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Driver Behavior–Based Intelligent System for Traffic Accident Detection and Early Warning

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ABSTRACT

This study presents an intelligent system for traffic accident detection and early warning based on driver behavior analysis. A driver behavior–based intelligent system for traffic accident detection and early warning operates by continuously monitoring the driver's actions using cameras and vehicle sensors. It collects real-time data such as eye movements, head pose, steering patterns, and acceleration signals. Advanced deep learning models such as YOLO and recurrent neural networks analyze these features to detect fatigue, distraction, or abnormal driving behavior. The system then evaluates the risk level based on predefined thresholds and contextual traffic conditions. When the risk exceeds a safety limit, it generates early warnings to prevent potential accidents. It is widely applied in smart vehicles, fleet management systems, and advanced driver assistance systems (ADAS). It helps monitor driver fatigue, distraction, and risky behaviors in real time to improve road safety. In commercial transportation, it supports logistics companies by reducing accident rates and operational costs. Experimental results show improved detection accuracy, high precision–recall performance, and reduced false alarms under diverse driving conditions. Overall, the system contributes to fewer traffic accidents, enhanced driver awareness, and more reliable intelligent transportation systems.

1. Introduction

Intelligent Transportation Systems (ITS) use cutting-edge information and communication technologies to make modern transportation networks safer, more efficient, and more environmentally friendly. ITS uses technologies like computer vision, data analytics, sensor networks, artificial intelligence, and wireless communication to let people monitor, control, and manage traffic systems in real time. The main goal of ITS is to improve transportation while lowering traffic jams, accidents, and damage to the environment. Transportation systems used to depend on fixed infrastructure and manual controls, which made it hard for them to adapt to changing traffic conditions. ITS, on the other hand, adds intelligence to transportation systems by letting them collect data all the time and make decisions automatically. Data comes from a number of places, such as cameras, sensors, GPS devices, and communication networks [1]–[6].

The Internet of Things (IoT) plays a crucial role in autonomous vehicles by enabling continuous connectivity between the vehicle, its surrounding environment, and transportation infrastructure. Through a network of IoT-enabled sensors, cameras, radar, and LiDAR, autonomous cars can collect, process, and exchange real-time data to perceive road conditions, detect obstacles, and make driving decisions. IoT also supports Vehicle-to-Everything (V2X) communication, allowing vehicles to interact with traffic signals, other vehicles, and cloud-based control centers to improve safety and optimize traffic flow. Moreover, IoT technologies enable remote monitoring, predictive maintenance, and over-the-air software updates, enhancing the reliability and efficiency of autonomous driving systems [7]–[15].

Driver behavior–based intelligent systems for traffic accident detection and early warning face several significant challenges. One major issue is the accurate and robust detection of diverse driver behaviors under varying lighting, weather, and traffic conditions. Real-time processing requirements impose strict constraints on computational complexity and system latency. Another challenge lies in handling individual differences in driving styles, which can lead to false alarms. Sensor noise, occlusion, and incomplete data further degrade system reliability [16]–[23]. Previous studies have explored vision-based, physiological-signal-based, and vehicle-dynamics-based approaches to address these issues. Machine learning and deep learning models have been widely applied for behavior recognition and risk prediction. Some works integrate multi-sensor data to improve robustness and accuracy. However, generalization across different drivers and environments remains a key limitation. Therefore, ongoing research continues to focus on adaptive models and real-world deployment challenges [24]–[31].

This study presents an intelligent system for traffic accident detection and early warning based on driver behavior analysis. The study is organized as follows. 2. Intelligent system for traffic accident is present in Section 2. Section 3 presents the system analysis and design. The numerical results and discussions are presents in Section 4. The study is included in Section 5.

2. Intelligent System for Traffic Accident

2.1. Convolutional Neural Network (CNN)

The convolutional neural networks (CNN) are show in in Fig. 1, CNN are a class of deep learning models primarily used for image processing, computer vision, and pattern recognition tasks. They are inspired by the visual cortex of the human brain and are particularly effective in handling spatial data [32]–[40]. CNNs are revolutionizing industries by providing efficient visual recognition capabilities. From healthcare to self-driving cars, their impact is vast and continuously growing. It is a neural network architecture that is well suited for problems where the data is images or video.

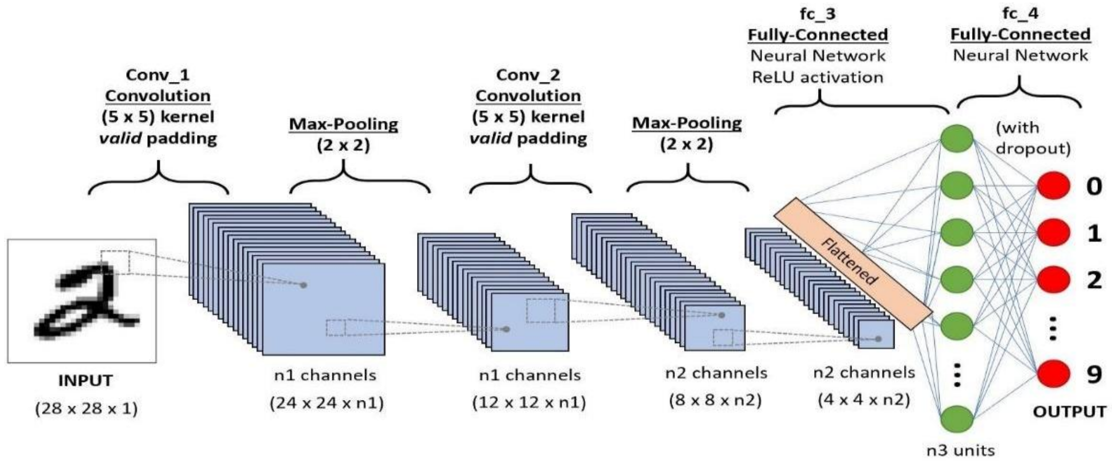

Fig. 1. The proposed method

The convolution layer is the core building block of a CNN. It is responsible for detecting features such as edges, textures, shapes, and patterns in images. A convolution operation is performed by sliding a small filter (kernel) over an input image or feature map. At each position, the dot product of the filter and the corresponding region of the input is computed and summed to produce a single output value. In this layer there are 4 main objects: input matrix, receptive field, filters, and feature map, that is show in Fig. 2.

2.2. Loss Function and Mathematical Formulation of YOLO

The YOLO (You Only Look Once) framework formulates object detection as a single regression problem, enabling simultaneous prediction of object locations, objectness confidence, and class probabilities in one forward pass. This unified formulation allows YOLO to achieve high detection speed while maintaining competitive accuracy, which is particularly suitable for real-time applications such as driver behavior monitoring [41]–[46].

In YOLO-based models, the overall loss function is composed of three main components: bounding box regression loss, objectness (confidence) loss, and classification loss. The total loss can be expressed as:

$$\mathcal{L}_{YOLO} = \mathcal{L}_{box} + \mathcal{L}_{obj} + \mathcal{L}_{cls} \tag{1}$$

where each term corresponds to a specific optimization objective in the detection process.

The bounding box regression loss measures the discrepancy between the predicted bounding box and the ground truth box. In modern YOLO versions (including YOLOv8), the Complete Intersection over Union (CIoU) loss is commonly adopted to improve localization accuracy. The bounding box loss is defined as:

$$\mathcal{L}_{box} = 1 - CIoU \tag{2}$$

The CIoU metric considers not only the overlap area (IoU) but also the distance between box centers and the aspect ratio consistency, providing more stable and accurate convergence during training. This is especially important for detecting fine-grained visual cues such as facial regions and hand movements in driver behavior analysis.

The objectness loss evaluates whether a predicted bounding box contains an object of interest. It is typically computed using Binary Cross-Entropy (BCE) loss:

$$\mathcal{L}_{obj} = -[y\log(\hat{y}) + (1-y)\log(1-\hat{y})] \tag{3}$$

where y denotes the ground truth object presence and $\hat{y}$ represents the predicted confidence score. This component enables the model to distinguish between background regions and regions containing driver-related behaviors.

The classification loss penalizes incorrect class predictions for detected objects. It is calculated as a categorical cross-entropy loss over the predefined behavior classes:

$$\mathcal{L}_{cls} = -\sum_{i=1}^{C} y_i \log(\hat{y}_i) \tag{4}$$

where C is the number of driver behavior classes, y_i is the ground truth label, and $\hat{y}_i$ is the predicted class probability. In this study, the classification loss enables the model to differentiate between behaviors such as *Awake*, *Drowsy*, *Texting_phone*, *Talking_phone*, and *Turning*.

By jointly optimizing localization, objectness confidence, and classification objectives, the YOLO loss formulation allows efficient end-to-end training and real-time inference. This mathematical design makes YOLO particularly suitable for embedded deployment scenarios, such as Raspberry Pi–based driver monitoring systems, where both accuracy and computational efficiency are critical.

3. System Analysis and Design

3.1. System Design

The system architecture of the proposed driver monitoring system is designed as a multi-layer framework to ensure real-time performance and high reliability. It integrates in-cabin sensors, including cameras and physiological sensors, to continuously capture driver behavior and state. The perception layer processes raw sensor data using computer vision and signal processing algorithms to extract meaningful features [47]–[54]. The connection model of the system is show in Fig. 2.

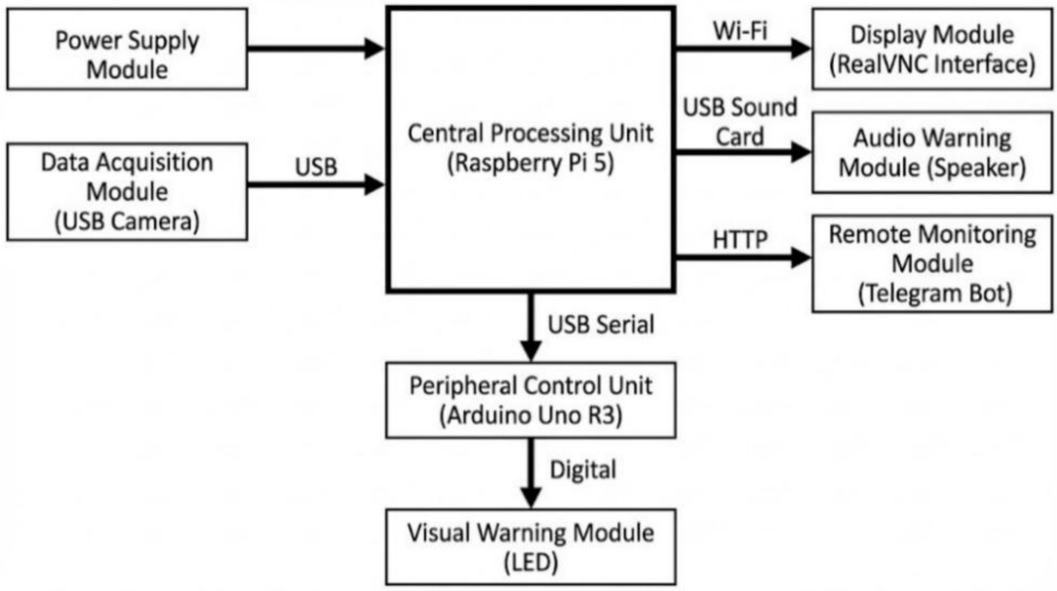

Fig. 2. Overall system architecture of the proposed driver monitoring system

These features are then transmitted to the analysis layer, where machine learning models detect fatigue, distraction, and abnormal driving patterns. A decision-making module evaluates the detected states and determines appropriate warning or intervention strategies. The communication layer enables data exchange between the vehicle, edge devices, and cloud servers for model updates and data storage. Finally, the human–machine interface provides timely visual, auditory, or haptic alerts to support safer driving.

3.2. Training Model

The YOLO model training workflow begins with collecting and annotating a large dataset of images containing the target objects. The dataset is then divided into training, validation, and testing sets to ensure robust performance evaluation. Preprocessing steps such as image resizing, normalization, and data augmentation are applied to improve model generalization. The YOLO network architecture is configured by selecting the appropriate version, input resolution, and anchor boxes. During training, images are fed into the network, and the model predicts bounding boxes, objectness scores, and class probabilities [55]–[62]. The overview of the YOLO model training show in Fig. 3.

4. Results and Discussion

In this section, the influence of the confidence threshold on the performance of the proposed YOLO-based driver behavior detection model is analyzed. The confidence threshold plays a critical role in balancing detection accuracy and system reliability, especially in real-time applications such as driver monitoring systems. To evaluate this effect, three performance curves are examined (Fig. 5, Fig. 6, Fig. 7), including the F1–Confidence curve, Precision–Confidence curve, and Recall–Confidence curve. These curves illustrate how the model’s performance changes when the confidence threshold varies from low to high values.

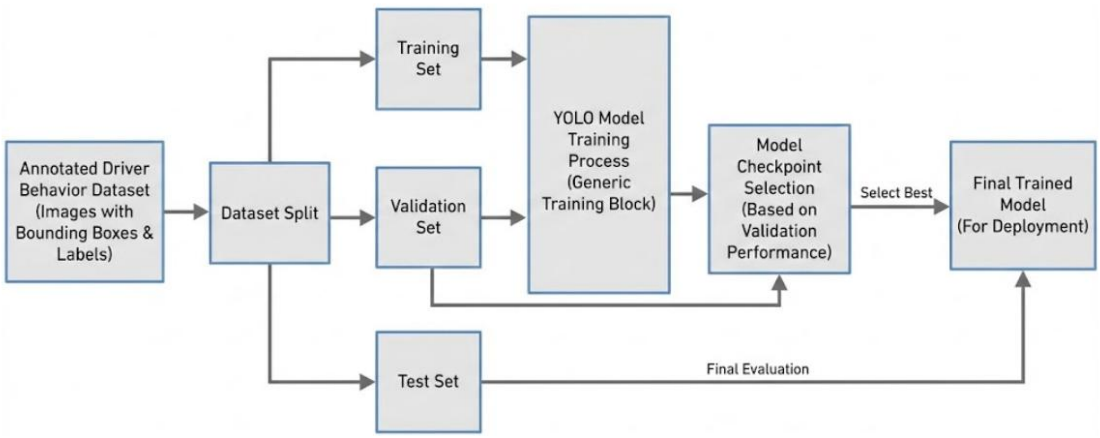

Fig. 3. Overview of the YOLO model training workflow

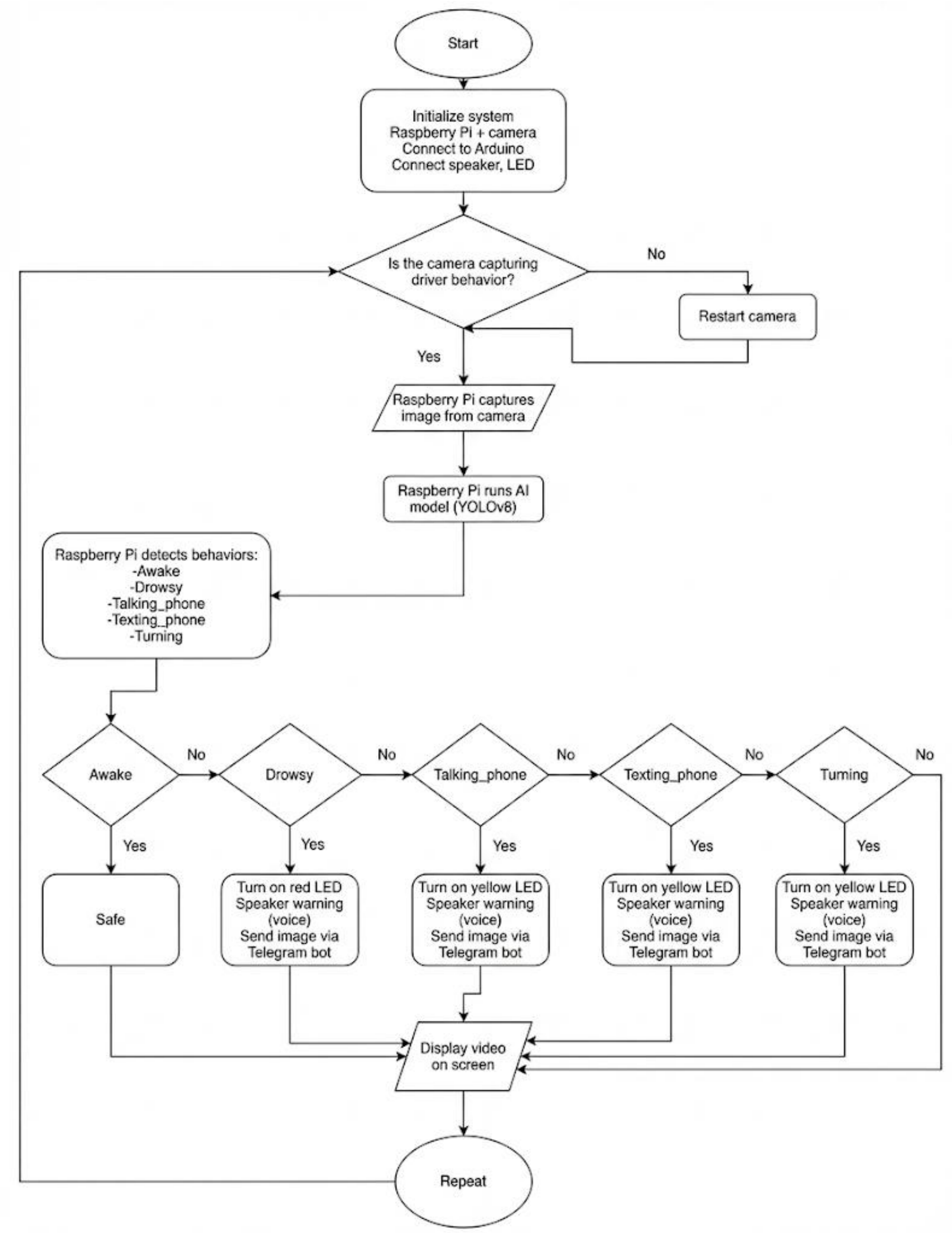

Fig. 4. Workflow of the proposed driver behavior detection and warning system

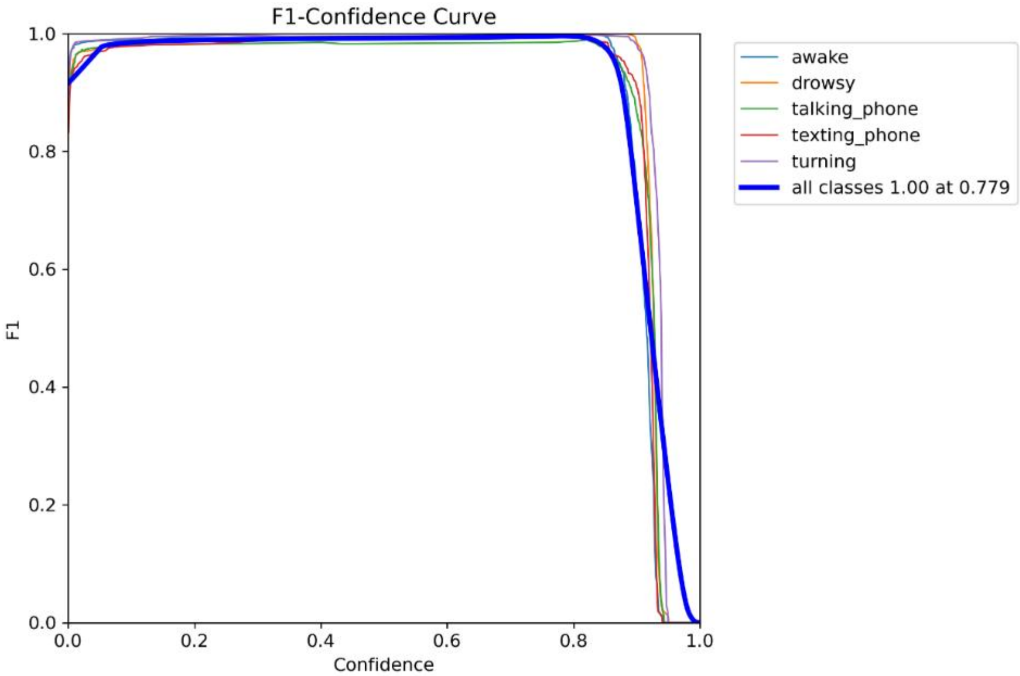

Fig. 5. F1-score versus confidence threshold

The F1–Confidence curve provides an overall assessment by combining precision and recall into a single metric. The experimental results show that the F1-score reaches its maximum value at a confidence threshold of approximately 0.77–0.80, indicating the optimal operating point for the system. This threshold ensures high detection accuracy while maintaining system stability, making it suitable for real-time deployment.

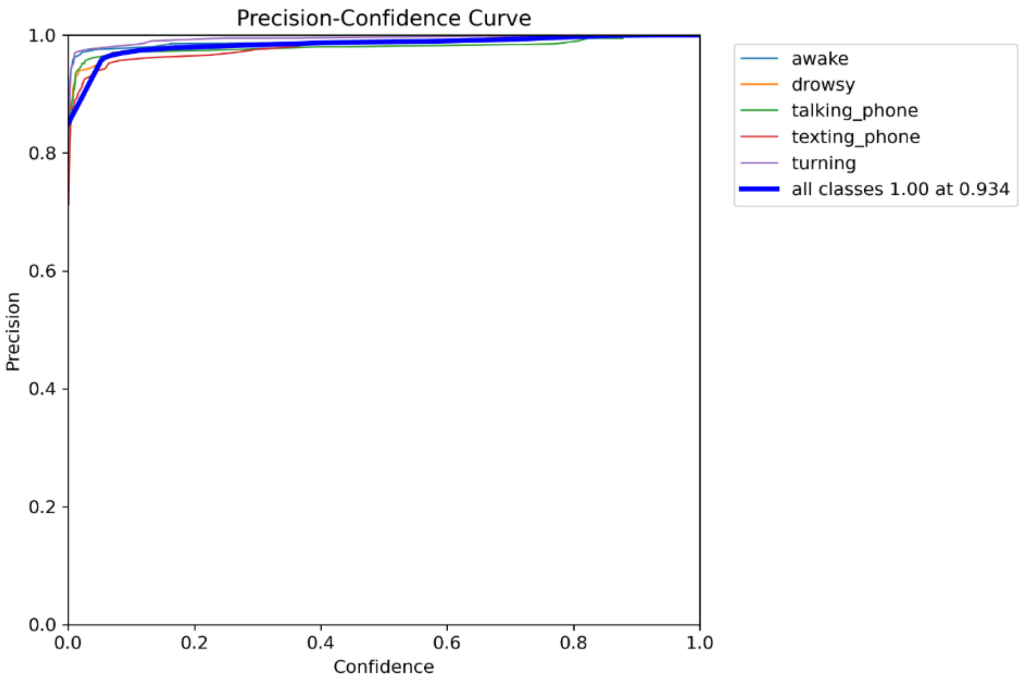

Fig. 6. Precision versus confidence threshold

Precision and the confidence threshold are closely related in classification systems. Increasing the confidence threshold usually improves precision because only predictions with higher certainty are accepted. However, this often reduces the number of predicted positive samples, potentially lowering recall. A lower confidence threshold includes more predictions, which may increase false positives and reduce precision. Therefore, selecting an appropriate confidence threshold is a trade-off that depends on the application requirements.

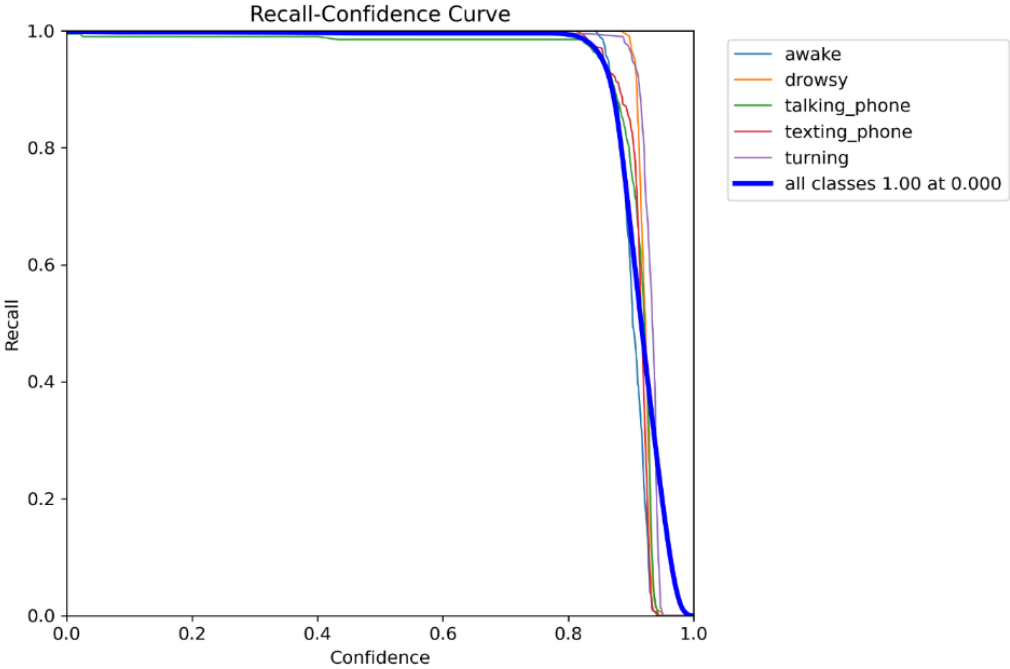

Fig. 7. Recall versus confidence threshold

Recall is strongly influenced by the choice of the confidence threshold in a classification model. When the confidence threshold is increased, fewer positive samples are detected, which typically leads to a decrease in recall. Lowering the confidence threshold allows the model to capture more true positive cases. However, this also increases the risk of including false positives. Thus, recall generally improves as the confidence threshold decreases, reflecting a trade-off with precision.

5. Conclusion

This study presents the design, implementation, and evaluation of an intelligent driver behavior detection and early warning system built on the YOLOv8 deep learning framework. The system was developed through systematic dataset preparation, model training, and deployment on an embedded platform. It is capable of recognizing multiple driver behavior classes, including awake, drowsy, texting_phone, talking_phone, and turning. Experimental results indicate that the trained model achieves reliable detection accuracy and stable real-time performance, even on resource-limited hardware such as Raspberry Pi. Quantitative metrics, including precision, recall, and mean average precision, confirm the effectiveness of the proposed approach. Qualitative evaluations further demonstrate accurate localization and classification under practical driving conditions.

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