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Research Paper

Real-Time Deep Learning-Based Drowsiness Detection: Leveraging Computer-Vision and Eye-Blink Analyses for Enhanced Road Safety

Konga Roja[1], Ms. Thalla Sushma[2]

[1]PG Scholar, Department of Computer Science and Engineering, Vaagdevi Engineering College, Warangal, 506005, Telangana, India
Email: rojakonga367@gmail.com

[2] Assistant Professor , Department of Computer Science and Engineering, Vaagdevi Engineering College, Warangal, 506005, Telangana, India
Email: sushmavisu410@gmail.com

Abstract**—***Driver drowsiness is one of the foremost causes of road traffic accidents because it reduces attentiveness, delays reaction time, and impairs decision-making. This paper presents a real-time, deep learning-based driver drowsiness detection system that combines convolutional neural network (CNN) image classification with facial-landmark-based geometric analysis to improve road safety. A custom image dataset comprising four driver states — Open, Closed, Yawn, and No_Yawn — was collected and used to train a MobileNetV2-based CNN through transfer learning. In parallel, the MediaPipe Face Mesh framework extracts facial landmarks to compute the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR), enabling continuous monitoring of eye closure and yawning behaviour. The fusion of image-based classification with geometric feature analysis improves detection robustness across varying illumination, head pose, and driving conditions. The proposed MobileNetV2-CNN model is benchmarked against an existing Random Forest (RF) classifier that relies solely on handcrafted EAR/MAR features. Experimental results show that the proposed model achieves an accuracy of 99.19%, precision of 99.22%, recall of 99.19%, and an F1-score of 99.19%, substantially outperforming the existing RF baseline, which attained an accuracy of only 83.01%. These results confirm that combining deep-learning-based visual recognition with geometric eye-blink analysis provides a reliable, non-invasive, and computationally efficient solution for real-time driver monitoring that can be integrated into Advanced Driver Assistance Systems (ADAS) to reduce fatigue-related accidents.*

Keywords**—***Driver Drowsiness Detection; Convolutional Neural Network (CNN); MobileNetV2; Transfer Learning; Eye Aspect Ratio (EAR); Mouth Aspect Ratio (MAR); MediaPipe Face Mesh; Computer Vision; Advanced Driver Assistance Systems (ADAS)*

I. INTRODUCTION

Driver drowsiness is a major contributor to road traffic accidents worldwide because it lowers attentiveness, slows reaction time, and impairs sound decision-making during driving. Early detection of driver fatigue is therefore essential for preventing accidents and improving overall road safety. Recent advances in Artificial Intelligence (AI), Deep Learning (DL), and Computer Vision (CV) have enabled the development of intelligent driver-monitoring systems capable of analysing eye movements and facial expressions in real time without requiring intrusive wearable hardware.

This paper presents a real-time driver drowsiness detection system that combines MobileNetV2-based transfer learning with facial-landmark analysis to accurately recognise behaviours such as prolonged eye closure and yawning. The Eye Aspect Ratio (EAR) and the Mouth Aspect Ratio (MAR) are computed from facial landmarks extracted using the MediaPipe Face Mesh framework, and these geometric indicators are used alongside a Convolutional Neural Network (CNN) image classifier to validate the driver's alertness state. By combining geometric feature analysis with deep-learning-based image classification, the proposed approach maintains stable performance across a wide range of driving scenarios, including variations in lighting, head pose, and camera angle.

Conventional drowsiness-monitoring techniques generally fall into two categories: wearable-sensor-based physiological monitoring and handcrafted, threshold-based computer-vision methods. Wearable approaches, although often accurate, are uncomfortable for continuous use and are rarely adopted by drivers in practice. Handcrafted geometric methods, on the other hand, are lightweight but their accuracy deteriorates under changing illumination, head orientation, and driving conditions because they cannot learn complex spatial patterns directly from images. There is therefore a clear need for a non-invasive, robust, and accurate driver-monitoring solution capable of reliably recognising fatigue using facial features alone. The present work addresses this need by fusing deep-learning-based visual classification with real-time geometric verification.

A. Motivation and Problem Definition

Because driver fatigue reduces alertness, slows reaction time, and degrades driving performance, it remains one of the principal causes of road accidents. Conventional monitoring techniques frequently suffer from low accuracy, poor resilience under varying lighting conditions, and dependence on biosensors that are uncomfortable for drivers. Consequently, there is a need for an efficient, non-invasive, and reliable driver-health-monitoring system capable of effectively recognising tiredness using facial features. The proposed system addresses these challenges by combining convolutional neural networks, transfer learning, and facial-landmark-based geometric evaluation to provide accurate and robust drowsiness recognition across diverse driving environments.

B. Contributions

- Development of a real-time driver drowsiness detection framework that fuses MobileNetV2-CNN-based image classification with MediaPipe-based EAR/MAR geometric analysis.
- Design and curation of a custom four-class facial-image dataset (Open, Closed, Yawn, No_Yawn) collected under varied lighting, pose, and background conditions.
- A multi-stage transfer-learning and fine-tuning strategy incorporating data augmentation, MixUp, label smoothing, and cosine-decay learning-rate scheduling to improve model generalisation.
- Comprehensive experimental evaluation comparing the proposed MobileNetV2-CNN model against an existing Random Forest (RF) baseline using accuracy, precision, recall, F1-score, and confusion-matrix analysis.

C. Paper Organisation

The remainder of this paper is organised as follows. Section II reviews related work on driver drowsiness detection and eye-blink analysis. Section III describes the existing Random Forest-based baseline system. Section IV presents the proposed research methodology, including dataset preparation, model architecture, and the hybrid decision-fusion algorithm. Section V presents the experimental results and discussion, and Section VI concludes the paper with directions for future work.

II. LITERATURE SURVEY

Research on driver drowsiness detection spans traffic-behaviour modelling, eye-blink and geometric analysis, deep-learning-based classification, multimodal emotion-aware detection, and physiological/EOG-based monitoring. This section reviews representative work in each category and identifies the gap addressed by the proposed hybrid framework.

A. Traffic-Behaviour Modelling and Vision-Based Foundations

Zeng et al. [1] proposed a multi-value cellular automata model for multi-lane traffic flow under Lagrangian coordinates to simulate and analyse real-time vehicular dynamics and congestion patterns, reporting close agreement with observed traffic conditions while maintaining low computational complexity. This work provides a useful foundation for understanding real-world traffic behaviour relevant to driver-monitoring research.

B. Eye-Blink and EAR-Based Drowsiness Detection

Dewi et al. [2] developed a real-time drowsiness detection approach based on the Eye Aspect Ratio (EAR) computed from facial landmarks extracted from live video, employing threshold-based decision logic to trigger alerts and reporting high detection accuracy while remaining computationally lightweight. Kim et al. [6] proposed a real-time eye-blink detection method for driver drowsiness monitoring based on continuous analysis of eye-closure duration. Moon et al. [7] presented a CNN-based eye-blink detection system that improved robustness over purely handcrafted feature approaches. You et al. [17] designed a real-time drowsiness detection algorithm that explicitly accounts for individual differences in eye shape and blink patterns to reduce false alarms across diverse drivers. Raudonis et al. [19] examined discrete eye-tracking techniques for medical and monitoring applications, and Liu and Liu [20] proposed a robust real-time eye detection and tracking method for rotated facial images under complex conditions.

C. Deep-Learning and CNN-Based Classification

Chand and Karthikeyan [3] proposed a CNN-based driver drowsiness detection system that incorporates emotion analysis, using deep convolutional features to classify facial states and reporting higher accuracy than handcrafted-feature baselines. Li et al. [15] developed a CNN-based wearable driver drowsiness detection system that combines physiological sensing with visual analysis. Sharan et al. [18] proposed a CNN-based driver-fatigue detection method using eye-state recognition, achieving strong classification performance. Albadawi et al. [8] presented a real-time machine-learning-based driver drowsiness detection system that uses visual behavioural features and was evaluated for deployment feasibility in real driving environments.

D. Multimodal and Emotion-Aware Detection

Mamieva et al. [4] proposed a multimodal emotion-detection framework that fuses facial and speech features through an attention-based mechanism, showing that combining audio-visual cues improves recognition accuracy over single-modality approaches. Kavitha et al. [9] presented a driver drowsiness detection method based on facial-expression recognition using vision-based landmark extraction to differentiate alert and fatigued states. Ghourabi et al. [10] proposed a joint-monitoring framework that simultaneously analyses yawning, blinking, and head-nodding behaviour, reporting improved reliability over single-cue methods.

E. Face-Detection Enhancements

Mamieva et al. [5] improved face-detection performance for small and difficult-to-detect faces by introducing enhanced feature-extraction and transfer-learning strategies, achieving high accuracy on challenging facial-recognition benchmarks. Reliable detection of small or partially visible faces is directly relevant to detecting driver faces under varied camera distances and head poses.

F. Physiological and EOG/Neuroimaging-Based Approaches

Sharifuzzaman Sagar et al. [11] reviewed drowsiness detection approaches based on combined neuroimaging modalities such as EEG, EOG, and fNIRS, highlighting the accuracy gains achievable through multimodal physiological fusion alongside practical deployment challenges such as sensor discomfort. Chang [12] reviewed electrooculography (EOG)-based human-computer interaction techniques covering signal acquisition and classification methods relevant to eye-movement monitoring. Estrany and Fuster-Parra [13] reviewed EOG-based eye-tracking methods for healthcare and biomedical applications. Vieira et al. [14] designed a tunable-gain, low-noise biopotential amplifier for EMG and EOG signal acquisition, contributing to the hardware foundation required for physiological drowsiness-monitoring systems. Jordan et al. [16] studied the performance-autonomy trade-off of smart connected glasses, examining the feasibility of wearable computing platforms for continuous physiological monitoring.

G. Research Gap

Existing literature can be broadly grouped into (i) handcrafted, threshold-based EAR/MAR approaches [2], [6], [7], [17], [19], [20], which are lightweight but sensitive to illumination and camera angle; (ii) purely deep-learning image-classification methods [3], [8], [15], [18], which improve accuracy but are rarely combined with real-time geometric verification; and (iii) physiological or EOG-based techniques [11]–[14], [16], which achieve strong accuracy but require intrusive wearable sensors that reduce driver comfort. Comparatively few studies integrate CNN-based transfer learning with real-time EAR/MAR geometric validation within a single non-invasive, camera-based framework. This paper addresses that gap by combining a MobileNetV2-CNN classifier with MediaPipe-based EAR/MAR computation to achieve both high classification accuracy and robust real-time geometric verification without requiring wearable sensors.

III. EXISTING SYSTEM

A. Random Forest-Based Drowsiness Detection

The existing baseline drowsiness-detection system relies on a Random Forest (RF) classifier operating on handcrafted geometric features. Facial landmarks are obtained using the MediaPipe Face Mesh framework, from which the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR) are computed to quantify eye closure and mouth-opening behaviour. These numerical features are supplied as input to the RF classifier, which builds an ensemble of decision trees and aggregates their predictions to categorise the driver as Open, Closed, Yawn, or No_Yawn. Because the RF model relies purely on predefined geometric thresholds rather than learned visual representations, its capacity to capture complex spatial patterns within facial images is limited, and its performance degrades under varying illumination, head pose, and driving conditions.

B. Working Procedure of the Baseline System

The RF-based baseline proceeds as follows: facial images from the four-class dataset are loaded and resized; MediaPipe Face Mesh extracts facial landmarks; EAR and MAR values are computed for each frame; the resulting feature vectors are supplied to the trained Random Forest classifier; and the classifier outputs a prediction corresponding to one of the four driver states. Model performance is evaluated using accuracy, precision, recall, F1-score, and the confusion matrix.

C. Limitations of the Existing System

- Depends entirely on handcrafted EAR/MAR features rather than automatically learned visual representations, making the model sensitive to landmark-extraction errors.
- Cannot learn complex spatial or textural patterns directly from facial images, limiting robustness under illumination and pose variation.
- Achieves comparatively low classification accuracy (83.01%) relative to deep-learning alternatives.
- Provides no mechanism for multi-stage fine-tuning or historical performance feedback to progressively improve accuracy.

IV. RESEARCH METHODOLOGY

A. Proposed System Architecture

The proposed framework introduces a real-time deep-learning-based driver drowsiness detection system that combines MobileNetV2, a Convolutional Neural Network (CNN), and computer-vision techniques to accurately detect driver fatigue. As shown in Fig. 1, facial images are collected and preprocessed, then passed to a MobileNetV2 backbone for high-level feature extraction, followed by additional CNN layers that perform the final four-class classification (Open, Closed, Yawn, No_Yawn). In parallel, MediaPipe Face Mesh extracts facial landmarks in real time to compute EAR and MAR values, which are fused with the CNN prediction to validate eye-closure and yawning behaviour before an alert is triggered.

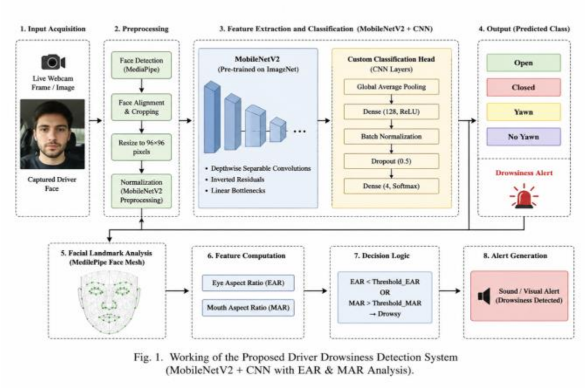

Fig. 1. Architecture of the proposed real-time MobileNetV2-CNN and EAR/MAR fusion framework.

B. Dataset Description and Collection

A custom facial-image dataset was developed specifically for this study to train and evaluate the proposed MobileNetV2-CNN model. It is organised into four classes: Open, Closed, Yawn, and No_Yawn, representing alert and fatigued driver states respectively. The dataset was collected from multiple participants under varied environmental conditions, including different facial expressions, head orientations, lighting conditions, and background environments, to simulate real-world driving scenarios. Each image was manually verified and assigned to its corresponding class to ensure accurate labelling, and images were organised into separate class folders to support automated loading and label generation.

C. Data Preprocessing and Augmentation

Before training, all images were resized to 96 × 96 pixels and normalised using the MobileNetV2 preprocessing function to ensure compatibility with the pretrained backbone. To increase dataset diversity and reduce overfitting, several data-augmentation techniques were applied, including rotation, width and height shifting, zooming, horizontal flipping, brightness adjustment, and MixUp augmentation, in which two training images and their corresponding labels are combined to generate a new synthetic sample. Categorical labels were encoded using one-hot encoding, and the dataset was divided into training, validation, and testing sets using stratified sampling to preserve class balance.

D. Facial Landmark Extraction and EAR/MAR Computation

The MediaPipe Face Mesh framework extracts a dense set of facial landmarks in real time from each captured frame. The Eye Aspect Ratio (EAR) is computed from the vertical and horizontal distances between specific eye landmark points, while the Mouth Aspect Ratio (MAR) is computed analogously from mouth landmark points. A calibration procedure establishes an adaptive closure threshold from a sample of open-eye frames, after which sustained EAR values below the threshold are flagged as eye closure and elevated MAR values are flagged as yawning, independent of the CNN classification branch.

E. MobileNetV2-CNN Model Architecture and Training Strategy

MobileNetV2, pretrained on the ImageNet dataset, is employed as the feature-extraction backbone. Additional layers, including global average pooling, dense, batch normalisation, and dropout, are appended for four-class classification. The model is trained in multiple phases using transfer learning: the classification head is first trained with the backbone frozen, after which selected deeper layers are unfrozen and fine-tuned jointly. Optimisation is performed using the Adam optimiser with cosine-decay learning-rate scheduling, while label smoothing and MixUp augmentation are used throughout training to improve generalisation and reduce overfitting.

F. Hybrid Decision-Fusion Algorithm

Algorithm 1 summarises the hybrid decision-fusion procedure executed for every incoming video frame, combining the CNN class prediction with the independent EAR/MAR geometric verification to reach a final drowsiness decision.

ALGORITHM 1. HYBRID CNN–GEOMETRIC DECISION FUSION

```
Input: video frame f
Output: driver state label L; alert flag A
1: detect facial landmarks on f using MediaPipe Face Mesh
2: compute EAR and MAR from the detected landmarks
3: resize and normalise f to 96×96 for MobileNetV2-CNN
4: p ← MobileNetV2-CNN(f)  // class probabilities
5: L_cnn ← argmax(p)
6: if EAR < EAR_threshold for T consecutive frames:
7:     flag_eye ← Closed
8: if MAR > MAR_threshold: flag_mouth ← Yawn
9: L ← fuse(L_cnn, flag_eye, flag_mouth)
10: if L ∈ {Closed, Yawn} persists beyond duration limit:
11:     A ← True; trigger alert
12: return L, A
```

G. Evaluation Metrics

Four standard classification metrics are used to evaluate and compare the existing RF baseline and the proposed MobileNetV2-CNN model:

- Accuracy: the proportion of correctly classified samples out of all test samples.
- Precision: the proportion of predicted positive samples for a class that are truly of that class.
- Recall: the proportion of actual samples of a class that are correctly identified.
- F1-score: the harmonic mean of precision and recall, providing a balanced measure of classification quality.

V. RESULTS AND DISCUSSION

A. Experimental Setup

The proposed system was implemented in Python using TensorFlow/Keras for deep-learning model development and MediaPipe for real-time facial-landmark extraction. Table I summarises the implementation environment used for training and evaluation.

TABLE I. IMPLEMENTATION ENVIRONMENT

Component	Detail
Language	Python 3
DL Framework	TensorFlow / Keras
Landmark Extraction	MediaPipe Face Mesh
Development IDE	PyCharm
Input Image Size	96 × 96 pixels
Dataset Classes	Open, Closed, Yawn, No_Yawn
Data Split	Train / Validation / Test (stratified)

B. Performance of the Existing Random Forest Model

The existing RF classifier, operating on handcrafted EAR/MAR features, achieved an accuracy of 83.01%, precision of 83.10%, recall of 83.01%, and an F1-score of 83.91%, as summarised in Table II. While the RF model classified the Closed-eye category reasonably well, its performance on the Open, Yawn, and No_Yawn categories was comparatively weaker, confirming that reliance on handcrafted geometric features alone limits classification robustness across diverse facial conditions.

TABLE II. PERFORMANCE OF THE EXISTING RF MODEL

Metric	Value (%)
Accuracy	83.01
Precision	83.10
Recall	83.01
F1-score	83.91

C. Performance of the Proposed MobileNetV2-CNN Model

The proposed MobileNetV2-CNN model achieved an accuracy of 99.19%, precision of 99.22%, recall of 99.19%, and an F1-score of 99.19%, as summarised in Table III. The classification report shows that the Open and Closed classes were classified with near-perfect accuracy, while the Yawn and No_Yawn classes also achieved high F1-scores, confirming that the combination of transfer learning, data augmentation, and multi-stage fine-tuning enabled the model to learn discriminative visual features effectively.

TABLE III. PERFORMANCE OF THE PROPOSED MODEL

Metric	Value (%)
Accuracy	99.19
Precision	99.22
Recall	99.19
F1-score	99.19

D. Comparative Analysis

Fig. 2 compares the Accuracy, Precision, Recall, and F1-score of the existing RF model against the proposed MobileNetV2-CNN model. The proposed model consistently outperforms the RF baseline across every metric, with the largest improvement observed in overall accuracy, confirming that the fusion of deep-learning-based visual classification with geometric EAR/MAR verification substantially improves detection reliability over handcrafted-feature-based classification alone.

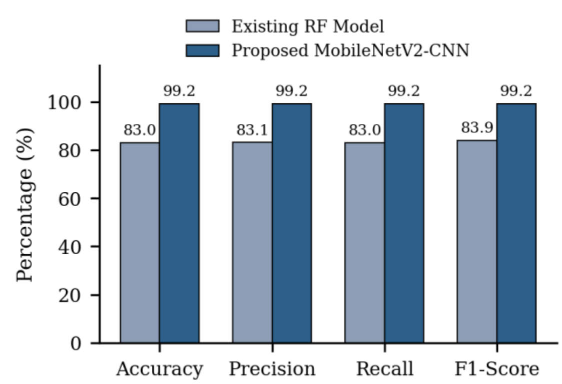

Fig. 2. Performance comparison between the existing RF model and the proposed MobileNetV2-CNN model.

E. Confusion Matrix Analysis

Fig. 3 presents the confusion matrix of the proposed MobileNetV2-CNN model across the four driver-state categories. The matrix shows that the vast majority of Open and Closed samples were classified correctly with negligible misclassification, while the Yawn and No_Yawn categories also achieved strong class separation, with only a small number of samples confused between visually similar states. This confirms that the proposed model generalises well across all four classes rather than favouring any single category.

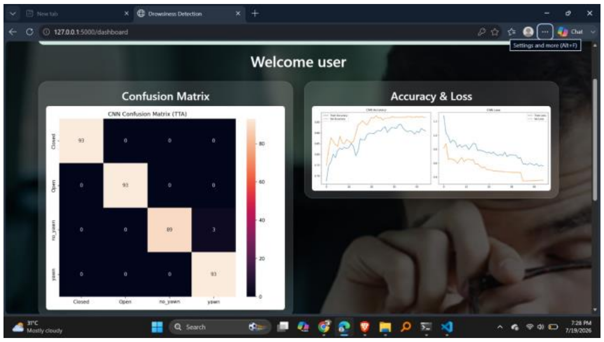

Fig. 3. Confusion matrix of the proposed MobileNetV2-CNN model on the test set.

F. Training and Validation Behaviour

Fig. 4 shows the training and validation accuracy and loss curves recorded during model training. Both training and validation accuracy increase steadily across epochs and converge to a high value, while training and validation loss decrease consistently without significant divergence. The close correspondence between the training and validation curves indicates that the model generalises well to unseen data and does not suffer from substantial overfitting.

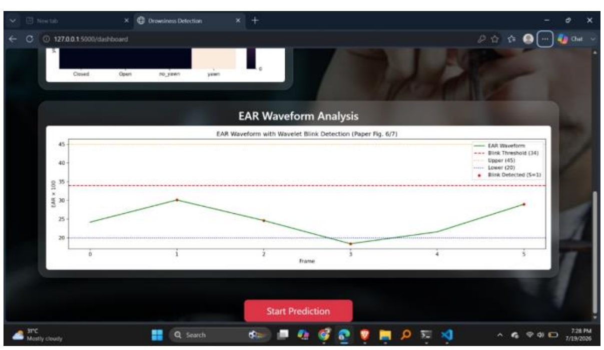

Fig. 4. Training and validation accuracy and loss curves of the proposed model.

G. Classification Reliability

Fig. 5 presents the overall proportion of correctly classified and misclassified test samples for the proposed model. Approximately 99.19% of samples were classified correctly, with only 0.81% misclassified, further confirming the reliability of the proposed MobileNetV2-CNN model for real-time driver-state recognition.

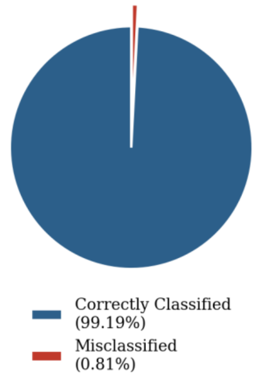

Fig. 5. Proportion of correctly classified versus misclassified samples for the proposed model.

H. Discussion

The experimental results validate the central hypothesis of this work: combining CNN-based visual classification with real-time geometric EAR/MAR verification yields substantially better drowsiness-detection performance than relying on handcrafted features alone. The proposed MobileNetV2-CNN model improved accuracy by approximately 16 percentage points over the existing RF baseline while retaining a lightweight architecture suitable for real-time deployment on standard camera hardware. These findings are consistent with the trends reported by the CNN-based studies reviewed in Section II [3], [15], [18], while additionally demonstrating that fusing learned visual features with geometric landmark analysis further improves robustness under varying illumination and head-pose conditions without requiring wearable physiological sensors.

VI. CONCLUSION

A. Conclusion

This paper presented a real-time deep-learning-based driver drowsiness detection system that combines MobileNetV2-based transfer learning, a Convolutional Neural Network classification head, and MediaPipe Face Mesh-based EAR/MAR geometric analysis to accurately monitor driver alertness. The proposed model was trained using a custom four-class dataset (Open, Closed, Yawn, No_Yawn) with data augmentation, MixUp, label smoothing, and cosine-decay learning-rate scheduling to improve generalisation. Experimental results show that the proposed MobileNetV2-CNN model achieves an accuracy of 99.19%, precision of 99.22%, recall of 99.19%, and an F1-score of 99.19%, substantially outperforming the existing Random Forest baseline, which attained an accuracy of only 83.01%. The confusion matrix and classification report further confirm that the proposed model correctly classifies nearly all test samples with minimal misclassification. By combining deep-learning-based image classification with geometric facial-landmark analysis, the proposed system offers a non-invasive, efficient, and reliable solution for real-time driver monitoring that can be integrated into Advanced Driver Assistance Systems (ADAS) to reduce fatigue-related road accidents.

B. Future Scope

Future work may focus on deploying the trained MobileNetV2-CNN model on embedded and low-power platforms, such as microcontroller-based or GPU-accelerated system-on-chip devices, to enable direct in-vehicle implementation. The system could also be extended by incorporating additional physiological or behavioural indicators, such as head-pose tracking, steering-wheel-grip monitoring, and heart-rate sensing, to further reduce false-alarm rates under challenging driving conditions. Additional future directions include collecting a larger and more diverse dataset covering drivers of different ages, ethnicities, and facial appearances under varied illumination and weather conditions, as well as exploring newer architectures such as Vision Transformers, EfficientNet, ConvNeXt, and hybrid CNN-Transformer designs to further improve classification performance while retaining computational efficiency.

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