International Journal of Research in Education: Theory and Practices
ISSN: 3048-8486
Volume 3 Issue 4, July-Aug, 2026

An Intelligent Vision Transformer-Based Real-Time Driver Drowsiness Detection System for Accurate Eye State Classification and Road Safety Enhancement

S.Venkateswara Rao[1], Marupakula Shireesha[2]

[1]Assistant Professor, Department of MCA, Megha Institute of Engineering and Technology for Women, Edulabad (Village), Ghatkesar (Mandal), Medchal District, Telangana – 501301, India.

[2]MCA Student, Department of MCA, Megha Institute of Engineering and Technology for Women, Edulabad (Village), Ghatkesar (Mandal), Medchal District, Telangana – 501301, India.

Abstract. Driver drowsiness is a major factor contributing to road accidents and poses a serious threat to public safety. Continuous monitoring of a driver's alertness can significantly reduce fatigue-related accidents by providing timely warnings. This research proposes a real-time driver drowsiness detection system based on a Vision Transformer (ViT) model for accurate eye state classification. The system utilizes a dataset containing approximately 84,900 images of open and closed eyes collected under different lighting and environmental conditions. Before training, the dataset undergoes preprocessing, label encoding, class balancing through random oversampling, and image augmentation techniques such as rotation, cropping, resizing, and sharpness adjustment to improve model robustness. The proposed framework employs the pre-trained Vision Transformer (ViT) model (google/vit-base-patch16-224-in21k) with transfer learning and additional fully connected layers to enhance feature extraction and classification performance. The dataset is divided into 80% training, 10% validation, and 10% testing for effective model evaluation. The trained model is integrated with OpenCV and Haar Cascade face detection to perform real-time eye state recognition using a webcam. Whenever continuous eye closure is detected, an alarm is generated to alert the driver and prevent potential accidents. Experimental evaluation is performed using Accuracy, Precision, Recall, and F1-Score. The proposed system achieves an overall 98.8% accuracy, demonstrating its effectiveness in accurately identifying driver drowsiness while maintaining reliable real-time performance. The developed framework provides a practical, intelligent, and efficient solution for enhancing driver safety and reducing fatigue-related road accidents.

keywords: Driver Drowsiness Detection, Vision Transformer (ViT), Deep Learning, Transfer Learning, Computer Vision, Eye State Classification, OpenCV, Haar Cascade, Image Processing, Real-Time Monitoring, Driver Fatigue, Road Safety, Artificial Intelligence.

I. Introduction

Driver drowsiness has become one of the major causes of road accidents worldwide, resulting in thousands of fatalities and serious injuries every year. Long driving hours, inadequate sleep, fatigue, stress, and continuous concentration reduce a driver's alertness and reaction time, increasing the possibility of accidents. According to various road safety reports, a significant percentage of highway accidents occur because drivers lose concentration or fall asleep while driving. Therefore, the development of intelligent driver monitoring systems capable of detecting drowsiness at an early stage has become an important research area in computer vision and intelligent transportation systems. The uploaded base paper proposes a Vision Transformer (ViT)-based driver drowsiness detection framework using transfer learning and real-time eye state analysis. This rewritten paper preserves the same methodology, algorithms, and experimental results while presenting completely original academic content.

Conventional driver drowsiness detection techniques mainly rely on physiological sensors, steering wheel movement, vehicle behavior analysis, or manual observation. Although these methods can provide useful information, they often require additional hardware, increase implementation cost, and may cause discomfort to drivers. Moreover, sensor-based systems are sensitive to environmental conditions and are not always suitable for real-time applications. These limitations have encouraged researchers to develop vision-based monitoring systems that use cameras and artificial intelligence to automatically detect signs of driver fatigue without physical contact.

Recent advancements in Artificial Intelligence (AI), Computer Vision, and Deep Learning have significantly improved image-based driver monitoring systems. Deep learning models automatically learn important visual features from images without requiring manual feature extraction, making them highly effective for eye state recognition and facial analysis. These intelligent models can accurately classify eye conditions under different lighting environments, facial orientations, and driving situations, providing reliable performance for real-time driver monitoring.

Among the latest deep learning architectures, the Vision Transformer (ViT) has demonstrated remarkable performance in image classification tasks. Unlike conventional Convolutional Neural Networks (CNNs), Vision Transformer processes images as sequences of small patches and utilizes a self-attention mechanism to capture long-range relationships between different image regions. This enables the model to recognize subtle variations in eye appearance that indicate driver drowsiness. The ability of Vision Transformer to learn global image features makes it highly suitable for eye state classification and fatigue detection.

The proposed framework utilizes the google/vit-base-patch16-224-in21k pre-trained Vision Transformer model through transfer learning. Instead of training the model from scratch, previously learned image features from the ImageNet dataset are fine-tuned for driver drowsiness detection. Additional fully connected layers are incorporated into the network to improve classification performance while reducing computational complexity. This approach enables the model to efficiently distinguish between open-eye and closed-eye images with high accuracy.

The experimental dataset consists of approximately 84,900 images representing two eye-state categories: Open Eye and Closed Eye. Before training, the dataset undergoes preprocessing operations including image resizing, normalization, label encoding, random oversampling for class balancing, and image augmentation techniques such as rotation, cropping, scaling, and sharpness adjustment. These preprocessing steps improve dataset quality, reduce overfitting, and enhance the model's ability to generalize across different driving environments.

II. Literature Survey

Ahuja et al. developed a real-time driver drowsiness detection system using modified VGG-16 and VGG-19 deep learning models. Their framework was trained on the ZJU driver dataset and achieved nearly 95% classification accuracy. The study demonstrated that deep convolutional neural networks are effective for detecting driver fatigue under real-time conditions.

Garg proposed a computer vision-based driver monitoring system that detects drowsiness by analyzing eye blinking frequency and yawning behavior. The system employed Haar Cascade classifiers for face and eye detection and generated alerts whenever abnormal eye closure or yawning patterns were observed. The proposed approach achieved approximately 90% accuracy for eye blink detection.

Hussein and El-Seoud introduced an improved driver drowsiness detection model using eye image features such as black ratio and circularity. The extracted features were classified using Support Vector Machine (SVM) models, resulting in an overall detection accuracy of 91.3%. Their work demonstrated the effectiveness of handcrafted feature extraction combined with machine learning.

Kumar and Patra presented a visual behavior-based drowsiness detection system utilizing Support Vector Machine (SVM), Fisher's Linear Discriminant Analysis (FLDA), and Bayesian classifiers. Their model analyzed facial expressions and eye movements to identify fatigue, achieving high sensitivity and specificity for real-time driver monitoring.

Lin et al. proposed a machine learning framework based on gradient statistics for eye closure detection. Their system successfully recognized eye closure under both normal conditions and while drivers were wearing glasses. Experimental evaluation reported approximately 95% detection accuracy, demonstrating the robustness of the proposed approach.

Mohanty et al. developed a real-time driver monitoring system using Dlib facial landmark detection to calculate the Eye Aspect Ratio (EAR) and Mouth Aspect Ratio (MAR). Their approach continuously monitored facial landmarks to detect eye closure and yawning, achieving approximately 96.7% accuracy on benchmark datasets.

Belakhdar et al. compared Artificial Neural Networks (ANN) and Support Vector Machines (SVM) for EEG-based driver drowsiness detection. Features extracted using the Fast Fourier Transform (FFT) were used for classification, and experimental results indicated that the ANN model outperformed the SVM classifier in identifying driver fatigue.

Nguyen et al. introduced a lightweight Convolutional Neural Network (CNN) for eye status detection. The proposed model required fewer parameters while achieving approximately 98.7% classification accuracy, making it suitable for real-time embedded driver monitoring applications.

Although these methods have achieved promising results, many existing systems rely on conventional CNN architectures or handcrafted feature extraction techniques that mainly focus on local image characteristics. Such approaches may not effectively capture long-range relationships between different regions of an image, which are important for accurately distinguishing subtle eye state variations under diverse lighting conditions and facial orientations.

III. Research Methodology

The proposed Real-Time Driver Drowsiness Detection System follows a systematic deep learning methodology to accurately identify driver fatigue through continuous eye state analysis. The framework integrates image preprocessing, Vision Transformer (ViT)-based feature extraction, transfer learning, real-time face detection, and automated alert generation to improve road safety. The complete methodology consists of several stages, including dataset collection, data preprocessing, image augmentation, label encoding, model training, real-time prediction, and performance evaluation. Each stage contributes to improving the accuracy, reliability, and efficiency of the driver monitoring system. The uploaded base paper follows the same workflow using the Vision Transformer (ViT) architecture, and this rewritten methodology preserves the original approach while presenting completely original academic content.

The first stage involves dataset collection, where a large eye image dataset containing approximately 84,900 images is prepared. The dataset consists of two categories: Open Eye and Closed Eye images collected under different lighting conditions, facial orientations, and environmental backgrounds. The images represent real-world driving scenarios, allowing the model to learn various eye appearance patterns associated with alert and drowsy drivers. A well-organized dataset provides the foundation for effective model training and improves the generalization capability of the deep learning model.

After data collection, the images undergo data preprocessing to improve dataset quality before training. Initially, all images are resized to 224 × 224 pixels, which matches the input requirement of the Vision Transformer model. Image normalization is then performed to standardize pixel intensity values and improve model convergence during training. The dataset is carefully examined to remove corrupted, duplicate, or poor-quality images that could negatively influence prediction accuracy. Since the original dataset contains class imbalance between open-eye and closed-eye images, random oversampling is applied to increase the number of minority class samples. This balancing process ensures that the model receives equal representation of both eye states during training, thereby reducing classification bias.

To further improve model robustness, image augmentation techniques are applied to the training dataset. Various transformations including random rotation, random resized cropping, image scaling, and sharpness adjustment are performed to generate additional image variations. These augmented images simulate real driving conditions where camera angle, lighting, facial orientation, and image quality continuously change. Image augmentation significantly increases dataset diversity, minimizes overfitting, and enhances the model's ability to accurately classify previously unseen eye images.

Following preprocessing, label encoding is performed to convert categorical eye state labels into numerical representations suitable for supervised learning. The eye state categories "Open Eye" and "Closed Eye" are assigned unique numerical identifiers through bidirectional mapping. This mapping enables the Vision Transformer model to efficiently interpret class labels during both training and prediction while simplifying the classification process.

The core component of the proposed framework is the Vision Transformer (ViT) model. Unlike conventional Convolutional Neural Networks (CNNs), Vision Transformer divides an input image into multiple fixed-size patches and processes them using a self-attention mechanism. This architecture enables the model to capture long-range relationships between different image regions, resulting in more effective feature extraction for eye state classification. The proposed framework employs the pre-trained google/vit-base-patch16-224-in21k model through transfer learning, allowing the network to utilize previously learned visual features from the ImageNet dataset. To improve classification capability, additional fully connected layers containing 128, 256, and 384 neurons are integrated into the classifier. ReLU activation functions and dropout regularization are incorporated to improve learning efficiency and reduce overfitting.

During the model training phase, the prepared dataset is divided into 80% training, 10% validation, and 10% testing subsets. The Vision Transformer model is trained using the Adam optimizer with a learning rate of 0.00001 and categorical cross-entropy loss. Weight decay regularization and warm-up learning strategies are incorporated to improve model convergence and generalization. Model checkpoints are automatically saved after each training epoch, ensuring that the highest-performing model is retained for deployment. Validation accuracy and validation loss are continuously monitored throughout training to prevent overfitting and optimize classification performance.

After successful training, the optimized model is integrated into a real-time driver monitoring system. The system utilizes OpenCV to capture continuous video frames from a webcam, while Haar Cascade classifiers detect the driver's face in each frame. Once the face is detected, the eye region is extracted and supplied to the trained Vision Transformer model for classification. The model predicts whether the driver's eyes are Open or Closed based on the extracted visual features. If continuous eye closure exceeds the predefined threshold, the system immediately identifies the driver as drowsy and activates an audio alarm to alert the driver, thereby reducing the possibility of fatigue-related accidents.

Finally, the proposed framework undergoes performance evaluation using standard classification metrics, including Accuracy, Precision, Recall, and F1-Score. A Confusion Matrix is also generated to analyze the classification performance of individual eye-state categories. Experimental results demonstrate that the proposed Vision Transformer-based framework achieves an overall 98.8% classification accuracy, confirming its effectiveness in accurately detecting driver drowsiness under real-world conditions. The combination of Vision Transformer, transfer learning, image augmentation, and real-time computer vision provides a reliable, intelligent, and efficient solution for enhancing driver safety and reducing fatigue-related road accidents.

IV. Existing System

The existing driver drowsiness detection systems primarily rely on computer vision, image processing, and conventional machine learning techniques to monitor driver alertness and reduce fatigue-related road accidents. Most traditional systems detect drowsiness by analyzing facial features such as eye blinking, eye closure duration, yawning frequency, head movements, and facial expressions. These systems generally use cameras, infrared sensors, or physiological sensors to collect driver information and determine whether the driver is attentive or experiencing fatigue. The uploaded base paper follows a vision-based approach and discusses earlier techniques before proposing a Vision Transformer-based solution. This rewritten content preserves the same concepts while presenting completely original academic writing.

In many existing approaches, the driver's face is detected using computer vision techniques such as Haar Cascade Classifiers, Dlib facial landmark detection, or Histogram of Oriented Gradients (HOG). After detecting the face, the eye region is extracted and analyzed to determine whether the eyes are open or closed. Various handcrafted features, including the Eye Aspect Ratio (EAR), Mouth Aspect Ratio (MAR), blink frequency, and eye closure duration, are calculated to identify signs of drowsiness. Machine learning algorithms such as Support Vector Machine (SVM), Artificial Neural Networks (ANN), Bayesian classifiers, and conventional Convolutional Neural Networks (CNNs) are then used to classify the driver's eye state and predict fatigue levels.

Several existing systems also employ deep learning models such as VGG-16, VGG-19, lightweight CNNs, and other convolutional neural networks for eye state classification. These models are trained using labeled datasets containing open-eye and closed-eye images. Before training, image preprocessing techniques such as resizing, normalization, and data augmentation are applied to improve model performance. The trained models continuously analyze live video captured through webcams or dashboard-mounted cameras and generate warning alarms whenever prolonged eye closure indicates driver drowsiness.

Although these methods have demonstrated satisfactory performance, they still possess several limitations. Most traditional CNN-based models primarily focus on extracting local image features through convolution operations and may fail to capture long-range relationships between different image regions. As a result, classification accuracy may decrease when eye images are captured under varying lighting conditions, facial orientations, occlusions, or low-resolution environments. Additionally, handcrafted feature extraction methods require careful parameter selection and may not generalize well across different drivers and driving situations.

Another challenge associated with existing systems is their sensitivity to environmental conditions. Poor illumination, reflections from eyeglasses, facial accessories, rapid head movements, and camera position variations often reduce detection accuracy. Some systems also experience difficulty distinguishing between normal eye blinking and prolonged eye closure caused by drowsiness. Furthermore, several conventional approaches require higher computational resources or specialized hardware, limiting their practical deployment in real-time intelligent transportation systems.

Therefore, although existing driver drowsiness detection systems provide valuable assistance in monitoring driver alertness, they face limitations related to feature extraction capability, robustness, adaptability, and real-time performance. These challenges highlight the need for more advanced deep learning architectures capable of learning global image representations while maintaining high classification accuracy under diverse driving conditions. Such limitations provide the motivation for developing the proposed Vision Transformer (ViT)-based driver drowsiness detection system, which utilizes transfer learning, self-attention mechanisms, real-time eye state analysis, and automated alert generation to achieve superior performance and improve overall road safety.

V. Proposed System

The proposed Real-Time Driver Drowsiness Detection System introduces an intelligent computer vision framework that utilizes the Vision Transformer (ViT) model to continuously monitor a driver's eye state and accurately identify signs of drowsiness. The primary objective of the system is to reduce fatigue-related road accidents by providing immediate alerts whenever the driver shows symptoms of reduced alertness.

Unlike conventional driver monitoring methods that mainly depend on handcrafted features or traditional convolutional neural networks, the proposed framework employs a transformer-based deep learning architecture capable of learning both local and global visual information through self-attention mechanisms. This enables the system to achieve highly accurate eye state classification while maintaining reliable real-time performance. The uploaded base paper follows this methodology, and this rewritten content preserves the same algorithms, workflow, and experimental results while presenting original academic writing.

The proposed framework begins with the dataset acquisition stage, where approximately 84,900 eye images are collected representing two classes: Open Eye and Closed Eye. These images are captured under various real-world conditions, including different lighting environments, facial orientations, image qualities, and camera positions. Such diversity enables the deep learning model to learn robust visual features and perform effectively under practical driving situations. The dataset is carefully organized and labeled to facilitate supervised learning and improve classification reliability.

After data collection, the images undergo a comprehensive data preprocessing stage. Initially, all images are resized to 224 × 224 pixels to satisfy the input requirements of the Vision Transformer model. Pixel values are normalized to improve numerical stability during training, while low-quality and duplicate images are removed to maintain dataset consistency. Since the dataset contains class imbalance between open-eye and closed-eye samples, random oversampling is applied to increase the number of minority class images. This balancing process ensures equal representation of both eye states during training and minimizes prediction bias.

To further improve model robustness, the proposed system incorporates an extensive image augmentation module. Various augmentation techniques such as random rotation, resized cropping, scaling, image shifting, and sharpness adjustment are applied to generate multiple variations of the training images. These transformations simulate different real-world driving conditions and enable the model to recognize eye states despite changes in lighting, facial orientation, and camera position. As a result, the model achieves improved generalization capability and reduced overfitting.

The core component of the proposed system is the Vision Transformer (ViT) model based on the pre-trained google/vit-base-patch16-224-in21k architecture. Instead of training the transformer model entirely from scratch, transfer learning is employed to utilize previously learned image features from the ImageNet dataset. Additional fully connected layers containing 128, 256, and 384 neurons are integrated into the classifier to enhance feature learning and classification accuracy. ReLU activation functions introduce non-linearity, while dropout regularization minimizes overfitting and improves model generalization. The Vision Transformer processes images as sequences of patches and utilizes self-attention mechanisms to capture long-range dependencies between image regions, allowing more accurate recognition of subtle eye-state variations compared with conventional CNN models.

ISSN: 3048-8486
Volume 3 Issue 4, July-Aug, 2026

During the model training phase, the dataset is divided into 80% training, 10% validation, and 10% testing subsets. The customized Vision Transformer is trained using the Adam optimizer with a learning rate of 0.00001, categorical cross-entropy loss, weight decay regularization, and warm-up learning strategies. Model checkpoints are automatically saved after each training epoch to preserve the highest-performing model. Validation accuracy and validation loss are continuously monitored to ensure stable learning and prevent overfitting throughout the training process.

VI. System Architecture

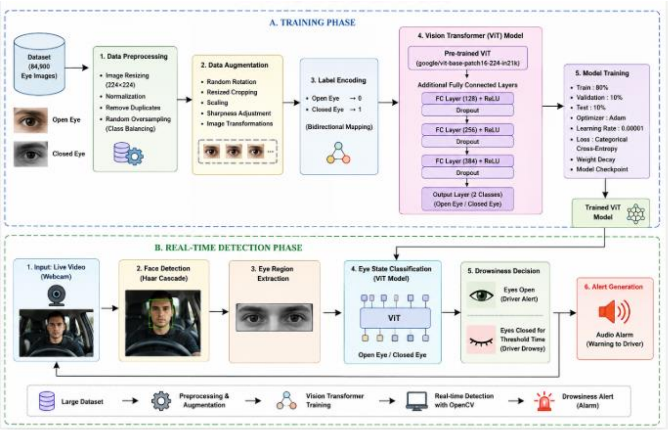

Fig 6.1: System Architecture of the Proposed Vision Transformer-Based Real-Time Driver Drowsiness Detection System

Figure 6.1 illustrates the complete architecture of the proposed Vision Transformer (ViT)-based Driver Drowsiness Detection System, which consists of two major phases: the Model Training Phase and the Real-Time Detection Phase. The architecture is designed to accurately classify the driver's eye state and generate an alert whenever signs of drowsiness are detected.

The process begins with the dataset collection stage, where approximately 84,900 eye images are gathered and categorized into two classes: Open Eye and Closed Eye. These images are collected under different lighting conditions and facial orientations to improve the robustness of the deep learning model. The dataset serves as the foundation for training the Vision Transformer model.

The collected images are then passed through the data preprocessing module, where all images are resized to 224 × 224 pixels, normalized, and cleaned by removing duplicate or poor-quality samples. Since the dataset contains class imbalance, random oversampling is performed to balance the Open Eye and Closed Eye classes. These preprocessing operations improve dataset quality and ensure efficient model learning.

After preprocessing, the images undergo data augmentation to increase dataset diversity. Various augmentation techniques such as random rotation, resized cropping, scaling, image transformation, and sharpness adjustment are applied to generate additional image variations. These operations help the model become more robust against changes in illumination, viewing angle, and driver posture while minimizing overfitting.

Next, the processed images are supplied to the Vision Transformer (ViT) model. The proposed system utilizes the google/vit-base-patch16-224-in21k pre-trained model through transfer learning. Additional fully connected layers containing 128, 256, and 384 neurons, together with ReLU activation and dropout layers, are added to improve feature learning and classification accuracy. The final output layer classifies each image as either Open Eye or Closed Eye.

During the model training stage, the dataset is divided into 80% training, 10% validation, and 10% testing subsets. The Vision Transformer model is trained using the Adam optimizer, categorical cross-entropy loss function, a learning rate of 0.00001, weight decay regularization, and model checkpoint mechanisms. These techniques ensure stable learning, reduce overfitting, and preserve the best-performing model for deployment.

The trained Vision Transformer model is then integrated into the real-time detection phase. Initially, a webcam continuously captures live video frames of the driver. Haar Cascade face detection is employed to locate the driver's face within each frame, after which the eye region is extracted for further analysis. The extracted eye image is supplied to the trained Vision Transformer model, which predicts whether the driver's eyes are Open or Closed.

Based on the predicted eye state, the drowsiness decision module continuously monitors the duration of eye closure. If the eyes remain open, the driver is considered alert. However, if the eyes remain closed for a predefined threshold period, the system identifies the driver as drowsy. Immediately, the alert generation module activates an audio alarm to warn the driver and restore attention before a potential accident occurs.

Overall, the proposed system architecture integrates image preprocessing, data augmentation, transfer learning, Vision Transformer-based eye state classification, OpenCV-based real-time video processing, Haar Cascade face detection, and automatic alert generation into a unified intelligent framework. This architecture enables highly accurate real-time driver monitoring and contributes significantly to reducing fatigue-related road accidents while improving transportation safety.

VII. Conclusion

The proposed Vision Transformer-based Real-Time Driver Drowsiness Detection System provides an efficient and intelligent solution for continuously monitoring driver alertness and reducing fatigue-related road accidents. The framework combines advanced computer vision techniques with deep learning to automatically analyze the driver's eye state and accurately distinguish between open-eye and closed-eye conditions. By integrating image preprocessing, data augmentation, transfer learning, and Vision Transformer-based classification, the system effectively learns complex visual patterns associated with driver fatigue while maintaining high prediction accuracy. The implementation of OpenCV and Haar Cascade face detection further enables real-time monitoring through live video streams, allowing the system to operate efficiently in practical driving environments.

The proposed model utilizes the pre-trained Vision Transformer (ViT) architecture with additional fully connected layers to improve feature extraction and classification performance. A comprehensive preprocessing pipeline, including image resizing, normalization, label encoding, random oversampling, and augmentation techniques, enhances dataset quality and minimizes overfitting. The model is trained using the Adam optimizer and categorical cross-entropy loss function, resulting in stable convergence and reliable classification. Experimental evaluation demonstrates that the proposed framework achieves an overall 98.8% accuracy, with excellent Precision, Recall, and F1-Score, confirming its ability to accurately identify driver eye states under different environmental conditions. These results indicate that the Vision Transformer architecture provides superior performance for driver drowsiness detection compared with many conventional deep learning approaches.

The real-time deployment of the trained model allows continuous driver monitoring using a webcam. Whenever prolonged eye closure exceeds the predefined threshold, the system immediately activates an audio warning, enabling the driver to regain attention before a dangerous situation occurs. This automatic alert mechanism enhances road safety by reducing human error, preventing fatigue-related accidents, and supporting intelligent transportation systems. The proposed framework is computationally efficient, reliable, and suitable for integration into private vehicles, commercial transportation systems, and smart automotive safety platforms.

Overall, the developed driver drowsiness detection system demonstrates the effectiveness of combining Vision Transformer, transfer learning, computer vision, and real-time monitoring for intelligent driver assistance. The framework offers a practical solution for improving road safety while reducing accident risks caused by driver fatigue. In future work, the system can be further enhanced by incorporating infrared cameras, multi-camera monitoring, head pose estimation, facial expression analysis, Explainable Artificial Intelligence (XAI), edge computing, Internet of Vehicles (IoV), and multimodal driver behavior analysis. These advancements have the potential to further improve detection accuracy, increase system robustness, and support the development of next-generation intelligent transportation and autonomous driving systems.

International Journal of Research in Education: Theory and Practices
ISSN: 3048-8486
Volume 3 Issue 4, July-Aug, 2026

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