



e-ISSN: 2319-8753 | p-ISSN: 2347-6710

# IJIRSET

International Journal of Innovative Research in  
**SCIENCE | ENGINEERING | TECHNOLOGY**



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

Volume 13, Issue 10, October 2024

**ISSN** INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA

**Impact Factor: 8.524**

9940 572 462

6381 907 438

ijirset@gmail.com

www.ijirset.com

# Driver Drowsiness Detection Leveraging Facial Features and Recurrent Neural Networks with Long Short-Term Memory

Puneetha B H, Kamala R

Assistant Professor, Department of Computer Science & Business systems, Bapuji Institute of Engineering & Technology, Davangere, Karnataka, India

Assistant Professor, Department of Information Science & Engineering, Bapuji Institute of Engineering & Technology, Davangere, Karnataka, India

**ABSTRACT:** Drowsiness is a transitional state between being awake and asleep, during which the ability to observe and analyze the driver's behavior diminishes. Fatigue-related lack of concentration is a significant factor contributing to the high number of road accidents. This study focuses on detecting driver drowsiness by utilizing facial features derived from specific facial points, particularly those associated with the eyes and mouth. Deep neural networks, particularly recurrent neural networks (RNNs) and long short-term memory (LSTM) units, have shown superior performance over many existing algorithms. These models are well-suited for processing sequential multimedia data, and the proposed method achieves an accuracy of 97.25%.

**KEYWORDS:** Computer vision, Deep learning, Driver drowsiness detection, Eye tracking, Face detection, Long short-term memory, Machine learning, Recurrent neural networks

## I. INTRODUCTION

The number of injuries and fatalities from road accidents is increasing each year, with many caused by driver errors such as speeding and drowsiness. Among these, driver drowsiness has become a critical focus for the automotive industry due to its dangerous nature. Detecting drowsiness is a challenge, as it often goes unnoticed, but it is a leading cause of accidents, second only to alcohol consumption. While advanced systems to detect alcohol impairment exist, identifying drowsiness in drivers remains difficult, especially in low to mid-range vehicles. Luxury cars, such as those from Mercedes-Benz and Volvo, feature warning systems that alert drivers at regular intervals. However, the need for a more sophisticated system to detect drowsiness based on facial features and driver behavior is evident, as drowsiness can lead to a significant delay in reaction time, potentially resulting in fatal accidents.

Lack of proper sleep and long journeys are the primary contributors to driver drowsiness. Regular breaks, supported by alarms or sound systems, are one way to mitigate the risk, but it is hard to predict exactly when a driver will become drowsy, as it can occur suddenly. Factors such as fatigue, alcohol use, sleep disorders, and medications can all contribute to this state. Accidents caused by drowsiness are severe, often resulting in significant loss of life and economic damage, particularly during nighttime driving.

Recent studies in the U.S. report that around 37% of drivers admit to falling asleep behind the wheel. In the past few years alone, approximately 1.35 million accidents were attributed to drowsy driving. These accidents tend to be more severe, as drivers struggle to control their vehicles due to delayed reaction times, leading to high mortality and morbidity rates. A survey by the National Sleep Foundation revealed that about 51% of those involved in such accidents were young drivers, with approximately 17% admitting to falling asleep while driving.

Detecting driver drowsiness is a complex task, but it has numerous potential applications. Companies like Volvo and Mercedes-Benz have developed systems, such as Driver Alert Control (DAC) and Attention Assist System (AAS), which monitor driving patterns and issue warnings when irregularities are detected. Bosch has also developed a system that uses sensors, signals, cameras, and velocity data to assess the driver's condition. However, these technologies are

typically found in luxury vehicles and are not accessible to the general public. Given the widespread use of lower-cost vehicles, there is an urgent need for a more affordable, efficient system.

In this work, we aim to address this gap by developing a cost-effective solution using machine learning techniques. A camera is used to monitor the driver's eyes, a critical indicator of drowsiness. The remainder of the paper is structured as follows: Section II reviews existing research on driver drowsiness detection; Section III details the proposed methodology, including features and classifiers; Section IV presents the results; and Section V concludes with future research directions.



**Figure 1:** A speedometer from high-end cars illustrating how the alert message is displayed at regular intervals.

## II. RELATED WORK

Research on detecting driver drowsiness began a few decades ago, driven by the urgent need to reduce the number of accidents caused by fatigue behind the wheel. Various approaches have been developed, which can be grouped into three main categories: (i) analyzing driving patterns, (ii) using physiological sensors, and (iii) employing computer vision and machine learning techniques.

### A. Driver's Driving Patterns

This approach focuses on analyzing the driver's driving behavior, specifically abrupt lane departures. The steering movements and deviations between the current and previous lane positions are calculated to identify signs of drowsiness. Some advanced systems automatically adjust the steering if the vehicle starts to veer off course. The method has demonstrated about 86% accuracy in detecting drowsiness but relies heavily on factors such as road conditions, lane markings, vehicle type, and driver experience.

### B. Physiological Sensors

Another approach utilizes physiological sensors like electrocardiogram (ECG), electrooculography (EOG), and electroencephalography (EEG) to detect drowsiness. These sensors measure specific brainwave signals, including alpha ( $\alpha$ ), theta ( $\theta$ ), and delta ( $\delta$ ) waves. Drowsiness is indicated by spikes in  $\theta$  and  $\delta$  waves, while  $\alpha$  waves decline more gradually. Though this method has achieved up to 96% accuracy, it is impractical for real-time use due to the discomfort drivers experience from wearing multiple sensors, as well as the high cost of implementation.

### C. Computer Vision and Machine Learning Approaches

Advancements in computer vision and machine learning have enabled more accurate and cost-effective detection of driver drowsiness. These methods analyze facial expressions, head movements, eye activity, and yawning duration to assess alertness. One early technique focused on tracking eye blinks, where an increased blink rate indicated drowsiness. Yawning detection has also been explored using the Viola-Jones object detection algorithm to locate the mouth. Given the importance of eye tracking in detecting drowsiness, many studies have focused on improving eye detection accuracy. Techniques like adaptive template matching, blob detection, and adaptive boosting have been combined to reduce processing time. Additionally, support vector machines (SVMs) have been used to enhance



detection accuracy. Feature extraction methods such as principal component analysis (PCA) and logical analysis of data (LAD) have also been applied to estimate eye parameters like blink rate and eye closure duration. Incorporating these approaches together offers a more comprehensive and accurate system for detecting driver drowsiness, although the challenges of real-time implementation and user comfort remain.

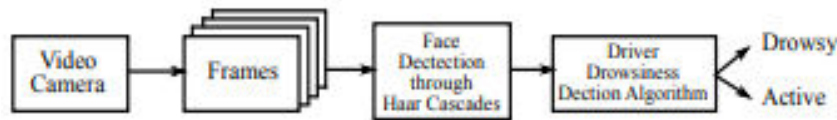


Fig. 2. A framework of driver drowsiness detection.

It is extremely challenging for fatigued drivers to control the steering at high speeds due to their drowsy state. This lack of control over the steering and speed often leads to fatal accidents. Therefore, analyzing the steering wheel behavior could provide valuable insight into detecting a driver's drowsiness. By utilizing physiological signals to monitor abrupt changes in steering, a vibration alert could be triggered to help reduce the risk of accidents.

In terms of image processing, convolutional neural networks (CNNs) have outperformed traditional feature-based systems. Initial efforts with shallow CNNs achieved approximately 78% accuracy in detecting driver drowsiness. Further advancements, such as AlexNet with three fully connected layers, five-layer networks, and the 16-layer VGG-FaceNet, have been applied to analyze image features, achieving up to 73% accuracy. Researchers have continued to refine CNN architectures to improve performance, particularly by framing drowsiness detection as a binary classification problem.

In this study, specific parameters extracted from the eyes, such as the distance between the pupil, eyelashes, and the white area of the eye, are crucial in determining the driver's drowsiness level. These parameters are fed into recurrent neural networks (RNNs) and long short-term memory (LSTM) models to assess the driver's state of alertness and predict drowsiness.

### III. METHODOLOGY

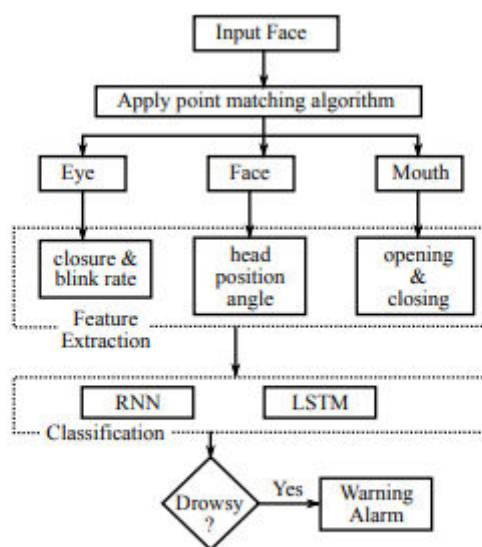


Fig. 3. The proposed approach for driver's drowsiness detection using eye, head, and mouth based features.

The framework for the driver drowsiness detection algorithm is illustrated in Figure 2. Initially, the video stream is recorded at 50 frames per second (fps). Each frame undergoes the Haar cascade approach to detect the face, while irrelevant parts are discarded. Once the face is accurately recognized, the proposed drowsiness detection algorithm is applied to determine whether the driver is active or drowsy, as detailed in Figure 3.

The eyes provide essential clues to assess the driver's drowsiness. The time it takes for the driver to close and open their eyes, along with the distance between the upper and lower eyelids, are key indicators. Efficiently designing a system to recognize these signs is critical. Since video processing can be time-consuming, convolutional neural networks (CNNs) are utilized to quickly detect drowsiness. The input video frames are captured based on the frame rate, and those showing eye closure are filtered for further analysis. If the number of closed-eye frames exceeds a set threshold, a warning message and buzzer are triggered, and a notification is sent to the driver's family.

Computer vision is a sophisticated field that uses numerous algorithms to detect facial movements, simplifying the detection of drowsiness. Video images are captured at 50 fps, and three key steps—face detection, tracking, and classification—are involved in determining whether the driver is drowsy.

#### **A. Face Detection and Tracking**

Processing grayscale images is less computationally intensive than RGB images, so the first step is to convert the images to grayscale. Histogram equalization is used to improve image contrast, enhancing face recognition. A real-time face detection algorithm, implemented using support vector machines (SVM) in OpenCV, is employed. However, the system struggles to detect faces during sudden head movements, which often occur when a driver is drowsy. CNNs have been shown to provide better accuracy in detecting faces than traditional feature-based approaches. In this case, driver images are directly fed into the CNN, which automatically extracts facial features with higher accuracy than previous methods.

#### **B. Feature Extraction**

Once the face is detected by CNN, the relevant dimensions are cropped from the grayscale image. Two approaches are used to extract features: locating the eyes on the detected face using a likelihood algorithm and observing changes in surface texture using Gabor wavelet transformation. Gabor wavelets capture texture variations such as bulges and wrinkles. Additionally, techniques like Histogram of Oriented Gradients (HOG), landmark localization, and Local Binary Pattern (LBP) can be applied to compute facial features.

#### **C. Algorithms and Techniques**

Most of the research on driver drowsiness detection is based on behavioral models, focusing on facial features such as head movements, eye blinking rate, eye state, and yawning. In many studies, a rotating camera is used to capture these features, which are then fed into classifiers such as SVMs, neural networks (NNs), or random forests (RFs). The SVM approach is particularly sophisticated for classifying data, requiring large datasets and relevant features for accurate classification. In this study, we extracted 68 facial landmarks (x, y) points using the DLIB library, a pre-trained model, to feed into the classifier for drowsiness detection, as illustrated in Figure 4.

#### **D. Long Short-Term Memory (LSTM)**

Detecting drowsiness from a single frame is challenging since it is difficult to determine whether a driver is merely blinking or falling asleep. To address this, we introduce the Conv-LSTM model, which consists of two sub-models: a CNN for feature extraction and an LSTM to interpret sequential frames. The process starts with extracting significant CNN features from video frames. These features are then passed to the LSTM, which predicts drowsiness or alertness based on a softmax layer. Figure 1 illustrates the flow of this model.

#### **E. Face ROI and Eye Detection Module**

We use the Viola-Jones Haar feature-based cascade classifiers for face detection. To avoid false positives, we first detect the face region of interest (ROI) and then apply eye detection within this area. After detecting the face and eyes in the first frame, CAMShift (Continuously Adaptive Mean-Shift) is used to track them over time, enabling the detection of open and closed eyes.

**F. Convolutional Neural Network (Inception-v3) Module**

We created a dataset of approximately 18,000 images each for alert and drowsy eyes to extract visual features. Using transfer learning, we adapted the pre-trained Inception-v3 model, which was initially trained on the ImageNet dataset. After 4,000 training steps, the model achieved an accuracy of 96.5% on the validation set. We extracted features from the final pooling layer (2048-dimensional vectors) and fed them into sequential neural models for further processing.

**G. Recurrent Neural Networks (RNNs) with Long Short-Term Memory (LSTM)**

LSTM networks are a specialized type of RNN, designed to handle long-term dependencies by using input, output, and forget gates to control information flow. For driver drowsiness detection, LSTM processes the features extracted from video frames. We used a 4096-wide LSTM layer followed by a 1024 dense layer with dropouts and trained the model over 100 epochs. The Adam optimizer, with a learning rate of 0.00005, was used to fine-tune the network weights

**IV. EXPERIMENTAL RESULTS**

**A. Dataset Collection**

The dataset for this study was collected from videos of different drivers in both drowsy and active states. To train the CNN effectively, a large number of images were required. Instead of taking static photos, we extracted frames from the recorded videos. Each frame was manually labeled as either "active" or "drowsy." After capturing eyelid and mouth data, the labeled images were divided into training and testing datasets. Around 30 drivers participated, with approximately 10 minutes of video recorded for each, capturing their active and drowsy states. Videos were recorded at 30 frames per second, resulting in a total of 18,000 images—70% (12,600) used for training and the remaining 5,400 for testing and validation.

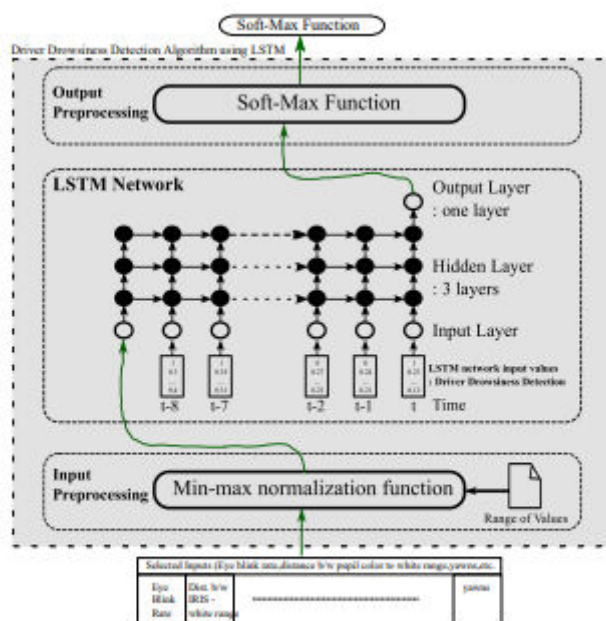


Fig. 5. The model for estimating the driver drowsiness using recurrent neural networks (RNNs) with long short term memory (LSTM)

**B. Result Analysis**

Detecting driver drowsiness is both crucial and challenging. The observations and proposed algorithm used for this task rely on the LSTM model. The labeled dataset was used to train the model with relevant features, and the testing data (unlabeled) was input into the trained model. The training process ran for several epochs, and the system's loss and accuracy metrics were tracked throughout. After sufficient training, the model was tested with unseen data, and the RNN-LSTM approach is detailed in Figure 5.

The driver drowsiness detection model is treated as a binary classification problem. It extracts and processes information at regular time intervals—every 10 ms in this case—resulting in a many-to-one structure. Figure 6 illustrates the LSTM model used for classifying the driver's state of alertness or drowsiness.

Before inputting data into the LSTM, preprocessing techniques, such as min-max normalization, were applied to scale the values to a range of [0-1]. The input data underwent linear transformation, while post-processing was performed on the output values to normalize them. The softmax layer was then used to generate predictions, ensuring that the sum of the output values equaled 1 after normalization.

The LSTM model was trained on various features, including facial parameters, eye movement, yawning frequency, and data from vehicle steering and lane analysis. These parameters were used to train and test the model, and the probability values were used to determine whether the driver was drowsy or alert. The proposed system achieved an accuracy of 97.20%, with around 55 epochs required for training. Figure 7 shows the detailed information on test and validation losses, as well as test and validation accuracies.

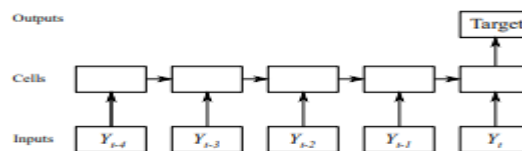


Fig. 6. LSTM Model which demonstrates the process from Input to Target.

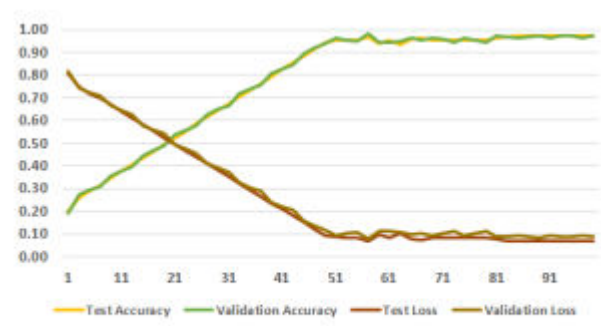


Fig. 7. Accuracy and Loss information obtained for Test and Validation data.

## V. CONCLUSION

The process of detecting driver drowsiness has become a critical application, as a significant portion of accidents are caused by driver fatigue. Traditional feature-based methods have not been highly effective, as they struggle with the non-linear nature of data from facial expressions, steering behavior, and lane deviations. In recent years, deep neural networks have shown great promise, with convolutional neural networks (CNNs) outperforming many traditional image processing methods. Recurrent neural networks (RNNs) with long short-term memory (LSTM) units have been introduced to manage time-series data effectively, proving to be more efficient than other feature-based techniques for classifying sequential data.

This study has utilized a limited set of features for driver drowsiness detection. Future work will focus on integrating additional parameters, such as the driver's sleep patterns, to enhance detection accuracy. The next steps will involve analyzing sleep, facial expressions, and lane deviation data, supported by the Internet of Things (IoT). By gathering comprehensive data from all these sources and applying it to optimized deep neural networks with appropriate hyperparameters, a more accurate drowsiness detection system can be developed. Furthermore, our goal is to create a cost-effective solution that can be implemented in low to mid-range vehicles.



#### REFERENCES

- [1] K. Ploesser, J. C. Recker, and M. Rosemann, "Towards a classification and lifecycle of business process change," in Proc. BPMDS, vol. 8. 2008, pp. 1–9.
- [2] Carmona and R. Gavalda, "Online techniques for dealing with concept drift in process mining," in Proc. Int. Conf. IDA, 2012, pp. 90–102.
- [3] B. F. van Dongen and W. M. P. van der Aalst, "A meta model for process mining data," in Proc. CAiSE Workshops (EMOI-INTEROP Workshop), vol. 2. 2005, pp. 309–320.
- [4] I. Žliobait'e, "Learning under concept drift: An Overview," CoRR, vol. abs/1010.4784, 2010 [Online]. Available: <http://arxiv.org/abs/1010.4784>.
- [5] J. Z. Kolter and M. A. Maloof, "Dynamic weighted majority: An ensemble method for drifting concepts," J. Mach. Learn. Res., vol. 8, pp. 2755–2790, Jan. 2007.
- [6] R.P. Jagadeesh Chandra Bose, Wil M.P. van der Aalst, Indr\_Zliobait, and Mykola Pechenizkiy, "Handling Concept Drift in Process Mining", Department of Mathematics and Computer Science, University of Technology, The Netherlands.
- [7] W. M. P. van der Aalst, M. Rosemann, and M. Dumas, "Deadline-based escalation in process-aware information systems," Decision Support Syst., vol. 43, no. 2, pp. 492– 511, 2011.
- [8] S. J. Delany, P. Cunningham, A. Tsymbal, and L. Coyle, "A case-based technique for tracking concept drift in spam filtering," Knowl. Based Syst., vol. 18, nos. 4–5, pp. 187–195, Aug. 2005.
- [9] W. M. P. van der Aalst, N. Lohmann, and M. L. Rosa, "Ensuring correctness during process configuration via partner synthesis," Inf. Syst., vol. 37, no. 6, pp. 574–592, 2012.
- [10] M. Pechenizkiy, J. Bakker, I. Žliobait'e, A. Ivannikov, and T. Kärkkäinen, "Online mass flow prediction in CFB boilers with explicit detection of sudden concept drift," SIGKDD Explorations, vol. 11, no. 2, pp. 109–116, 2009.
- [11] M. Dumas, W. M. P. van der Aalst, and A. H. M. Ter Hofstede, Process Aware Information Systems: Bridging People and Software Through Process Technology. New York, NY, USA: Wiley, 2005





INTERNATIONAL  
STANDARD  
SERIAL  
NUMBER  
INDIA



# INTERNATIONAL JOURNAL OF INNOVATIVE RESEARCH

IN SCIENCE | ENGINEERING | TECHNOLOGY

 9940 572 462  6381 907 438  [ijirset@gmail.com](mailto:ijirset@gmail.com)



[www.ijirset.com](http://www.ijirset.com)

Scan to save the contact details