IJERST

International Journal of Engineering Research and Science & Technology

www.ijerst.org

ISSN : 2319-5991

Vol. 22 No. 2(1) (2026)

ijerst.editor@gmail.com

editor@ijerst.com

ISSN 2319-5991 www.ijerst.com

Peer Reviewed, Referred & Indexed Journal

Research Paper

A DEEP LEARNING APPROACH FOR DRIVER DROWSINESS DETECTION USING CNN AND MOBILENETV2

[1]Rajasri, [2] C Nikita,[3] D Radika, [4] A Akshitha,[5] N Akash
[1]AssistantProfessor, [2345]Students
Department of CSE(AI & ML)
Siddhartha Institute of Technology & Sciences, Narapally
rajasribomma@siddhartha.org.in, 23TQ1A6632@siddhartha.co.in, 23TQ1A6643@siddhartha.co.in,
23TQ1A6659@siddhartha.co.in, 23TQ1A6641@siddhartha.co.in,

Abstract

Driver drowsiness is a significant factor contributing to road accidents worldwide, making its early detection essential for enhancing road safety. This study presents a deep learning-based approach for detecting driver fatigue using facial image analysis. The proposed system employs a Convolutional Neural Network (CNN) with transfer learning using the MobileNetV2 architecture to automatically extract meaningful features from facial images and classify the driver's state as either alert or drowsy.

To improve model performance and robustness, input images are preprocessed and augmented to handle variations in lighting conditions, facial orientation, and image quality. MobileNetV2 serves as an efficient feature extractor, while additional fully connected layers perform accurate classification. The model effectively identifies visual indicators of drowsiness, such as partially closed eyes and reduced facial activity.

Additionally, the system supports real-time monitoring by integrating with OpenCV, enabling continuous analysis of driver behavior during vehicle operation. Experimental results demonstrate that the proposed framework achieves reliable and efficient detection while maintaining low computational complexity due to the lightweight nature of MobileNetV2.

Overall, the system provides a practical and scalable solution for real-time driver monitoring and can be integrated into intelligent transportation systems and advanced driver assistance systems to reduce accidents caused by driver fatigue.

I. Introduction

Driver drowsiness is one of the leading causes of road accidents worldwide and has become a major concern in modern transportation systems. Fatigue and sleep deprivation significantly impair a driver's reaction time, concentration, and decision-making ability. According to various road safety reports, a large number of accidents occur each year due to drivers falling asleep or losing focus while driving. These incidents often result in severe injuries, property damage, and loss of human lives. Therefore, developing an efficient system to detect driver drowsiness at an early stage is essential to enhance road safety and prevent accidents.

With the rapid advancement of Artificial Intelligence (AI) and Computer Vision technologies, intelligent driver monitoring systems have gained significant attention. Traditional approaches for detecting driver fatigue relied on manual observation or vehicle-based indicators such as steering patterns and lane deviation. However, these methods are often unreliable because they identify drowsiness only after it has already affected the driver's behavior. As a result, research has shifted toward vision-based systems that analyze facial features and driver behavior directly to detect early signs of fatigue.

Vision-based driver monitoring systems use cameras to capture images or video streams of the driver and apply computer vision techniques to analyze facial expressions, eye movements, and head posture. Common indicators of drowsiness include frequent blinking, slow eye movements, prolonged eye closure, and yawning. By identifying these visual cues, it becomes possible to detect fatigue at an early stage before it leads to dangerous situations.

However, training deep learning models from scratch requires a large amount of labeled data and high computational resources, which may not always be available. To overcome this limitation, transfer learning techniques are widely used. Transfer learning allows pre-trained models to be adapted for specific tasks, reducing training time and improving performance, especially when working with limited datasets.

II. Literature Survey

Driver drowsiness detection has been widely studied using deep learning and computer vision techniques. Various researchers have proposed different models and approaches to improve the accuracy and efficiency of fatigue detection systems.

Ahmed et al. [1] proposed a deep learning-based driver drowsiness detection system using Convolutional Neural Networks (CNN) and VGG16 models to classify facial expressions such as eye states and yawning. Their CNN model achieved high accuracy of 97% with excellent precision and recall, demonstrating the effectiveness of CNN-based approaches.

Ahmed et al. [2] introduced a multi-CNN ensemble model using InceptionV3 to analyze facial regions such as eyes and mouth extracted through MTCNN. Their model achieved 97.1% evaluation accuracy, showing that combining multiple CNN models can improve performance.

Akrout et al. [3] utilized MediaPipe Face Mesh for facial landmark extraction and combined MobileNetV3 with LSTM networks to classify different levels of fatigue. Their system achieved around 98.4% accuracy and demonstrated the importance of temporal analysis in fatigue detection.

Bandaru et al. [4] compared multiple deep learning architectures including CNN, VGG, ResNet, and MobileNetV2. Their study showed that MobileNetV2 achieved around 95% accuracy with low computational cost, making it suitable for real-time applications.

Babar et al. [5] proposed a lightweight approach by combining MobileNetV2 feature extraction with Logistic Regression for eye-state detection. The model achieved nearly 99% accuracy while maintaining computational efficiency, highlighting the benefits of hybrid models.

Basheer Ahmed et al. [6] developed a CNN-based system for detecting fatigue using eye movements and facial expressions. Their model achieved 97% accuracy, reinforcing the effectiveness of CNNs in visual fatigue detection.

Dakshnakumar et al. [7] compared advanced deep learning models such as VGG19, EfficientNetB7, and MobileNetV2. EfficientNetB7 achieved the highest accuracy (99.87%), while MobileNetV2 also performed well with lower computational requirements.

Delwar et al. [8] analyzed multiple deep learning models including CNN, VGG16, and MobileNet for facial analysis. Their results showed that MobileNet achieved efficient real-time performance with 92.75% accuracy.

Farida et al. [9] focused on embedded systems using ESP32-CAM and compared MobileNetV2 with EfficientNet-B0. While EfficientNet achieved slightly higher accuracy (98%), MobileNetV2 required fewer resources, making it suitable for edge devices.

Fonseca et al. [10] conducted a comprehensive survey of 81 deep learning-based drowsiness detection systems. Their study concluded that most models achieve over 95% accuracy, proving the reliability of deep learning in this domain.

Hamdi et al. [11] proposed a hybrid model combining YOLO for face detection and MobileNetV2 for classification. Their system achieved 99.98% accuracy, demonstrating the effectiveness of combining object detection with classification models.

Hanson et al. [12] implemented real-time detection systems using SSD MobileNetV2 and Faster R-CNN on embedded devices like Raspberry Pi. Their approach achieved high accuracy with real-time performance.

Hassan et al. [13] explored attention-based CNN models such as CBAM, SE, and ECA. The CBAM-based model achieved 99.63% accuracy, showing that attention mechanisms can significantly improve model performance.

Hossain et al. [14] studied driver distraction detection using CNN, ResNet50, and MobileNetV2. Their results showed MobileNetV2 performed best in terms of accuracy and efficiency.

Ilmadina et al. [15] focused on yawning detection using deep learning models such as MobileNetV2 and ResNet50. Their study achieved around 99% accuracy, highlighting the importance of facial expression analysis in detecting fatigue.

III. System Analysis

Driver drowsiness detection systems aim to improve road safety by identifying fatigue in drivers at an early stage. The system analyzes driver facial features such as eye closure, blinking rate, and yawning to determine alertness levels. Traditional systems rely on behavioral or vehicle-based indicators, which are often inaccurate and delayed. With the advancement of deep learning, vision-based systems have become more effective and reliable. These systems use cameras and image processing techniques to continuously monitor the driver. The proposed system utilizes Convolutional Neural Networks (CNN) with transfer learning for accurate detection. It processes facial images in real-time and classifies the driver's state as alert or drowsy. The system ensures robustness by handling variations in lighting, pose, and image quality. It is designed to be computationally efficient for real-time applications. Overall, the system provides a smart and automated solution to reduce accidents caused by driver fatigue.

Existing System

Existing driver drowsiness detection systems primarily rely on traditional methods such as steering behavior, lane deviation, and physiological signals. Some systems use sensors to monitor heart rate or brain activity, which can be intrusive and uncomfortable for drivers. Others depend on simple image processing techniques to detect eye closure or yawning, but these methods are sensitive to lighting conditions and camera quality. Many existing approaches lack real-time performance and fail to detect early signs of fatigue. Additionally, they often require expensive hardware or complex setups. Machine learning-based systems without deep learning have limited accuracy due to manual feature extraction. These systems may not generalize well across different drivers and environments. As a result, their reliability in real-world scenarios is limited. Hence, there is a need for a more accurate and efficient solution.

Disadvantages of Existing System

- Low accuracy in real-world conditions
- Delay in detecting drowsiness
- Requires expensive or intrusive sensors
- Sensitive to lighting and environmental changes
- Limited scalability and adaptability

Proposed System

The proposed system introduces a deep learning-based approach for driver drowsiness detection using CNN and transfer learning. It uses the MobileNetV2 model as a feature extractor to analyze driver facial images efficiently. The system captures real-time video using a camera and processes frames using OpenCV. Preprocessing and data augmentation techniques are applied to improve model robustness. The model automatically learns important features such as eye closure and yawning without manual intervention. Fully connected layers are used for accurate classification of driver states. The lightweight architecture ensures fast processing suitable for real-time applications. The system is non-intrusive and does not require any wearable sensors. It performs well under different lighting and environmental conditions. Overall, the proposed system provides an efficient, scalable, and reliable solution for driver safety.

Advantages of Proposed System

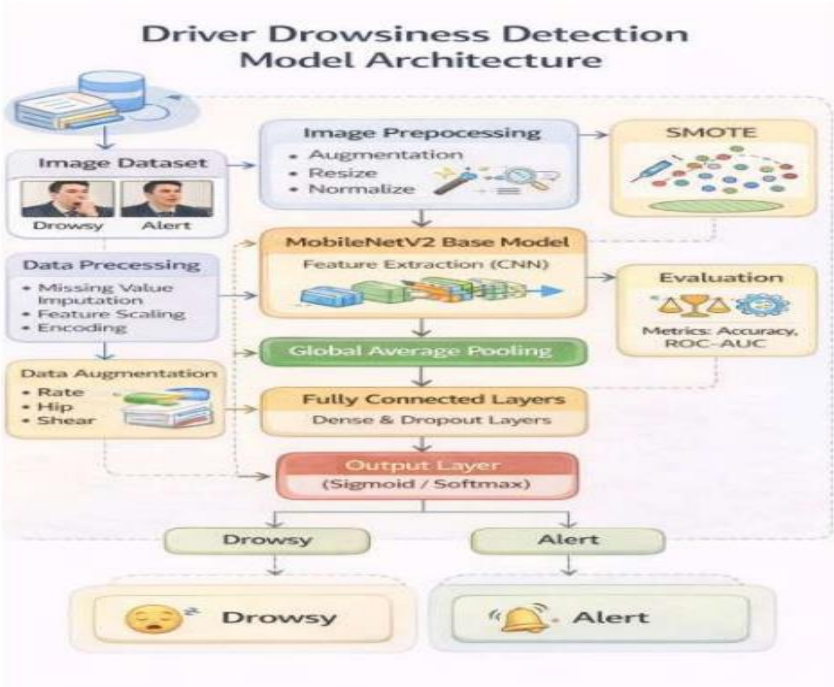
- High accuracy using deep learning
- Real-time detection capability
- Lightweight and computationally efficient
- Non-intrusive (no sensors required)
- Robust to lighting and pose variations
- Suitable for embedded and mobile systems

IV. Methodology

The methodology begins with collecting a dataset of driver facial images representing both alert and drowsy states. The images are preprocessed to remove noise, resize, and normalize them for consistent input. Data augmentation techniques such as rotation, flipping, and brightness adjustment are applied to increase dataset diversity. The processed images are then fed into the MobileNetV2 model, which acts as a feature extractor using transfer learning. The extracted features are passed to fully connected layers for classification. The model is trained and validated using labeled data to achieve high accuracy. During real-time implementation, video frames are captured using OpenCV and processed continuously. The trained model predicts the driver's state for each frame. If drowsiness is detected, an alert or warning system can be triggered. This approach ensures continuous monitoring and early detection of fatigue.

System Architecture

The proposed driver drowsiness detection system is designed using a deep learning-based architecture that integrates image processing and real-time monitoring. The system begins by capturing video input through a camera, which continuously records the driver's facial expressions. The captured frames are then passed to the preprocessing stage, where images are resized, normalized, and enhanced to ensure consistency and improve quality. These processed images are fed into the MobileNetV2 model, which acts as a feature extractor using transfer learning. The model identifies important facial features such as eye closure, blinking patterns, and yawning

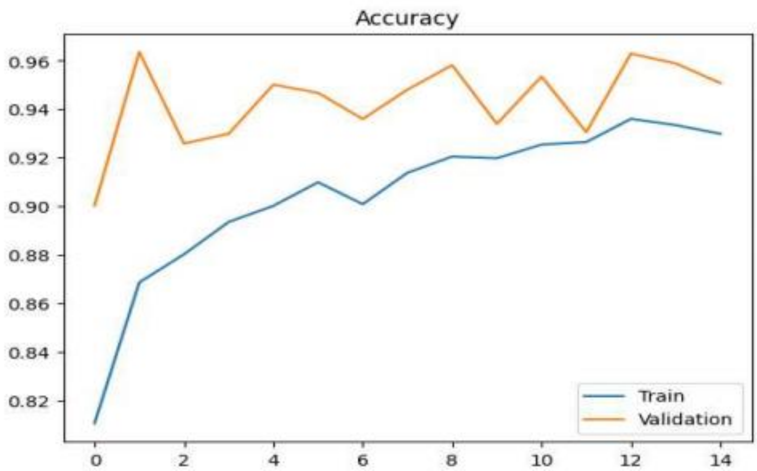


V. Result and Output

Non Drowsy

Drowsy

Non Drowsy



VI. Conclusion

In conclusion, the proposed driver drowsiness detection system provides an effective and reliable solution for improving road safety by identifying driver fatigue at an early stage. By leveraging deep learning techniques, particularly Convolutional Neural Networks and transfer learning with MobileNetV2, the system achieves high accuracy in classifying driver states. The use of image preprocessing and data augmentation enhances the robustness of the model under varying environmental conditions. Additionally, the integration of real-time video processing using OpenCV enables continuous monitoring of the driver without the need for intrusive sensors. The lightweight architecture ensures fast performance, making it suitable for real-time and embedded applications. Overall, the system has the potential to significantly reduce accidents caused by driver drowsiness and can be integrated into advanced driver assistance systems for safer transportation.

References

[1] Kumar, R. D., Prudhviraj, G., Vijay, K., Kumar, P. S., & Plugmann, P. (2024). Exploring COVID-19 through intensive investigation with supervised machine learning algorithm. In Handbook of Artificial Intelligence and Wearables (pp. 145-158). CRC Press.

[2] Swathi, B., Vijay, K., Sushanth Babu, M., & Dinesh Kumar, R. (2024, November). Machine Learning Techniques in Cloud Based Intrusion Detection. In The International Conference on Artificial Intelligence and Smart Environment (pp. 557-564). Cham: Springer Nature Switzerland.

[3] Sv satyakrishna, shirisha rangu ,bhargavi nalacheruve.(2024) Prospective investigation on colorectal cancer with SMOTE on machine learning Algorithm

[4] Dr.G.Vishnu Murthy, BhargaviNalacheruve 1Professor, Department of computer Science & engineering, Anurag University, TS, India. 2Student, Department of computer Science & engineering, Anurag University, TS, India.

[5] V. N. S. Manaswini, K. K, C. Nigam, S. S. Ali, R. Niranjana, and Suman, “Real-Time Object Detection in Drone Surveillance Using YOLOv5,” in Proc. 2025 3rd Int. Conf. IoT, Communication and Automation Technology (ICICAT), Gorakhpur, India, 2025, pp. 1–6, doi: 10.1109/ICICAT68430.2025.11414670.

[6] B. Soundarya, V. N. S. Manaswini, M. Ayyakrishnan, R. D. Kumar, “Contextual Analysis of Big Data Analytics in Intelligent Transportation Frameworks,” in Intersection of Artificial Intelligence, Data Science, and Cutting-Edge Technologies: From Concepts to Applications in Smart Environment, Lecture Notes in Networks and Systems, vol. 1353, Cham: Springer, 2025, doi: 10.1007/978-3-031-88304-0_79.

[7] R. D. Kumar, V. N. S.Manaswini, “Applications of blockchain in smart cities: detecting fake documents from land records using blockchain technology,” in Blockchain for Smart Cities, Elsevier, 2021, pp. 105–117, doi: 10.1016/B978-0-12-824446-3.00017-X.

[8] Tejavath Veeramma, Badarla Anil, Guguloth Ravinder, “An advanced movie recommender using collaborative filtering and sentiment analysis,” International Research Journal of Modernization in Engineering Technology and Science, vol. 7, no. 7, July 2025, doi: 10.56726/IRJMETS81618.

[9] Ravi Kumar Banoth, Ramana Murthy B V, “Automatic crop recommendation system using LightGBM and decision tree machine learning models,” Journal of Machine and Computing, vol. 5, no. 1, pp. 343, Jan. 2025, doi: 10.53759/7669/jmc202505026.

[10] Ravi Kumar Banoth, Dr. B.V. Ramana Murthy, “Smart agriculture through IoT and machine learning for analyzing carbon footprints,” in Proc. Int. Conf. Computer Science and Communication Engineering (ICCSCE), Apr. 2025.

[11] Ravi Kumar Banoth, B. V. Ramana Murthy, "Soil image classification using transfer learning approach: MobileNetV2 with CNN," SN Computer Science, vol. 5, art. no. 199, 2024, doi: 10.1007/s42979-023-02500-x.