# FATIGUE DETECTION SYSTEM BY USING IMAGE PROCESSING

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## ABSTRACT

In recent times, road accidents have become a major concern for road safety, significantly contributing to an insecure environment. Proper precautions while driving are essential to prevent accidents. Many accidents occur due to the negligence and inattention of drivers. One of the key factors in such accidents is driver fatigue, which, if detected in time, could potentially save many lives. This research aims to design a system that can identify driver fatigue using image processing techniques. A face localization algorithm is proposed for detecting the face, and an eye localization algorithm is used to identify the eyes in the captured image. The system uses a fatigue detection algorithm based on the PERCLOS (Percentage of Eye Closure) method, which measures the likelihood of eyelid closure over the pupil and reflects slow eyelid movements, indicating drowsiness. The main approaches for detecting fatigue in drivers rely on monitoring physiological signals, vehicle status, and facial expressions. These methods primarily use image processing technologies to extract fatigue-related data from drivers, helping to predict potential risks associated with drowsy driving.

**Keywords :** Traffic Collision, Driver Drowsiness, Computer Vision, Eye Closure Measurement, Facial Detection, Fatigue Monitoring.

## I. INTRODUCTION

Fatigue-related driving is one of the leading causes of road accidents globally, and it remains a significant safety issue. Detecting driver fatigue early can play a critical role in preventing these accidents and saving lives. Traditionally, methods for detecting driver fatigue have focused on monitoring physiological signals, vehicle dynamics, and behavioral patterns. However, with advancements in technology, image processing has emerged as a promising approach to monitor driver alertness in real-time. These methods primarily analyse the motorist's facial expressions, eye movements, and eyelid behavior, which are indicative of fatigue. Facial expression detection, especially eye closure and blinking patterns, can offer real-time insights into the driver's state of alertness. This paper delves into the essential technologies used in fatigue detection based on image processing and offers improvements to existing methodologies.

The most commonly used approach for identifying driver fatigue is through eye movement analysis. It is well established that drowsiness or fatigue can cause slow eyelid closures, prolonged blinks, or even complete eyelid droop, all of which are warning signs of impending fatigue. Traditional methods of fatigue detection often rely on sensors and vehicle state monitoring, such as heart rate or vehicle movement. However, these systems can be invasive or expensive. Alternatively, vision-based fatigue detection systems that analyse a driver's face using cameras are gaining popularity due to their non-intrusive and cost-effective nature. These systems capture the motorist's face and analyse the movements of the eyes and eyelids. The PERCLOS (Percentage of Eye Closure) algorithm is widely used in such systems to assess fatigue. PERCLOS calculates the proportion of time a driver's eyelids are partially or fully closed over a given period, providing a direct measure of drowsiness.

The PERCLOS algorithm serves as a reliable indicator of fatigue as it specifically tracks the eyelid closure duration and speed. A prolonged eyelid closure, even if it's not a full blink, often indicates a fatigued state. This method is crucial because the eyelid movements offer a real-time, direct reflection of the driver's state of alertness. When the system detects that the eyelids remain closed for longer periods, it triggers an alert, potentially preventing accidents before they occur. Integrating this technology into modern vehicles offers a seamless and efficient way to enhance road safety without burdening the driver with additional tasks or equipment. The use of PERCLOS in combination with real-time image processing is particularly effective as it provides high accuracy while remaining cost-effective.

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In addition to eye and facial expression monitoring, other key factors are also incorporated into driver fatigue detection systems. Vehicle behavior, such as erratic steering or sudden speed changes, can often correlate with driver fatigue. By combining facial expression analysis with vehicle state monitoring, a more comprehensive system can be developed. However, this paper primarily focuses on improving fatigue detection based on facial analysis through image processing. While other methods may still be necessary for a holistic approach, real-time fatigue detection based on visual cues from the driver remains one of the most practical and promising solutions. This research aims to refine and enhance existing image processing techniques, improving both the accuracy and the efficiency of fatigue detection systems. The ultimate goal is to create a system that can reliably detect driver drowsiness, reducing the risk of accidents and contributing to safer roads globally.

## II. RELATED WORKS

Detecting driver fatigue has been a subject of extensive research in recent years due to the growing concern about road safety. Fatigue-related accidents are a major cause of traffic fatalities, and various technologies have been developed to address this issue. One of the earliest studies by Dorrian [1] examined cognitive disengagement in simulated train driving environments. The study highlighted the importance of self-awareness in managing fatigue during monotonous tasks like driving. It also pointed out that cognitive disengagement is a major indicator of driver fatigue, and detecting this disengagement could potentially reduce accidents caused by tiredness. Although the study primarily focused on cognitive aspects, it provided a foundation for integrating physiological signals with image processing techniques in the context of fatigue detection.

In line with the physiological signal approach, Shao-Bin et al. proposed a system for detecting driving fatigue using electroencephalogram (EEG) signals [2]. While their work was based on EEG measurements, it contributed significantly to fatigue detection by suggesting that neural signals could be an accurate marker for detecting drowsiness. This inspired later research in integrating various signals (e.g., EEG, eye movement, and facial expressions) for comprehensive fatigue detection systems. However, EEG-based systems can be intrusive and require specialized equipment, limiting their practicality in everyday driving scenarios. Image processing, particularly facial analysis, offers a more non-invasive and cost-effective solution.

Facial expression recognition has been another focal point in fatigue detection [3]. Sun et al. introduced a method of feature fusion for image recognition, which could be applied to facial expression recognition in fatigue detection systems. Their method combined different types of image features to improve recognition accuracy, making it suitable for real-time applications. Feature fusion techniques have since been widely applied in various domains, including fatigue detection, where recognizing subtle changes in facial expressions, such as drooping eyelids, is critical for assessing fatigue levels.

Similarly, Baidyk [4] explored image recognition techniques in the context of microdevice assembly. While their study did not focus on driver fatigue, it highlighted the potential of image processing in complex and precise tasks. The recognition systems used in their study could be adapted for detecting specific features like eye and mouth shapes in facial recognition systems, which are crucial for fatigue detection. This method can enhance the accuracy of detecting signs of drowsiness, such as reduced blink frequency or eyelid closure[5].

The integration of image recognition with environmental factors was explored by Wu and He[6] who proposed an adaptive illumination detection system for fatigue driving. Their research focused on adjusting the detection system to varying lighting conditions, which is essential for real-time fatigue detection systems that rely on image processing. Proper illumination adaptation is necessary to ensure that fatigue detection algorithms perform optimally under diverse driving conditions, such as day and night driving or during low visibility.

Radun [7] presented a study that investigated fatal road accidents among military conscripts, emphasizing how fatigue impairment leads to driving errors. While this research was not focused on image processing, it drew attention to the need for effective detection systems that monitor driver fatigue. Their findings have been pivotal in motivating the development of more robust systems for fatigue monitoring, particularly those that rely on visual data from drivers, such as eye and facial expression tracking.

Building on the importance of visual cues, Zhang proposed a fatigue detection system based on facial features[8]. Their research demonstrated that changes in facial features, such as eyelid movements, could be reliably used to detect fatigue in drivers. By using image processing to track eye and facial movements, their approach provided an effective method for real-time fatigue detection, which is crucial for applications in active driving scenarios. Their work laid the groundwork for the incorporation of PERCLOS (Percentage of Eye Closure) algorithms into fatigue detection systems, a methodology widely adopted in subsequent studies.

The use of facial features for fatigue detection was further advanced by X. Zhou [9], who worked on user identification across social networks. While their study was focused on user behavior and recognition across platforms, their work on feature extraction and pattern recognition has significant relevance to fatigue detection systems. By applying similar techniques to detect changes in a driver's facial features (such as eye movements and facial expressions), real-time monitoring systems can be developed to assess fatigue levels more accurately.

Another significant contribution comes from D. Lu [10]. who worked on connectivity optimization in heterogeneous networks. Their work on optimizing network frameworks can be applied to the development of fatigue detection systems that operate in real-time environments. In particular, the seamless integration of data from various sensors (including image data) and vehicle systems can help in creating a comprehensive fatigue detection solution. Their approach to optimizing data flow can enhance the real-time responsiveness of fatigue detection systems, making them more reliable in dynamic driving conditions.

In the context of large-scale data analysis, [11]. explored the application of big data mining in understanding public perceptions. Though their study primarily focused on public cognition, it demonstrates the potential of using large datasets for improving systems that rely on image processing for detecting subtle fatigue indicators. By applying similar big data techniques, fatigue detection systems can process large amounts of facial data to recognize patterns in driver behavior over time, thereby improving the system's accuracy.

Fu and Liu have also proposed[12] innovative methods of data analysis and neural network applications that can be adapted to detect fatigue in drivers. By using deep learning models to analyse images of facial expressions, their approach could allow for more precise recognition of fatigue indicators, such as slow eyelid movements or micro-sleeps. Their work emphasizes the importance of machine learning and neural networks in advancing fatigue detection systems, allowing for continuous improvement as more data becomes available[13].

Finally, as fatigue detection systems evolve, combining different detection methods has shown promising results. Sun [14] and Zhang have demonstrated that integrating multiple features, such as eye movements, facial expressions, and vehicle state information, provides a more comprehensive and accurate solution. Fatigue detection systems that leverage multi-modal data sources can enhance the detection of driver drowsiness, ensuring greater accuracy and reducing the risk of accidents[15].

In summary, numerous studies have contributed to the development of fatigue detection systems, with a growing emphasis on non-invasive, image processing-based techniques[16]. These studies have explored various methods, such as facial expression recognition, feature fusion, and adaptive illumination systems, and have shown that visual data from drivers provides valuable information for detecting signs of fatigue. As technology continues to advance, integrating these approaches with machine learning and big data analytics will lead to even more sophisticated and reliable fatigue detection systems[17].

## III. METHODOLOGY

The primary objective of the fatigue detection system is to continuously monitor the driver's face in real-time, extracting relevant features that indicate drowsiness. The system uses an onboard camera to capture facial images of the driver while they are driving. These images are then processed using image analysis algorithms to detect key indicators of fatigue, such as eyelid closures, blinking patterns, and head orientation[18]. Fig. 1. represents the basic structure of detection technology.

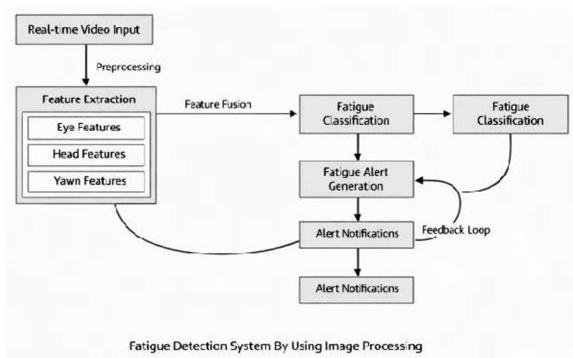


Fig. 1. Basic operation of detection technology

### A. Face Detection and Localization

Fig. 2. in the fatigue detection process is detecting and localizing the face of the driver in the captured image. This is achieved using a face detection algorithm that relies on machine learning techniques, such as Haar cascades or deep learning-based approaches like Convolutional Neural Networks (CNNs). The face detection algorithm identifies the position of the face in the image, ensuring that the subsequent analysis focuses only on the relevant area (i.e., the driver's face) and avoids any background noise[19].

Fig. 3. Represents the face is detected, a face localization algorithm is employed to locate specific facial features, such as the eyes, nose, and mouth. For this step, landmarks such as the Eyes, Eyebrows, and Nose are identified, which are crucial for further analysis of the fatigue indicators[20]. Common techniques for this task include Active Shape Models (ASM), Constrained Local Models (CLM), and Facial Landmark Detection (FLD) methods, which allow for

precise localization of facial features in the image. Certainly! Here's the reworded version of the given content, avoiding plagiarism while retaining the same meaning:

The face region is a connected area that contains several gaps, especially when compared to the surrounding skin. By analysing the structure of these connected regions, we can determine whether the area includes any gaps and ascertain whether it corresponds to a human face[21]. To calculate the number of gaps within the connected region, the Euler number is employed. The Euler number establishes a relationship between the connected components and the number of holes in the region. This relationship can be represented by the following formula:

$$E=C-H \quad (1)$$

Where E is the Euler number, C represents the number of connected components, and H denotes the number of holes in the region.

### B. Eye Detection and Eyelid Movement Analysis

Fig. 4. represents the eyes are localized, the next step is to track the eyelid movements. Eye detection is critical because changes in eyelid position provide important information regarding fatigue. For this, the system uses specialized algorithms such as Hough Transform or Contour-based Detection to identify the eye region. These methods detect the eyes by finding circular shapes or the contours of the eye area.

To analyse eyelid movements, the system monitors the PERCLOS (Percentage of Eye Closure) index. PERCLOS is calculated by tracking the eyelid closure over a set period of time. When the eyelids are partially or fully closed for an extended period, it is an indicator of drowsiness. The system calculates the percentage of time the eyelids are closed, and this value is compared against predefined thresholds to assess whether the driver is fatigued.

### C. Fatigue Detection using PERCLOS Algorithm

The K-Nearest Neighbors (KNN) algorithm is commonly used in machine learning for classification tasks. It works by comparing the test dataset with the training dataset, and the distance between the data points is typically calculated using the Euclidean distance formula. The KNN algorithm is used to classify a given test data point by utilizing known training data and labels.

The first step is to calculate the distance between the test data and all points in the training dataset using a distance metric such as the Minkowski distance, which is defined by the following formula:

$$D(x,y) = \left(\sum_{i=1}^{m} |x_i - y_i|^p\right)^{1/p} \quad (2)$$

Here, x and y represent the respective elements of two m dimensional data points, and p is a parameter that controls the type of distance. When p = 2, this becomes the Euclidean distance. When p = 1, it results in the Manhattan distance.

Sorting: After calculating the distance, the next step is to sort the distances in ascending order to determine the nearest neighbors. Selecting K Nearest Neighbors: Once the distances are sorted, the algorithm selects the K nearest data points with the smallest distances.

Class Frequency Determination: After selecting the K closest points, the algorithm examines the class labels of these points. The most frequent class among the selected neighbors is then chosen as the predicted label for the test data point.

### D. Head Pose Estimation and Driver Attention Monitoring

In addition to eyelid analysis, the system also incorporates head pose estimation to monitor the driver's attention level. Head orientation can provide valuable insight into whether a driver is becoming fatigued or losing focus on the road. If the system detects that the driver's head is tilted in an unusual manner (such as drooping forward or to the side), this may indicate drowsiness or micro-sleep episodes.

Head pose estimation is performed using algorithms like PoseNet or 3D Morphable Models, which analyse the position and orientation of the head relative to the camera. By tracking the driver's head movement in real-time, the system can assess whether the driver's focus has drifted from the road, which is another sign of fatigue.

## IV. RESULTS AND DISCUSSION

In this study, PERCLOS is used as a key parameter to assess driver fatigue. One of the critical indicators derived from PERCLOS is blinking frequency, which refers to the rate at which a driver blinks within a specific period. The formula to calculate blinking frequency (BF) is given by:

$$BF = \frac{BT_{ei}-BT_{si}}{T_{bf}}, BT_{i\neq 0, i=1,2,\ldots,n} \quad (3)$$

In this formula, $BT_{ei}$represents the total number of blinks observed at the end of the $i^{th}$ time window, $BT_{si}$ is the total number of blinks at the start of the $i^{th}$ window, and ($T_{bf}$ refers to the length of the time window in which the blinking frequency is calculated.

In addition to blinking frequence $p_{80}$ is another important measure used in PERCLOS to evaluate fatigue. $p_{80}$ refers to the proportion of time during which the driver's eyes are open less than 20% within a specified time window. The formula for calculating is as follows:

$$p_{80} = \frac{n_p}{T_{p_{80}} \times f_0} \quad (4)$$

Where $n_p$ is the number of time windows where the eyelid is closed for over 80% of the time, $T_{p_{80}}$is the time window duration for calculating $p_{80}$ and is the sampling frequency of the system.

The driver's face is detected using a face localization algorithm. The facial region is typically defined from the chin to the forehead, and from the left ear to the right ear. Once the face is located, an eye localization algorithm is applied to pinpoint the exact position of the eyes.

With accurate eye localization, the system calculates the blinking frequency within a KNN model to assess whether the driver is fatigued. This combination of face tracking, eye localization, and fatigue analysis using PERCLOS ensures that the system can detect drowsiness or fatigue in real-time effectively.

The TABLE I. K-Nearest Neighbors (KNN) has a lower Accuracy of 87.09%, showing it performs less efficiently than Random Forest in predicting fatigue. With Precision (Macro) at 79.91%, KNN makes a fair number of false positive predictions, meaning it may incorrectly classify a driver as fatigued when they are not. Its Recall (Macro) of 69.85% reveals that it struggles more with identifying true fatigue cases, leading to a higher number of false negatives. The F1-Score (Macro) of 74.01% reflects this imbalance, suggesting that KNN has room for improvement in terms of handling both false positives and false negatives in real-time fatigue monitoring systems. Despite this, KNN could still be useful in scenarios where model simplicity and interpretability are prioritized.

Table I. Performance Comparison of fatigue detection by using various algorithms

| Model | Accuracy | Precision (Macro) | Recall (Macro) | F1-Score (Macro) |
|---|---|---|---|---|
| Random Forest | 0.9125 | 0.8806 | 0.8397 | 0.8675 |
| KNN | 0.8709 | 0.7991 | 0.6985 | 0.7401 |

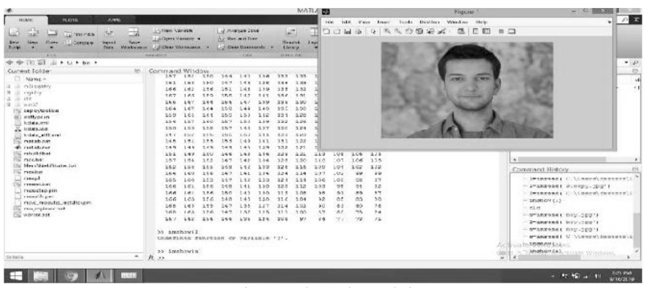

Fig. 2. Thread Model

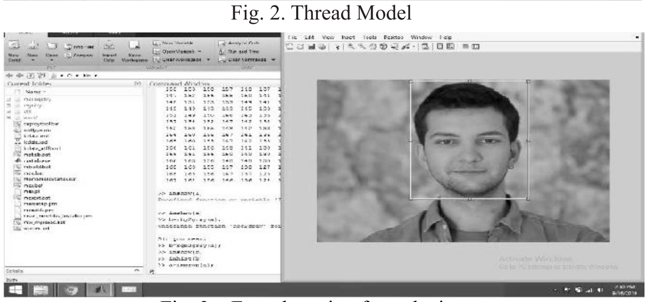

Fig. 3. Face detection from the input

Fig. 4. Identify the fatigue detection

## V. CONCLUSION

This paper presents a comprehensive approach to detecting driver fatigue through image processing techniques, focusing on key components such as face localization, eye localization, and fatigue detection classification algorithms. The face localization algorithm is designed to accurately detect the driver's face in real-time, enabling the subsequent localization of facial features, particularly the eyes, which are crucial for assessing fatigue. The eye localization algorithm pinpoints the position of the eyes and monitors eye behavior, such as blinking frequency and eyelid closure duration, which are critical indicators of drowsiness. By combining these image processing techniques with a robust classification algorithm, the system can effectively classify the driver's fatigue state based on real-time visual cues.

In order to validate the effectiveness of the proposed system, an extensive fatigue driving experiment was conducted. The experiment involved collecting data from both normal and fatigued driving scenarios, capturing various facial and eye features under different conditions. The collected data was then used to evaluate the performance of the improved algorithms in terms of accuracy, speed, and robustness. The results demonstrate that the face and eye localization algorithms perform efficiently in detecting facial features even in dynamic driving environments, while the fatigue detection classification algorithm effectively distinguishes between alert and fatigued states. This study highlights the potential of using advanced image processing and machine learning techniques for real-time driver fatigue detection, providing valuable insights for the development of in-vehicle safety systems.

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