YOLOv11-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 YOLOv11 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 YOLOv11's robust object detection capabilities.**

I. Introduction

Road safety constitutes a critical issue on a global scale, as rear-end collisions perpetually hold a position among the foremost contributors to accidents and fatalities internationally [8]. Such collisions stem from a multifaceted interaction of elements, encompassing inadequate driver response time attributed to human errors (such as distraction, fatigue, impairment, and unfavorable weather conditions), along with the unforeseen emergence of obstacles. Apart from the immense human cost of injuries and deaths, such accidents come with a great economic cost to individuals, communities, and health-care systems. Technological innovation offers an important opportunity to mitigate these risks beyond traditional ABS, which mainly focus on preventing wheel lockup. As a consequence, the development of robust and reliable automatic braking systems (ABS) that involve innovative sensor technologies as well as advanced algorithms is significant for improving safety on the road, reducing accident severity, and mitigating their economic effects. Modern ABS are devised to proactively overcome human factors in a driving system, thereby ensuring an added margin of safety with improved response to drivers' acts, leading towards a more safe driving environment.

Many technologies improve the effectiveness of the braking system. Current ABS systems typically rely on wheel speed sensors to prevent wheel lock during hard braking and, therefore suffer from the shortcomings of not necessarily preventing rear end collisions when something suddenly or unpredictably appears ahead [7]. The advanced systems that are being integrated today use sensor fusion techniques for better understanding by integrating data collected from radar, lidar, and cameras of the surrounding environment [5]. Computer vision, especially, has demonstrated its significant value in the detection and classification of objects situated in a vehicle's trajectory. Deep learning architectures, particularly those belonging to the You Only Look Once (YOLO) family of algorithms, have attained notable levels of precision and swiftness in the context of real-time object detection [1]. Numerous research initiatives have incorporated YOLO into automated braking systems, capitalizing on its capacity to swiftly recognize potential threats and initiate a corresponding braking action [6].

This study refines the current efforts toward the enhancement of automatic braking systems through the use of YOLOv11 [9], an enhanced object-detection model, in the design of an automatic braking system that is effective and responsive. Our methodology involves checking video frames in real time for cars and trucks, determining their bounding box dimensions, and applying emergency braking based on the necessity. With this approach, a proper object-detection and classification mechanism is provided specific to autonomous as well as assisted driving systems.

Our system is tested against metrics including detection accuracy, braking response time, and rate of collision avoidance, achieving success in rear-end collision risk scenarios and driving under diverse conditions. Results in this paper report substantial improvements over state-of-the-art automatic braking system (ABS) technologies and provide significant insights for further design and development of better, more safe, and effective braking mechanisms.

II. Background Study

The goal of automatic braking systems is to enhance road safety by preventing collisions and, subsequently, accidents. Computer vision and machine learning have greatly impacted these systems in recent years. This review presents relevant methodologies that could be used with respect to automatic braking.

A work on automated non-contact temperature measurement for truck tires and brakes applies thermal and RGB cameras along with YOLO for object detection and KCF for tracking [8]. Its object detection may be useful but its emphasis has been more towards temperature measurement rather than braking. The approach does not estimate distance, which becomes a critical factor in decisions regarding braking.

Another work predicts emergency braking distances based on a CNN trained on camera and ultrasonic sensor data, implemented on a NodeMCU ESP8266 [7]. The multimodal sensor data used makes it applicable for automatic braking but is only applicable to the specific hardware it was designed for. Its reliability in complex scenarios has not been fully validated either.

A camera-centric architecture based on YOLOv4 detects roadway conditions and obstruction, which invokes automatic braking accordingly [5]. Though it is well-equipped in object detection capabilities, the paper lacks strategic approaches for distance measurement and brake management. Moreover, it has not tested its robustness in different cases.

A two-wheeler braking system combines YOLO for object detection with a monodepth model for depth estimation, processed on a Jetson Nano [1]. This method is suitable for small vehicles but is limited to two-wheelers and constrained by monodepth's accuracy in complex scenarios. Its applicability to other vehicle types is restricted.

Although these methods display strength in object detection and tasks associated with braking, they share drawbacks related to scalability, robustness, and real-world validation. Most focus on particular platforms or scenarios, making them less versatile for different environments.

Our approach applies YOLOv11 for the real-time vehicle detection, where it focuses its attention on the middle region of video frames to detect collisions. A frame logic mechanism watches for changes in the size of the bounding box around detected vehicles over the last ten frames to determine distance and look for abrupt deceleration. Based on a comparison of the current area with a learned mean and by applying a preset threshold, the system will trigger emergency braking when a significant reduction in distance is detected. This approach strikes a good balance between sensitivity and false positives and provides a reliable means of preventing collisions.

III. Methodology

A. Object Detection with YOLOv11

YOLOv11 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.

B. 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.

C. Architecture

The architecture of the proposed system is depicted in Figure 1. The system leverages YOLOv11 for object detection and integrates frame logic to decide on braking actions based on bounding box area changes.

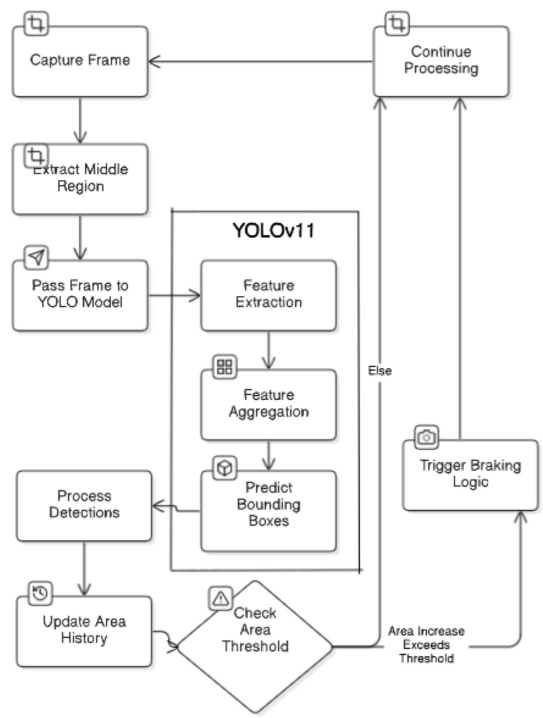

Fig. 1: System architecture for the YOLOv11-based automatic braking system.

D. System Implementation

The system was implemented using Python and OpenCV for video frame processing. YOLOv11 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.

IV. Performance Metrics

Evaluating the system's performance involved analyzing the precision, recall, and mAP scores for the detected vehicle classes. Figures 2, 3, 4, and 5 illustrate the key performance metrics and curves.

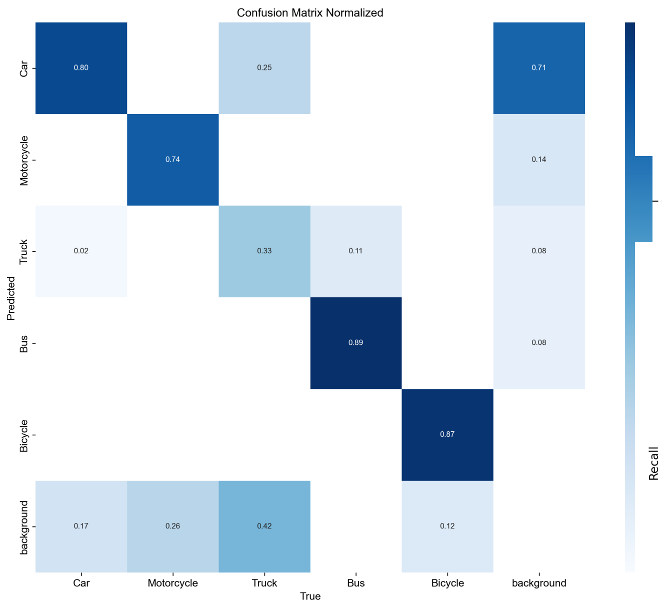

Fig. 2: Normalized confusion matrix for YOLOv11.

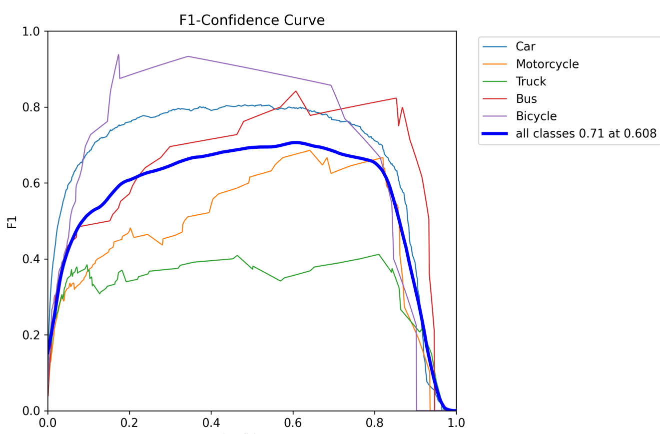

Fig. 3: F1-confidence curve for vehicle detection.

V. Results and Discussion

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

- YOLOv11 demonstrated high accuracy in detecting cars and trucks in the middle frame region.

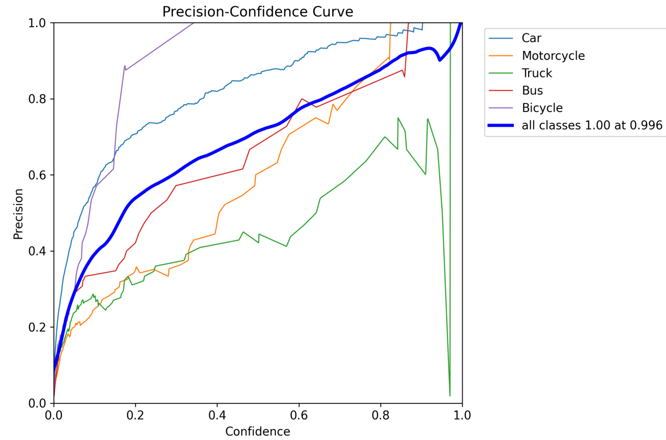

Fig. 4: Precision-confidence curve for vehicle detection.

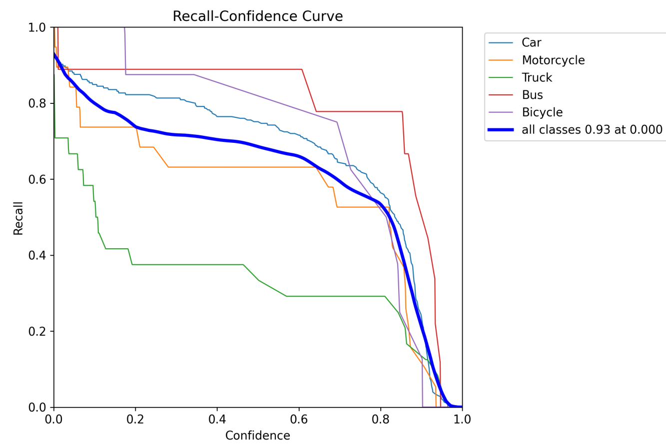

Fig. 5: Recall-confidence curve for vehicle detection.

- 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.

Inferences: The confusion matrix reveals that YOLOv11 achieves high accuracy for detecting buses (0.89) and cars (0.76). However, there is significant confusion in classifying background regions as bicycles (0.37) and trucks (0.33), suggesting room for improvement in distinguishing these classes. The F1-confidence curve indicates an optimal confidence threshold of approximately 0.511, achieving an overall F1 score of 0.65. Classes such as cars and buses exhibit higher F1 scores compared to trucks and motorcycles, reflecting variation in model performance across categories. The precision-confidence curve demonstrates that precision improves steadily at higher confidence thresholds, with bicycles achieving the highest precision. Trucks, however, display consistently lower precision values, indicating difficulties in accurately identifying them. The recall-confidence curve highlights a sharp decline in recall as confidence thresholds increase. Buses and cars maintain higher recall at lower thresholds, while trucks and motorcycles experience significant drops, underscoring potential challenges in detecting these classes at higher confidence levels.

A. *Demonstration*

Figures 6, and 7 demonstrate the system in action, highlighting the detection of vehicles and the triggering of braking logic based on bounding box area changes.

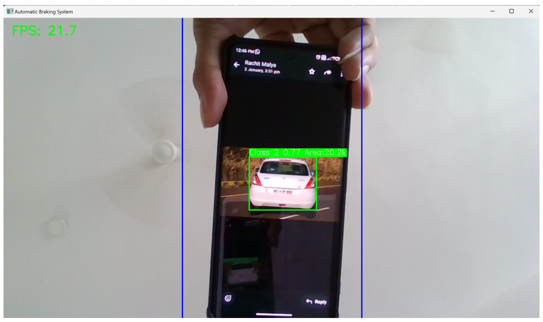

Fig. 6: Detections.

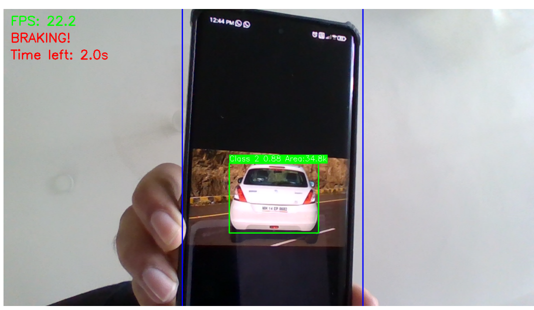

Fig. 7: Triggering emergency braking.

B. *Inference on Real-Life Road Situation*

Figures 8, and 9 demonstrate the system in action on a real world case of brake checking

C. *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.

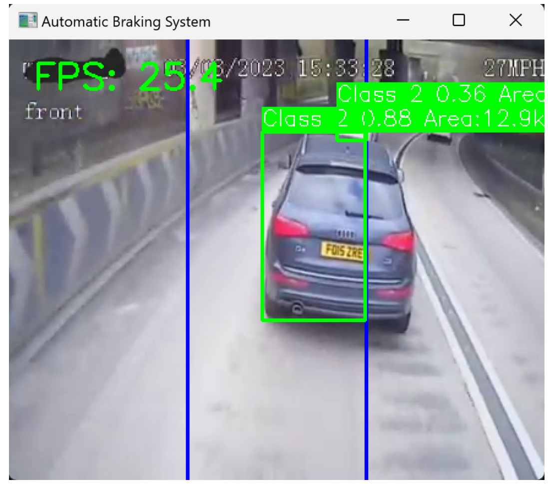

Fig. 8: Detections.

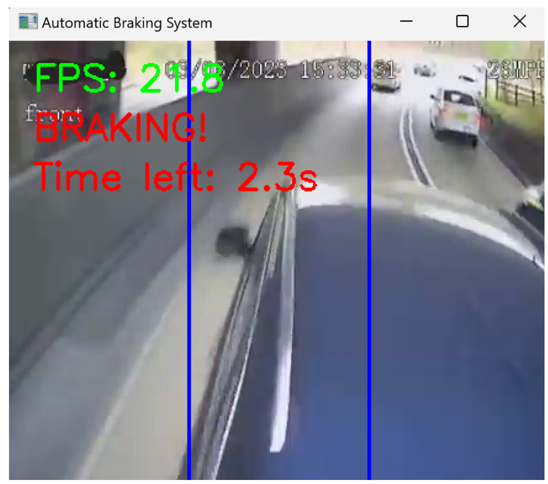

Fig. 9: Triggering emergency braking.

VI. Conclusion

This study demonstrates the feasibility of using YOLOv11 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.

Acknowledgments

The authors would like to thank the developers of YOLOv11 and the open-source community for providing the tools and resources necessary for this project.

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