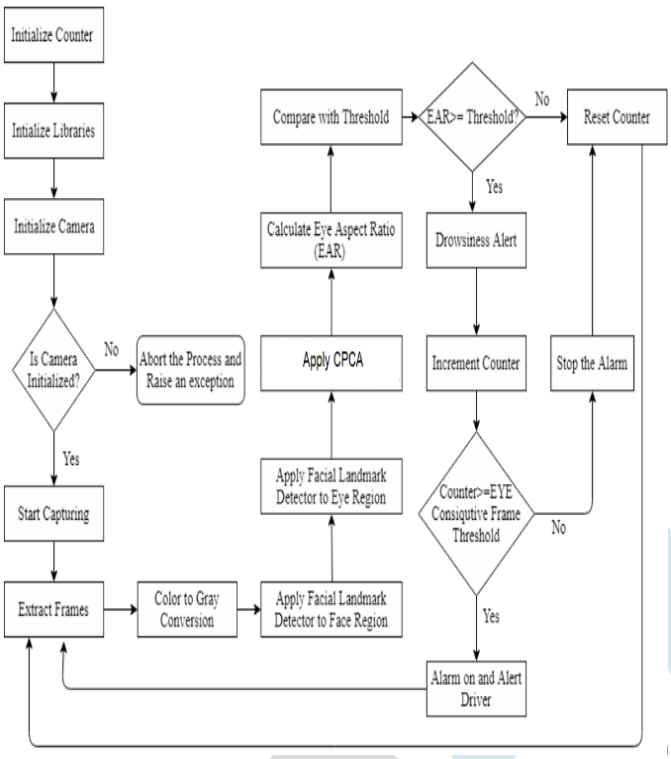

Fig 6 Modeling diagram

Determination of Eye State: The EAR calculated in the previous step is used to determine the eye state. The eye state is categorized as "closed" if the distance is zero or close to zero; otherwise, the eye state is identified as "open."

Detection of Tiredness: The algorithm's final step is to identify the person's condition using a predetermined drowsiness condition. The typical flicker span of an individual is 100-400 milliseconds (for example 0.1-0.4 of a second). Therefore, if a person is sleepy, his eye closure must exceed this time. We decided on a five-second time limit. Drowsiness is detected and an alert pop is triggered if the eyes are closed for more than five seconds.

Figure 6 below is the modelling diagram of the proposed work it shows all the steps according to which the coding is written in MATLAB.

IV. RESULTS

The indexes of the 68 coordinates can be visualized in the image below:

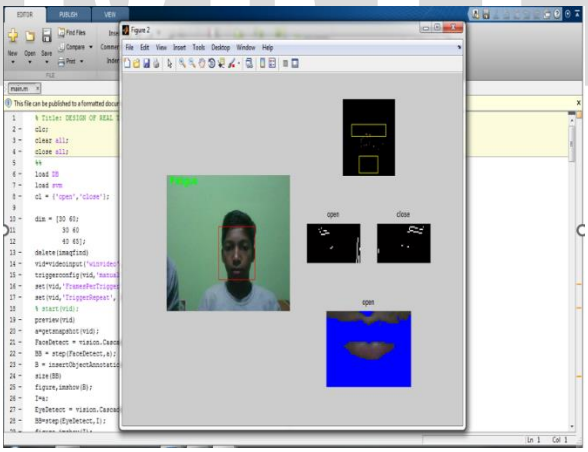

Fig. 7 Detection of both the eyes

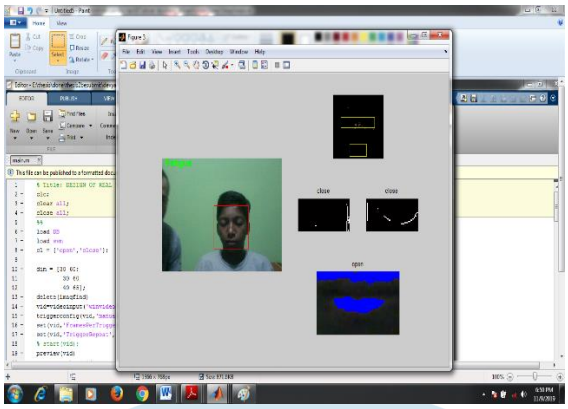

Fig 8 Drowsiness state

The following steps were taken to implement drowsiness detection using MATLAB:

Capturing video with a camera during the runtime successfully.

The video that was captured was broken up into frames, and each frame was looked at. Successfully identifying drowsiness, followed by eye detection.

If successive frames of eye closure are observed, the condition is considered to be drowsy; otherwise, it is considered to be a normal blink, and the loop of capturing images and analyzing the driver's state is repeated. The eye is either not surrounded by a circle or it is not detected during the drowsy state in this implementation, and the appropriate message is displayed.

The observed results for recognizing drowsiness are shown in Table 1, which can be found below. The detection rate that we were able to achieve is 79.93 per cent for recognizing one of the 40 faces that were available for drowsiness, and the detection time that was required for recognizing drowsiness was 10.18 seconds, as shown in Table 4.3. MATLAB was used to develop the results, which were developed for nine distinct Drowsiness database test conditions.

TABLE 1 DROWSINESS DETECTION RATE

No of Input Images/ Eigen Eyes/ Size of database	Drowsiness recognition rate
40	79.93
80	79.50
120	78.87
160	78.52
200	78.40
240	78.33
280	78.07
320	77.91
360	77.78

Table 2: The timing results

No Input Images	Time taken in seconds
40	10.18
80	11.51
120	12.93
160	13.43
200	13.89
240	14.28
280	15.03
320	15.82
360	16.11

Table 3 below shows the comparative results of the proposed CPCA method with available methods [1], [2] & [3].

TABLE 3 COMPARATIVE RESULTS

Work	Work	Accuracy	Delay
[1]	Use hybrid Neural network and modified SVM classifier.	83.25%	
[2]	Use CNN on ECG signals to detect drowsiness.	75.87 %	12.82 sec
[3]	posture index detection based on supervised ML and estimate drowsiness based on that.	61.8 %	-
[4]	A new deep learning framework based on the hybrid of 3D conditional generative adversarial network and two-level attention bidirectional long short-term memory network (3DcGAN- LABiLSTM) has been proposed for robust driver drowsiness recognition.	82.8 %	-
This work	Cross-Correlation on PCA (CPCA) for fast eye detection then matching using mean error detection.	81.3 %	12.18 sec

From table 3 above it can be observe that propose work drowsiness detection accuracy is higher than base work [2] and [3], however this work accuracy is less in compare with base work [1] and [4]. Proposed work is using supervised ML and it can be used in small embedded systems with real time detection, but in [1] and [4] was based on deep learning based neural network which itself needed high end computer for real time operations. Table 3 also show the time delay comparison here it can be seen that this work needed less time than base work [2].

V. CONCLUSION

An algorithm for detecting eye blinks in real time was presented. We quantitatively demonstrated that regression-based facial landmark detectors and Haar feature-based cascade classifiers are accurate enough to accurately estimate the level of openness and positive images of drowsiness. Nonetheless, they are resistant to low image quality—particularly low resolution—and the wild. Since drowsiness detection is a method for determining whether or not a person is drowsy based on an image, real-time video, or other data, Numerous methods for detecting drowsiness have been developed in this field. The proposed CPCA work is a novel concept for multiple drowsiness detection. It employs a mathematical method for locating approximations, which we have used to identify drowsiness parameters (features). The new base thesis work's proposed CPCA procedure is a combination of correlation and PCA. As we know, correlation is used to compare signals. The proposed CPCA procedure uses correlation to compare eye variance. Finally, we can say that the proposed CPCA work on drowsiness detection was carried out as planned, at a high detection rate and speed, and that the drowsiness annotation was completed.

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