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# Improved Driver Fatigue Detection using Blinking and Yawning Rate

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**ABSTRACT**: Fatigue-induced driving is a prevalent cause of road accidents. Hence, multiple authors have proposed various methods to detect driver drowsiness at an early stage to prevent such occurrences. This scholarly piece introduces an efficient approach to detect exhaustion by examining the blinking and yawning rate of driver. The partitioning process generates a representation, which assists in identifying the pupil and mouth. To ensure greater accuracy and applicability in determining eye openness, a composite network comprising a classification network and an evaluation network is developed. The partitioning network employs a lightweight Linknet architecture to categorize pixels in eye and mouth images, which enables the accurate extraction of the pupil and mouth. The decision network utilizes the representation extracted to assess the extent of eye and mouth openness. Finally, the model is tested on a larger dataset, and it achieves state-of-the-art accuracy of 92%.

**KEYWORDS:** LinkNet, fatigue detection, facial features, PERCLOS(percentage of eyelid closure ),EOR(Eye opening ratio), MOR(mouth opening ratio)

## I. INTRODUCTION

Extended periods of driving can result in driver fatigue, leading to drowsiness and an elevated risk of traffic accidents. Studies have demonstrated that the probability of a traffic collision due to a driver's exhaustion is roughly 4 to 6 times higher compared to a well-rested driver[1]. Driver weariness is accountable for nearly 20% of all annual traffic accidents, contributing to over 40% of severe incidents[2]. Thus, an immediate and precise approach is required to determine the driver's level of fatigue. An accurate technique for detecting driver fatigue could assist in reducing road accidents by 90% [3]. Therefore, an urgent need exists for a methodology that can accurately identify the driver's weariness status.

Currently, there exist three types of methods for detecting fatigue: Firstly, a physiological signal, such as electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), or electrocardiogram (ECG), is utilized to measure the level of exhaustion [4], [5]. Secondly, a system that depends on factors such as steering wheel movement, lane position, acceleration, and proximity to other vehicles is employed. However, this type of system has limitations, as it is restricted by factors like roads, states, driving locations, and vehicles used[6], [7]. Thirdly, driver fatigue detection is based on the facial characteristics of the driver. This method involves monitoring facial expressions, as the frequency of yawning and blinking increases when the driver is sleepy[8], [9]. This approach is divided into two directions: the first direction uses conventional image processing techniques to evaluate an image, primarily utilizing AdaBoost, ASM local locating, and skin feature localization to detect a human face. Subsequently, tiredness characteristics are obtained using a straightforward image processing technique. The support vector machine and the PERCLOS fatigue criterion [10], which is a reliable marker for drowsiness detection, are then used to determine the fatigue state based on the characteristics of exhaustion. The second direction employs deep neural network (DNN) image processing techniques[11],[12],[13].

Using the conventional approach, the convolutional neural network (CNN) receives the eye and mouth images directly and computes the eye and mouth condition (shown in Fig. 1). Additionally, the deep learning network models are engineered to ensure that the network's predictive performance is adequate.

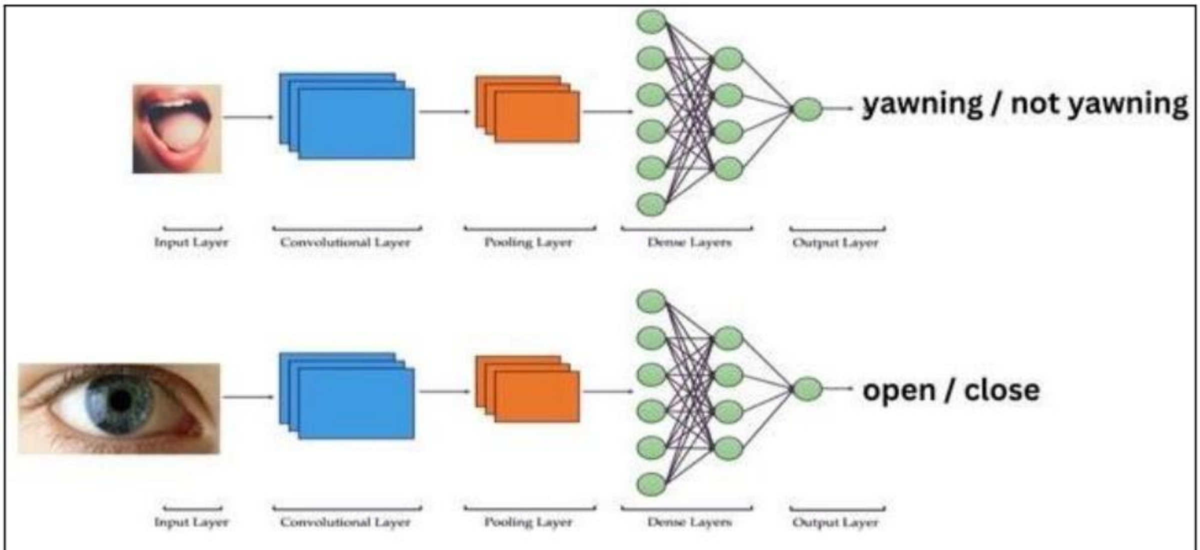


Fig 1 : Sate of eye and mouth using Convolutional Neural Network

Nevertheless, it is crucial to avoid excessively deep models as they could jeopardize the prediction time. To overcome this issue, we propose a partition-based model that uses both the important indicators of fatigue, which are yawning and blinking, because a slow blinking rate cannot always be an accurate measure of fatigue. This model splits into two networks; the first detects and segregates the eye and mouth, while the second one calculates the extent of eye and mouth opening.

## II. Related Works

Tian and Qin [14] developed a system for detecting driver fatigue based on the analysis of the driver's eye states. Their system uses the Cb and Cr components of the YCbCr colour space. The YCbCr color space is a widely used color model in digital image processing, which separates color information into luminance (Y) and chrominance (Cb and Cr) components.

Malla et al. [15] developed a system for detecting driver fatigue using facial recognition that is not sensitive to changes in lighting conditions. To achieve this, they used the Haar algorithm to detect objects and the face classifier implemented by[16] in OpenCV libraries. The system works by first deriving the eye regions from the facial region using anthropometric factors. Then, the system detects the eyelids to measure the level of eye closure. By analysing changes in the level of eye closure, the system can detect when the driver is becoming drowsy or fatigued. The Haar algorithm is a popular object detection algorithm that uses features known as Haar-like features to identify objects in an image.

Bhowmick and Kumar [17] developed a system for detecting driver fatigue using facial recognition. They used the Otsu thresholding [18] to extract the face region from an image. The Otsu thresholding algorithm is a popular method for image segmentation, which automatically determines the optimal threshold value to separate foreground objects from the background. Once the face region is extracted, the system localizes the eyes by locating facial landmarks such as the eyebrows and possible face centre. This is done using facial recognition techniques and machine learning algorithms.

Hong et al. [19] developed a system for detecting the driver's eye states in real-time to identify the drowsiness state of the driver. The system uses the optimized Jones and Viola method to detect the face region in an image. The Jones and Viola method is a popular method for detecting faces in an image using Haar-like features and a machine learning algorithm. Once the face region is detected, the system obtains the eye area using a horizontal projection. The horizontal projection is a mathematical operation that

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computes the sum of pixel values along the horizontal axis of an image. This provides a simple and efficient way to locate the eyes in the image. Also, the use of IR spectrum-based techniques for eye detection is a fast and reasonably precise approach to imaging. These techniques rely on the physiological and optical characteristics of the eye in the IR spectrum.

Zhu et al. [20] used an imaging technique in the infrared (IR) spectrum for eye detection. This technique involves capturing images of the driver's face using IR cameras, which can detect the heat emitted by the eyes. The initial eye detection was done using this technique. Later, to improve the accuracy of eye detection, the authors used a machine learning algorithm called Support Vector Machine (SVM).

The approach proposed in [21] for eye detection assumes that the eye is the darkest point in the face. The authors binarized the face image and detected massive contours in the binary image to locate the primary central moment of the two largest contours, which were identified as the eye centre. While this method is simple and computationally efficient, its accuracy may be limited by lighting conditions and other dark areas on the face.

## III. Proposed Works

In our research on fatigue detection, the eye and mouth regions are crucial for analysing the subject's state. We have used the Dlib library to extract the eye and mouth status from the facial images. Dlib provides a set of 68 key marks on the face, which include points for the edges of the eyes, nose, and mouth. By tracking the movements of these key markers, we can determine whether the subject is drowsy or not. In addition, we have also used the opening of the mouth as an indicator of yawning. To obtain more accurate measurements, we have applied a Gaussian threshold to crop the eye and mouth regions from the facial images. Overall, we can develop a more effective method for detecting fatigue in subjects by leveraging information from the eye and mouth regions.

Secondly, we further process the image using segmented eye and mouth separately, passing them to the classification part, which primarily consists of LinkNet, a deep neural network architecture that was specifically designed for efficient semantic segmentation. It is a modified version of U-Net that uses residual connections and batch normalization to achieve high accuracy while maintaining a small number of parameters. As depicted in Figure 2, the LinkNet Architecture's left segment conducts down sampling through the utilization of 2D Convolution, Batch Normalization, Rectified Linear Unit (ReLU), and Maxpooling operations. This section is composed of said operations. The opposing side executes up sampling by incorporating layers from the down sampling side.

The segmentation task is binary, with the foreground being the eye or mouth region, and the background being the rest of the facial image. The input images are pre-processed to ensure that the eye and mouth regions are aligned and centred. We then train two separate LinkNet models, one for the eye region and another for the mouth region. During training, we use a binary cross-entropy loss function to optimize the parameters of the LinkNet models. We also use data augmentation techniques such as random cropping, flipping, and rotation to increase the size of the training set and improve the robustness of the models. To evaluate the performance of our proposed approach, we use a dataset of facial images with ground-truth segmentations of the eye and mouth regions. We report various metrics such as accuracy, precision, recall, and F1-score to measure the performance of our models.

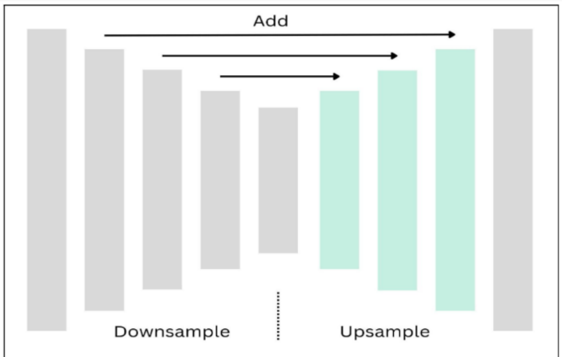

Fig 2: LinkNet Architecture

The outcome of the classification segment is subsequently transmitted to the assessment segment, following a pixel-to-pixel weighing operation with the initial input. The resultant layer is then repeated 4 times wit 16,32,64,128-channel convolutional layer and superimposed onto the classification segment's output to obtain the concluding layer.

The final layers of the eye and mouth expressions are utilized to assess the degree of eye and mouth opening. To accurately anticipate driver performance, PERCLOS has proven to be a reliable and valid gauge of fatigue[22]. This measurement is based on the proportion of time the eyes remain shut over the pupil, with higher values indicating greater levels of sleepiness or exhaustion. The eye-opening ratio is used to calculate PERCLOS, which is the ratio of the maximum height of the eye to its width. A refreshed eye typically has a ratio of around 0.5, whereas a tired eye has a ratio of nearly 0.1.

The formula for calculating PERCLOS is:

**RPERCLOS = [t_closed / (t_open + t_closed)] x 100%**

In the formula, RPERCLOS represents the ratio of open eyes to closed eyes, t_open represents the total in which eyes were open, and t_closed represents the total time in which eyes were closed, within a certain period.

By means of the network that detects facial features and locates feature points, the coordinates of the facial landmarks were acquired. The figures, namely 3(a), 3(b), demonstrate that these landmarks facilitate the computation of the eye aperture ratio (EOR).

## IV. Results

The precision of our model on the bespoke dataset is roughly 92%, an exceptional achievement as illustrated in Figures 4 and 5.

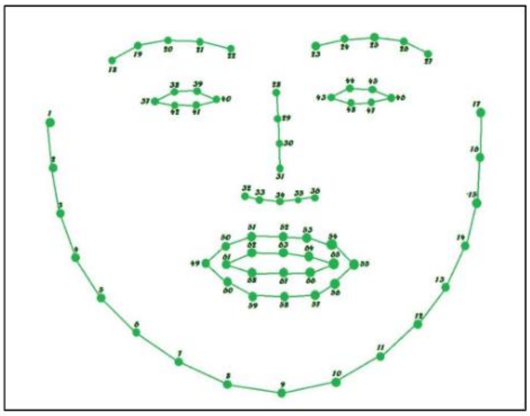

Fig 3(a): 68 face landmarks

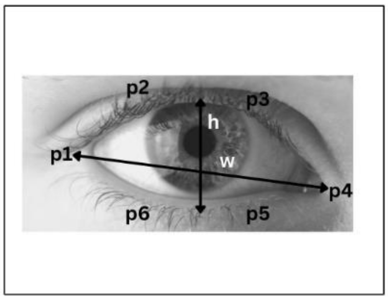


Fig 3(b): Calculation for EOR

**EOR = [ (|p2-p6| + |p3-p5|) / (2*|p1-p4|)]**

Likewise, we shall compute the extent of the mouth aperture(MOR) to identify the occurrence of yawning. The degree of mouth opening can be categorized into three phases: speaking, yawning, and closing. While driving, the driver's mouth would remain closed, whereas, during yawning, the width of the mouth would increase significantly, distinguishing it from speaking. The mouth aperture during yawning would measure approximately twice the size of the mouth, and if this configuration persists for twenty frames, it implies that the driver is yawning. We will utilize this method to monitor the driver's level of alertness and prevent drowsy driving.

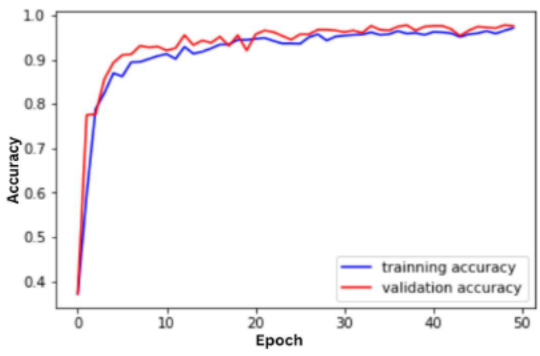


Fig 4: Training and Validation Accuracy

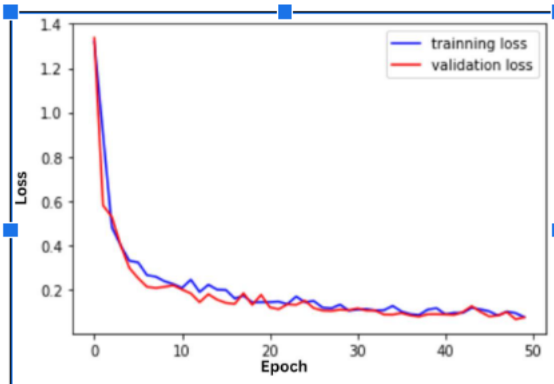


Fig 5: Training and Validation Loss

| | Precision | ReCall | F1Score |
|---|---|---|---|
| Yawn | 0.83 | 0.95 | 63 |
| No Yawn | 0.89 | 0.88 | 74 |
| Closed | 0.99 | 0.94 | 215 |
| Open | 0.96 | 0.97 | 226 |
| Accuracy | | | 578 |
| Macro Average | 0.92 | 0.93 | 578 |
| Weighted Average | 0.95 | 0.94 | 578 |

Table 1: Classification wise Accuracy and Precision

We utilized Dlib, TensorFlow, OpenCV, and Keras to devise algorithms and train our model, incorporating 50 training epochs in the process. Upon completion of training on 5000 images, we assessed our model on 2900 photos extracted from the custom dataset.

## V. Conclusion

This research paper outlines our proposed approach for detecting fatigue, which involves utilizing crucial indicators such as yawning and blinking. To achieve this, we utilize a model consisting of both classification and assessment networks that are fed separate images of the eyes and mouth. We utilize Linknet for the classification network, as it has proven to be exceptionally proficient in semantic segmentation compared to other networks. The aperture of both the eye and mouth regions are then analysed separately to calculate the yawning and blinking rates of the driver. The results obtained from this approach are outstanding, and the method can be applied in real time. Our findings provide a solid foundation for future research aimed at further improving the accuracy of the approach.

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