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REAL-TIME DYNAMIC DROWSINESS DETECTION USING CONVOLUTIONAL NEURAL NETWORKS

Rohan Khandare[1], Gurpreet Kukkar[2], Mushahid Ali[3]

Department of Computer Engineering, Dr. D. Y. Patil Institute of Technology, Pimpri, Pune, India[1,2,3]

Abstract: Driver fatigue and reckless driving are major contributors to road accidents, resulting in the loss of precious lives and compromising road traffic safety. Effective and precise solutions to detect driver drowsiness are crucial in preventing accidents and enhancing road safety. Numerous driver drowsiness detection systems have been developed using diverse technologies, each focused on detecting specific parameters related to the driver's tiredness.This research proposes a novel multi-level distribution model for detecting driver drowsiness, employing Convolutional Neural Networks (CNN) technology. The model utilizes a 2D Convolutional Neural Network to analyze the driver's facial patterns, capturing their behavior and emotions accurately. OpenCV is employed to build the suggested model, and the experimental results demonstrate its superior efficiency in recognizing the driver's emotions and level of tiredness compared to existing technologies.

Keywords: ReLu, Voila Jones Algorithm, Support Vector Machine, Convolution Neural Network, Haar Cascade, OpenCV, Keras, TensorFlow

I. INTRODUCTION

There has been a notable increase in the frequency of business accidents in India, often involving buses and large vehicles like motorcars, trucks, and exchanges. The leading causes of these mishaps are dozing off and exhaustion. Driving under such conditions poses serious dangers, as it impairs the driver's judgment and attention. To prevent falling asleep at the wheel, drivers can take precautions like ensuring they get adequate sleep before driving, consuming coffee, or taking breaks when feeling fatigued. However, it has been observed that when drivers feel tired, they often neglect to adopt these safety measures and continue driving. Hence, the ability to recognize drowsiness becomes crucial as a means of reducing traffic accidents. Yawning and reduced alertness are prominent indicators of exhaustion and drowsiness. Factors such as insufficient sleep, prolonged uninterrupted driving, or medical conditions like brain diseases can lead to a decline in the driver's attention level. Several studies on road accidents have revealed that fatigue contributes to approximately 30% of accidents. Extended driving durations lead to excessive weariness and mental strain, which can result in drowsiness or impaired cognitive functioning in drivers. Addressing these issues through effective drowsiness detection systems becomes paramount in enhancing road safety and preventing accidents.

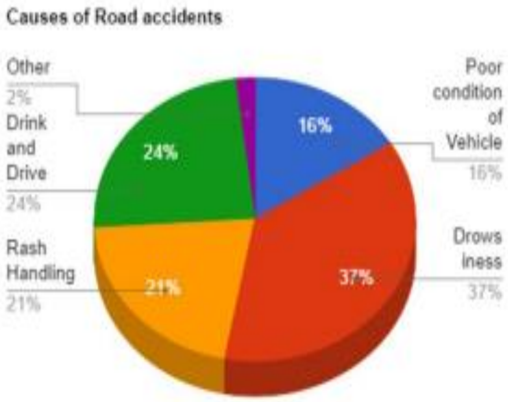

Fig 1. Causes of Road Accidents

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Drowsiness is a complex phenomenon that signifies a decline in the driver's alertness and cognitive state. While there is no direct method to detect fatigue, various indirect approaches can be employed. The integration of technology in all aspects of road safety is of utmost importance. A systematic approach is necessary, emphasizing innovation in automotive components, vehicle safety, and road engineering. Leveraging technologies such as vehicle data management, connectivity, driving apps, and dark spot identifications will play a significant role in enhancing road safety. These measures collectively contribute to an improved road safety framework that addresses the critical issue of driver drowsiness and its impact on accidents.

II. DESIGN OF PROPOSED SYSTEM:

Step 1 - Capture an image from a camera as the input.
To obtain input from the camera, we implemented an infinite loop that captures photographs at regular intervals. The camera access is facilitated by using the OpenCV function cv2.VideoCapture(0) to set up the capture object (cap). Within the loop, each frame is retrieved using cap.read() and stored in a variable called frame for further processing.

Step 2: Detect the presence of a face in the image and outline a Region of Interest (ROI) around it.
To find the face in the image, we must first convert it to grayscale because the OpenCV method for object identification only accepts grayscale images as input. Colour information is not required to detect the items. To detect faces, we will employ the haar cascade classifier. This line instructs our classifier to use face = cv2.CascadeClassifier('path to our haar cascade xml file'). The detection is then done using faces = face.detectMultiScale(gray). It produces an array of detections with x,y coordinates and height, which is the width of the object's border box. We can now iterate through the faces, drawing boundary boxes for each one.for (x,y,w,h) in faces:
cv2.rectangle(frame, (x,y), (x+w, y+h), (100,100,100), 1)

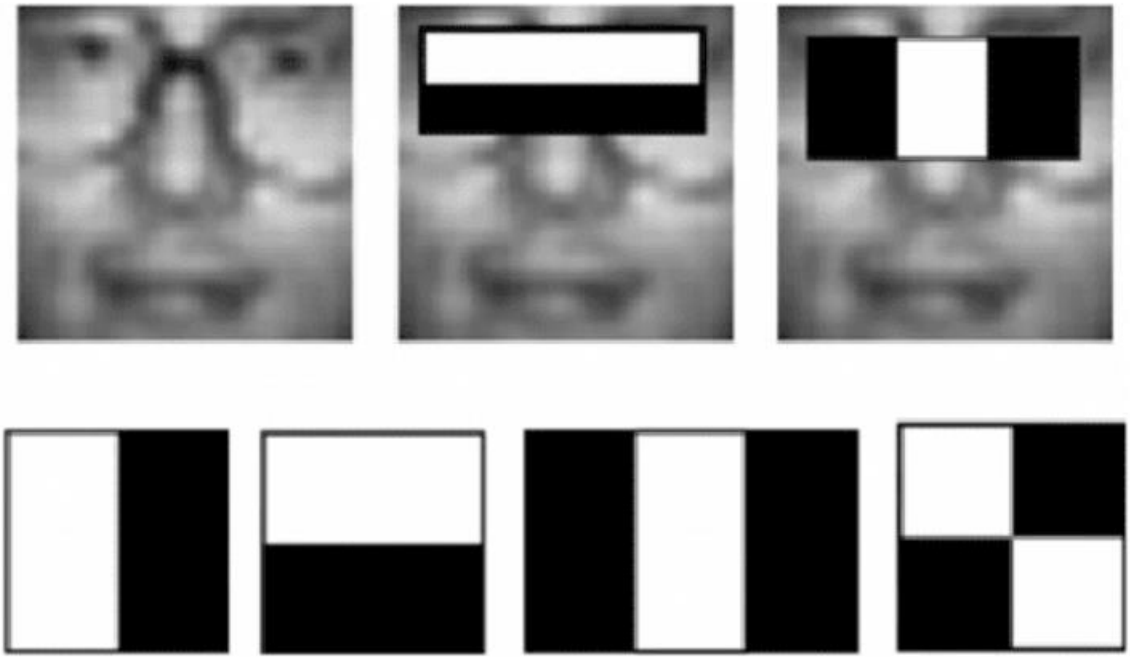

Fig 2. Region of Interest

Step 3: Retrieve the eyeballs from the Region of Interest (ROI) and feed them as input to the classifier.
The same face detection method is applied to detect eyes in the image. We configure the cascade classifier for eyes, namely leye and reye, and then proceed to detect the eyes using left_eye = leye.detectMultiScale(gray). Subsequently, we extract only the eye data from the entire image by capturing the eye's bounding box and using the code l_eye = frame [y : y+h, x : x+w].

The variable l_eye holds the extracted eye image data. This eye data will then be fed into our CNN classifier to predict whether the eyes are open or closed. Similarly, the right eye is extracted and stored in r_eye.

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Step 4: The classifier will ascertain whether the eyes are in an open or closed state.
The CNN classifier is employed to predict the state of the eyes. Before inputting the image into the model, certain operations are performed to ensure that it conforms to the required dimensions. Initially, the color picture is converted to grayscale using r_eye = cv2.cvtColor(r_eye, cv2.COLOR_BGR2GRAY). The image is then resized to 24*24 pixels as the model was trained on images of this size, achieved through cv2.resize(r_eye, (24,24)). To enhance convergence, data normalization is carried out by dividing r_eye by 255, making all values range from 0 to 1 (r_eye/255 = r_eye).
The classifier is fed with the preprocessed eye images. The model is loaded using Model = load_model('models/cnnCat1.h5'). Subsequently, the model is used to predict each eye's state with lpred = model.predict_classes(l_eye). If the value of lpred[0] is 1, the eyes are classified as open; conversely, if the value of lpred[0] is 0, the eyes are identified as closed.

Step 5 - Assess the drowsiness level of the person by computing a score.
The score represents a numerical value that tracks the duration the individual's eyes remain closed. When both eyes are closed, the score increases, and when both eyes are open, the score decreases. The outcome is displayed on the screen using the cv2.putText() method, providing an indication of the person's current state, such as "Open".
A threshold value is set, for instance, if the score surpasses 15, it indicates that the person's eyelids have been closed for an extended period. When this occurs, an alarm is triggered using sound to alert the person, accomplished through the play() function.

III. ALGORITHM

Our drowsiness detection system relies on closed eyes as the primary indicator. Initially, we employ the Viola-Jones face detection algorithm to detect and locate the face in the image. Subsequently, the Viola-Jones eye detection algorithm is applied to the identified face region to extract the eye regions. These extracted eye regions serve as input to our Convolutional Neural Network (CNN).

To capture intricate features, our CNN comprises four convolutional layers. These convolutional layers help extract deep features from the eye images. The extracted features are then passed through a fully connected layer for further processing and analysis. By combining the Viola-Jones face and eye detection algorithms with the powerful CNN architecture, our drowsiness detection system demonstrates effective performance in recognizing closed eyes and identifying potential drowsiness in individuals.

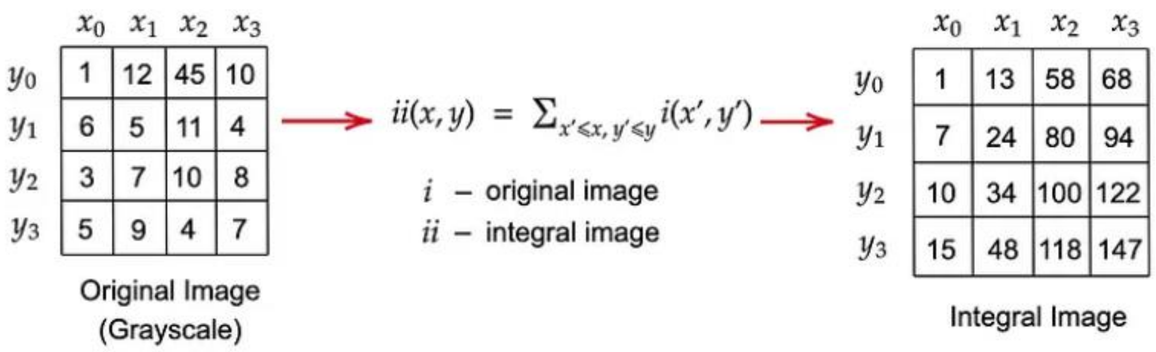

Fig 3. Convolution Layer

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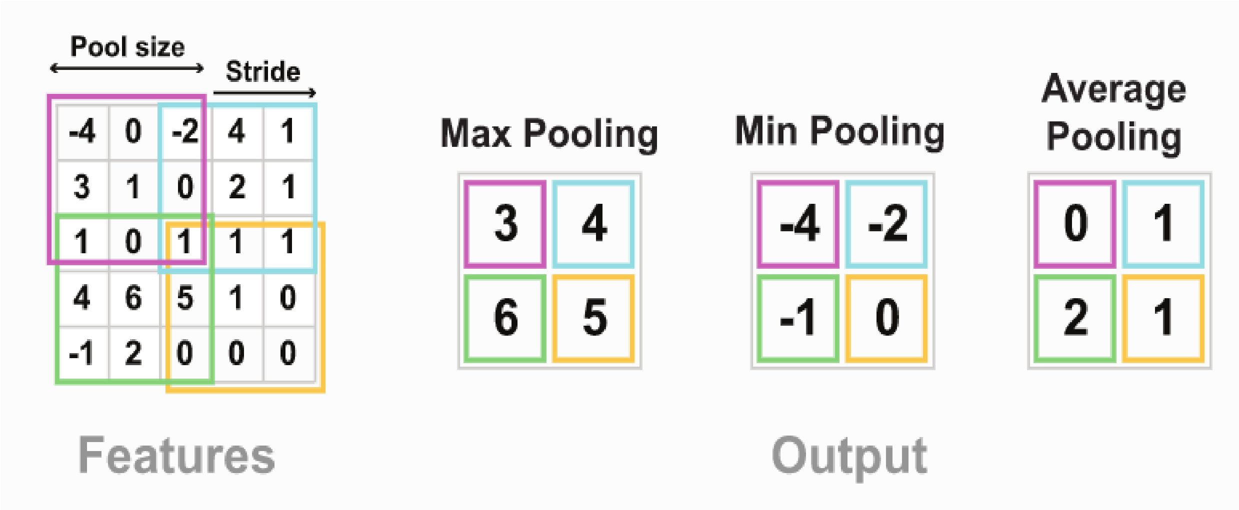

Fig 4. Pooling Layer

The Softmax layer of the CNN classifies the images into two categories: sleepy and non-sleepy.

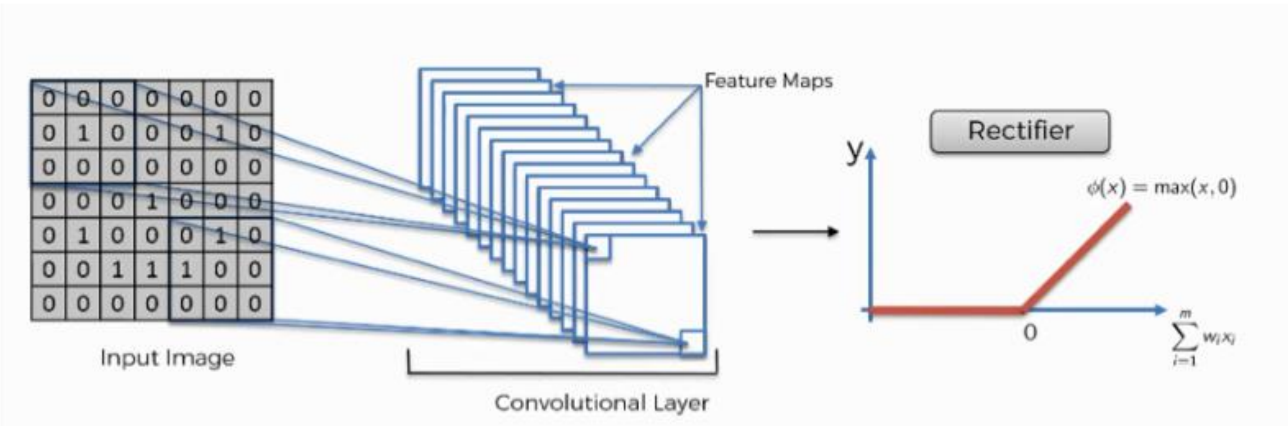

Fig 5. ReLu

IV. ARCHITECTURE

To identify tiredness, only the eyes region is necessary, and the entire facial region may not be required. The initial step involves detecting the face in the photos using the Viola-Jones face detection technique. Subsequently, the Viola-Jones eye detection algorithm is applied to extract the eye region from the facial images after the face has been identified.

The Viola-Jones object detection algorithm, introduced in 2001 by P. Viola and M. Jones, is employed for face detection. This algorithm utilizes three methods: Haar-like features, AdaBoost, and the Cascade classifier, to efficiently detect faces. In this research, the Haar cascade classifier implementation of the Viola-Jones technique was adopted, utilizing Python's OpenCV library.

The Haar cascade classifier utilizes Haar features to identify faces in the photos, providing an effective method for face detection in the system.

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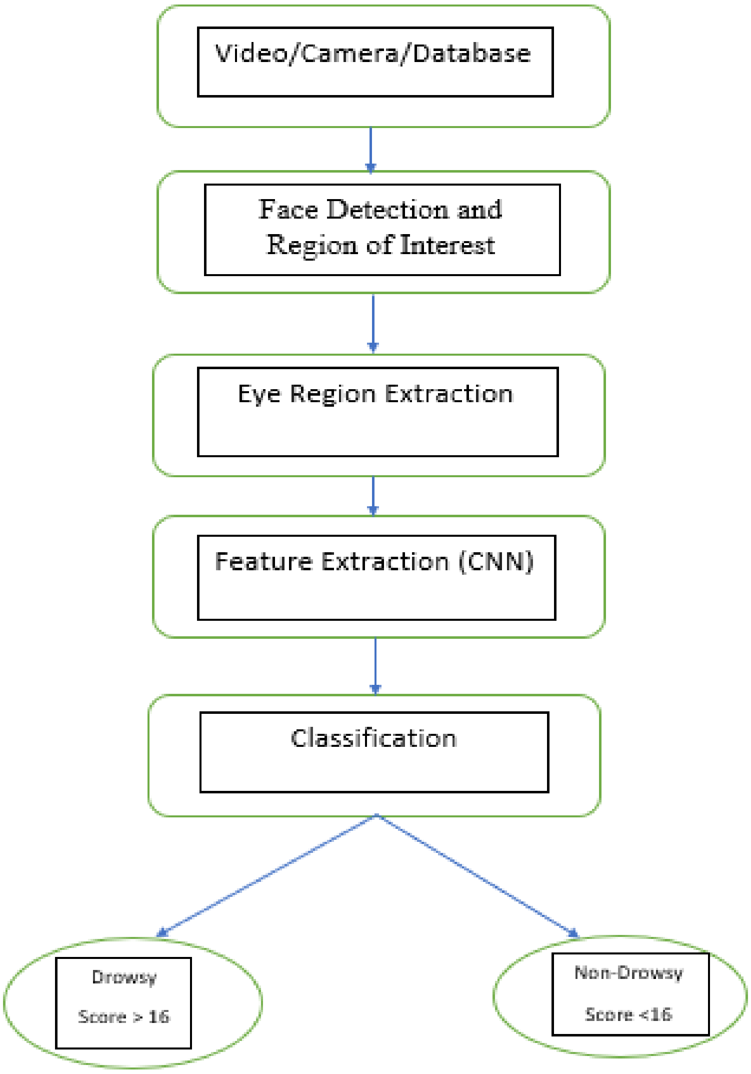

Fig 6. Architecture of the Detection System

We curated the dataset used in this model by developing a script that captures eyeball images from a camera and saves them locally, labeling them as 'Open' or 'Closed'. Subsequently, we manually cleaned the dataset by removing any irrelevant images to ensure its quality. The dataset consists of approximately 7000 photos of people's eyes, taken in various lighting conditions.

For constructing the model, we utilized Keras and Convolutional Neural Networks (CNNs). CNNs are a type of deep neural network particularly effective in image categorization tasks. The CNN architecture comprises three essential layers: the input layer, the output layer, and a hidden layer with multiple layers.

The core operation in a CNN is convolution, where a filter performs 2D matrix multiplication on the layer and the filter itself. This process enables the model to effectively learn and extract meaningful features from the eye images, ultimately enhancing its accuracy in determining whether the eyes are open or closed.

V. FACE DETECTION OUTPUT

Upon selecting the monitoring option from the provided GUI, the face recognition process initiates promptly, capturing multiple frames per minute.

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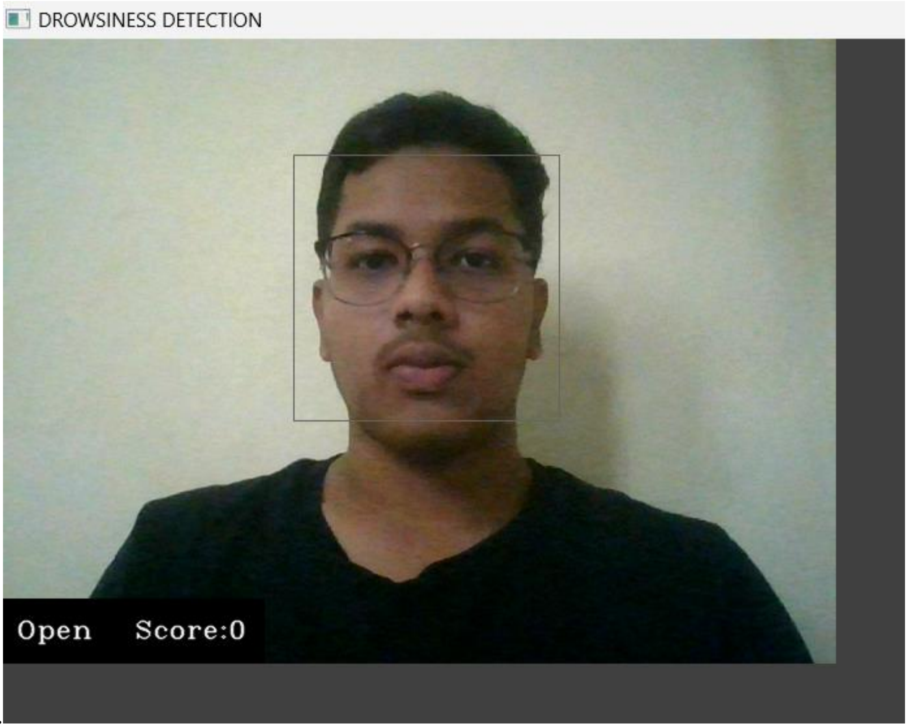

Fig no.7: Output of normal face detection

Drowsiness detection:
Upon closing eyes our drowsiness system gives an alert to the driver and hence the window shows the alert message on the display.

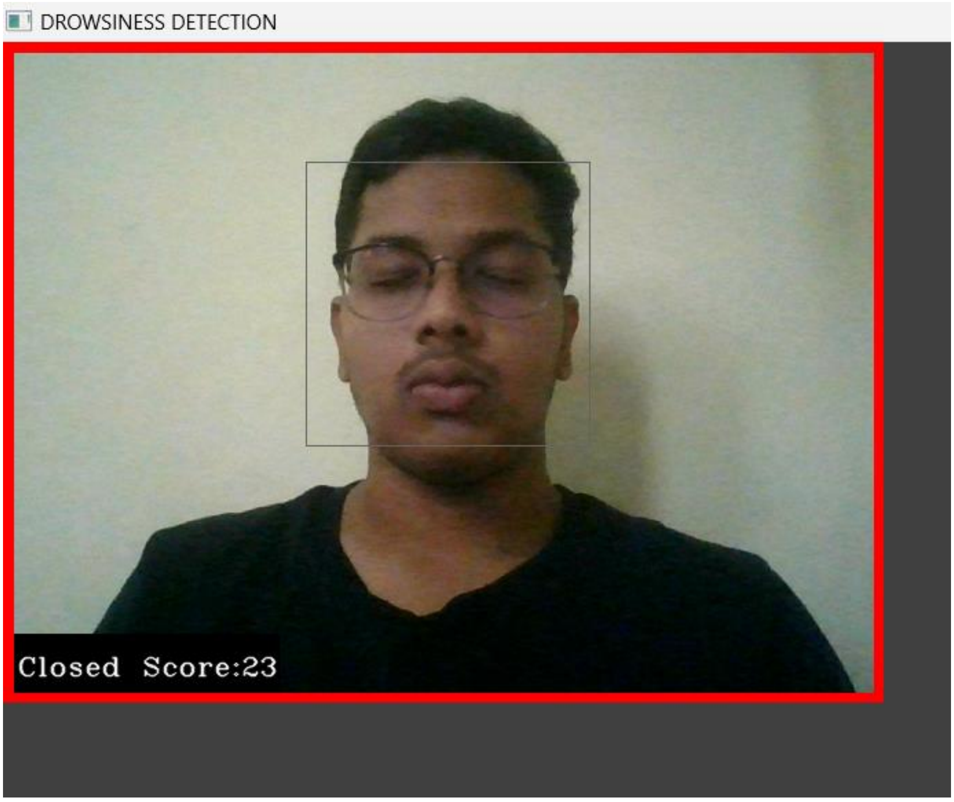

Fig no.8: Output of drowsiness alert by calculating EAR

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In real-life scenarios, illumination conditions vary throughout the day, leading to changes in luminance. Therefore, the model needs to be capable of detecting faces under diverse lighting conditions. To account for this variability, we have taken into consideration three fundamental conditions that can impact the face recognition performance of the model. These conditions are as follows :-

1. Normal front light
2. Side light; slightly dark
3. Backlight

The analysis of these conditions is given in the following table.

SR. No.	Condition	Input	Output	Accuracy
1	Normal Front Light	60	60	100%
2	Side Light	60	57	95%
3	Backlight	60	56	93%

VI. CONCLUSION

This paper explores various approaches for drowsiness detection, proposing an innovative technique centered on eye condition assessment. The system determines whether the eye is alert or drowsy, sounding an alarm when drowsiness is detected. The Viola-Jones detection technique is utilized to identify facial and ocular regions. Stacked deep convolutional neural networks are employed for feature extraction during the learning phase.

The CNN classifier utilizes a SoftMax layer to categorize the driver's state as awake or asleep. The primary objective is to develop a lightweight system suitable for embedded systems, delivering reliable performance. The system successfully identifies drowsy driving behavior by detecting facial landmarks in images captured using a device and feeding this data to a trained CNN-based Deep Learning model.

This system can be seamlessly integrated into dashboards of next-generation vehicles, supporting advanced driving assistance technologies and providing interventions when drivers show signs of fatigue. Upon consistent prediction of drowsiness, the proposed system efficiently detects driver alertness and issues timely warnings. Future work will explore transfer learning to further enhance system performance. Although the current technology already performs well in low illumination, there remains potential for improvement in facial feature detection under challenging lighting conditions.

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