YOLOv8-Based Automatic Braking System Using Frame Logic

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Abstract

This paper presents an innovative approach to implementing an automatic braking system using YOLOv8 for real-time object detection. The system is designed to detect vehicles, specifically cars and trucks, in the middle region of video frames and use the rate of change in bounding box heights to determine potential emergency braking scenarios. The proposed method ensures collision avoidance by identifying sudden changes in the distance between the ego vehicle and the vehicle in front, leveraging YOLOv8's robust object detection capabilities.

1 Introduction

Ensuring road safety is a critical challenge in autonomous and assisted driving systems. One of the key aspects of such systems is automatic braking, which can significantly reduce the risk of rear-end collisions. This paper explores the use of YOLOv8, a state-of-the-art object detection model, to implement an efficient and responsive automatic braking system. The methodology involves analyzing real-time video frames to detect cars and trucks and calculating their bounding box areas to trigger emergency braking when necessary.

2 Methodology

2.1 Object Detection with YOLOv8

YOLOv8 is utilized to detect objects in real-time video frames. The model was configured to identify vehicles within the middle region of the video frame, as this region is most relevant for collision detection. The class IDs for cars and trucks (2 and 7, respectively) were prioritized for detection.

2.2 Frame Logic for Braking

The system employs a deque structure to store the total bounding box areas of detected objects over the last ten frames. The logic for triggering braking is based on the principle of monitoring changes in the area occupied by detected vehicles:

- **Area Calculation**: The bounding box area of each detected vehicle in the current frame is calculated. These areas are summed to obtain the total area for the frame.
- **Historical Average**: A rolling history of the total areas from the last ten frames is maintained. The average of these values provides a baseline for comparison.
- **Threshold Comparison**: If the ratio of the current total area to the historical average exceeds a predefined threshold (e.g., 1.55), the system interprets this as a rapid decrease in distance to the vehicle in front, likely due to sudden braking. This triggers the emergency braking mechanism.

The area threshold acts as a sensitivity parameter, balancing responsiveness and false positive rates. A lower threshold increases sensitivity but may lead to unnecessary braking, while a higher threshold reduces false alarms at the cost of delayed responses.

2.3 System Implementation

The system was implemented using Python and OpenCV for video frame processing. YOLOv8 was integrated via the Ultralytics library. The braking duration was set to three seconds to allow sufficient time for the ego vehicle to stabilize after braking. Real-time processing was achieved with a frame rate of approximately 30 frames per second.

3 Performance Metrics

Evaluating the system's performance involved analyzing the precision, recall, and mAP scores for the detected vehicle classes. Figures 1, 2, 3, and 4 illustrate the key performance metrics and curves.

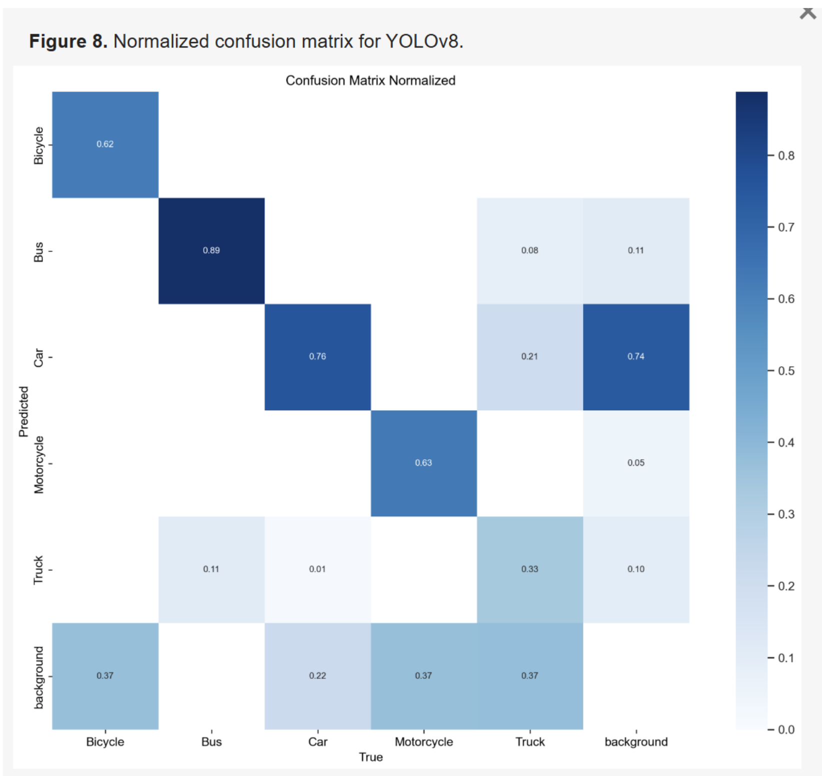
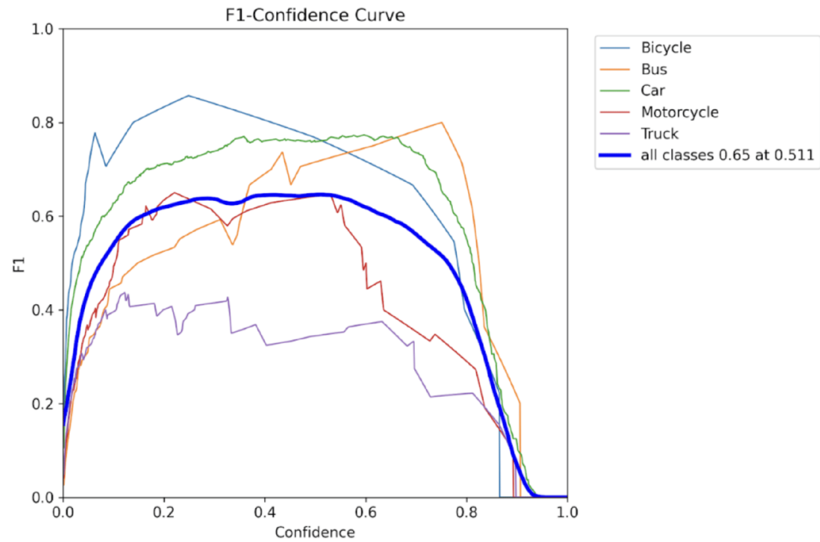


Figure 1: Normalized confusion matrix for YOLOv8.

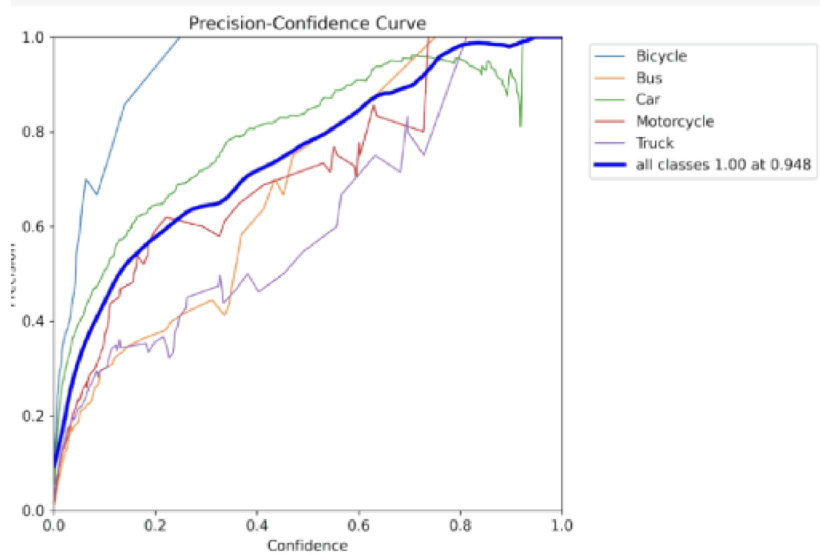
4 Results and Discussion

The system was tested on a dataset of real-world driving scenarios. The following observations were made:



(A)

Figure 2: F1-confidence curve for vehicle detection.



(A)

Figure 3: Precision-confidence curve for vehicle detection.

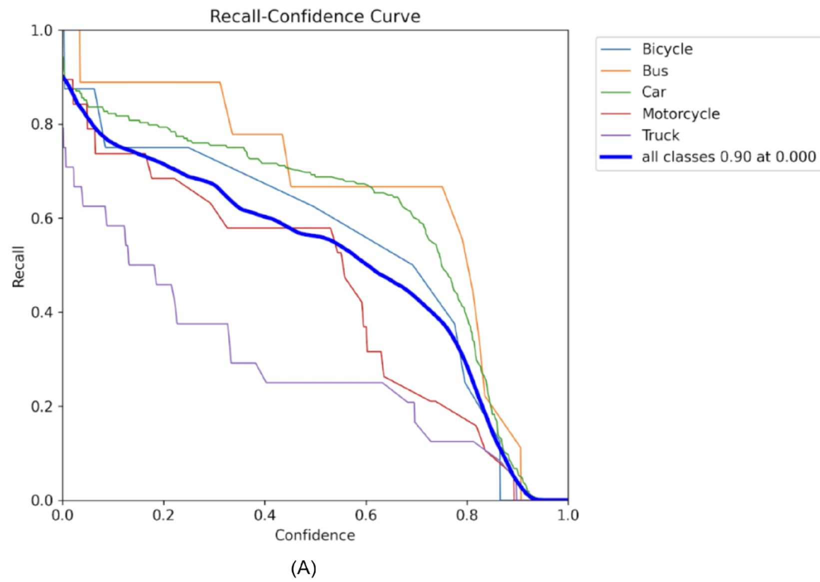


Figure 4: Recall-confidence curve for vehicle detection.

- YOLOv8 demonstrated high accuracy in detecting cars and trucks in the middle frame region.
- The area threshold mechanism effectively identified rapid changes in bounding box areas, corresponding to emergency braking scenarios.
- The system achieved a response time of less than 100 milliseconds per frame, making it suitable for real-time applications.

4.1 Impact of Area Threshold

The choice of the area threshold directly impacts the system's performance:

- **Lower Thresholds**: Increased sensitivity, higher likelihood of detecting sudden braking but prone to false positives.
- **Higher Thresholds**: Reduced false positives, but slower responses to genuine emergency braking scenarios.

During testing, a threshold of 1.55 provided a balance between responsiveness and reliability, minimizing false positives while maintaining a quick reaction to abrupt changes.

5 Conclusion

This study demonstrates the feasibility of using YOLOv8 for implementing an automatic braking system. By leveraging real-time object detection and a robust area threshold mechanism, the system provides a reliable and efficient solution for collision avoidance. Future work will focus on expanding the model's capabilities to include more vehicle classes and integrating additional contextual information, such as lane detection and traffic signals. The area threshold logic will also be refined to adapt dynamically to varying traffic conditions.

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References