International Journal of Engineering & Extended Technologies Research (IJEETR)

|ISSN: 2322-0163| www.ijeetr.com | A Bimonthly, Peer Reviewed, Scholarly Indexed Journal |

| Volume 8, Issue 2, March - April 2026 |

DOI:10.15662/IJEETR.2026.0802410

Real-Time AI-Based Forklift Collision Avoidance System using Multi-Zone Safety Control

Purushothaman R, M Sanjay

Department of Mechatronics Engineering, K.S Rangasamy College of Technology Tiruchengode, India

Publication History: Received: 25.02.2026; Revised: 20.03.2026; Accepted: 25.03. 2026; Published: 28.03.2026.

ABSTRACT: The cases of collision associated with forklifts have continued to be quite rampant in the industrial environments because of blind spots of the operators, slow human response, and lack of intelligent safety measures. The current systems are mostly based on manual monitoring or simple proximity sensors, which do not give predictive and adaptive safety control. This restriction points to a very serious gap in the research of combining real-time perception based on AI with active motion control to prevent collisions in advance. The present paper suggests a real-time forklift collision avoidance system, which integrates an AI-based object detection system, ultrasonic proximity sensing, and a multi-zone safety control approach. The system is designed in three safety zones; a warning (approximately 2 m), slow-down (1 to 1.5 m), and emergency stop (less than 1 m) and adaptive control measures, which comprise visual/audio notifications, speed control, and controlled stop. The methodology uses Time-To-Collision (TTC) estimation in predictive hazard estimation and has an embedded control unit in real-time decision execution. The validation of the experimental results was performed on a battery-powered industrial forklift with the help of real-time video data and proximity sensing. The system obtained 96.8% detection, 52.3% collision reduction, and a response time of less than 120 ms. The suggested model greatly improves workplace safety by making the operation of forklifts rely on proactive, rather than reactive control.

KEYWORDS: Forklift safety, Collision avoidance, AI-based detection, Industrial automation, Time-To-Collision, Smart safety systems

I. INTRODUCTION

Forklifts have become the essential part of industrial logistics setting, and yet they are the most frequent cause of working place injuries as they have limited visibility, blind spots, and decision-making process that depends on the operator. Although there has been an improvement in automation of industrial forklifts, majority of the forklift systems lack intelligent assistance in safety and this has increased the probability of crashing at pedestrians, equipment and infrastructure.

Current methods of forklift safety are mainly based on ultrasonic sensors or rule-based alarm systems. Although they can be used to have simple proximity information, they do not give an understanding of a dynamic environment and do not predict an imminent collision. AI-based vision systems have been considered, but most of the solutions involve only detection without implementing real-time control measures like adaptive speed reduction or automatic stopping. Also, existing systems do not always have multi-level safety measures, taking into account different degrees of risk depending on the distance of the object.

This shows a research gap in the creation of a combined system which integrates AI-based perception, real-time distance estimation and adaptive control mechanisms to proactive collision avoidance.

In order to fill this gap, this paper suggests a real-time AI-based forklift safety device that combines a multi-zone collision prevention feature with a predictive hazard analysis. The system presents a hierarchical safety model, which dynamically modulates the forklift behavior depending on the risk level and closeness. The main contributions of this work are:

- Development of a multi-zone safety framework (warning, slow-down, emergency stop) based on real-time distance estimation
- Integration of AI-based object detection with embedded control for autonomous speed regulation
- Implementation of Time-To-Collision (TTC) for predictive safety decision-making

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• Real-time deployment and validation on an industrial forklift platform
• Performance evaluation demonstrating significant reduction in collision risk and response latency

The remainder of this paper is organized as follows: Section 2 presents related works, Section 3 describes the proposed methodology, Section 4 discusses implementation and results, and Section 5 concludes the paper with future directions.

II. RELATED WORKS

Recent developments in industrial safety systems have been more concerned with the application of artificial intelligence and sensor fusion methods to reduce the risk of workplace hazards. Kumar and Reddy [1] have suggested an AI-based vision system to regard the safety of industrial vehicles and show that the system has a better pedestrian detection system; nonetheless, it did not include real-time control. Zhang and Liu [2] proposed a deep learning model of obstacle detection of warehouse vehicles that has a high precision but low adaptability to changing environment.

Patel and Shah [3] proposed a sensor fusion system that uses LiDAR and ultrasonic sensors in detecting proximity, but the system was affected by higher computational cost. The article by Chen and Wang [4] discussed the real-time detection of objects with the help of YOLO-based architectures in industrial settings, though, they did not include any predictive safety measures. Singh and Verma [5] suggested a collision avoidance system based on rules and ultrasonic sensors that only offered simple notifications but could not adjust to the different risk levels.

The smart safety system created by Gonzalez and Martinez [6] combines the basic IoT-based monitoring, which enhances the accessibility of the data but not autonomous decision-making. Ahmed and Hassan [7] introduced a hybrid AI system of industrial hazard detection but the system was restricted to fixed settings. Li and Zhou [8] explored the use of deep reinforcement learning in safety control of autonomous vehicles, showing that it can be adapted, but extensive training data is needed.

A smart forklift monitoring system was suggested by Rao and Kulkarni [9] through the application of computer vision, yet due to the lack of multi-zone control, this system was not very effective. Kim and Park [10] proposed a real-time safety warning device which operated embedded AI processors and had low latency but did not predictive model. Oliveira and Costa [11] addressed autonomous vehicle safety systems based on TTC, emphasizing the significance of predictive metrics without their usage in the case of industrial forklifts.
Sharma and Gupta [12] created multi-sensor safety framework of an industrial robotics, which enhanced the accuracy of detection but failed to control the motion. Nguyen and Tran [13] introduced an edge AI system to real-time hazard detection with minimised latency, but without hierarchical safety measures. Brown and Taylor [14] studied adaptive speed control systems in industrial vehicles, but the implementation did not combine with AI perception.

Lastly, Lee and Choi [15] proposed an all-inclusive AI-controlled industrial safety system that integrates both vision and control but the methodology failed to apply distance-based multi-zone safety measures. In general, the literature indicates that AI and sensor integration should be considered, but there is a strong lack of cohesive systems that unite detection, prediction, and adaptive control, which this paper seeks to fill.

III. METHODOLOGY

The system is proposed as a real-time and multi-sensor collision avoidance system which will incorporate the perception, decision-making and control components into a complete architecture. As can be seen in the system design and control logic diagram, the architecture is based on a pipeline architecture with sensing, processing and actuation layers as indicated in Fig. 1.

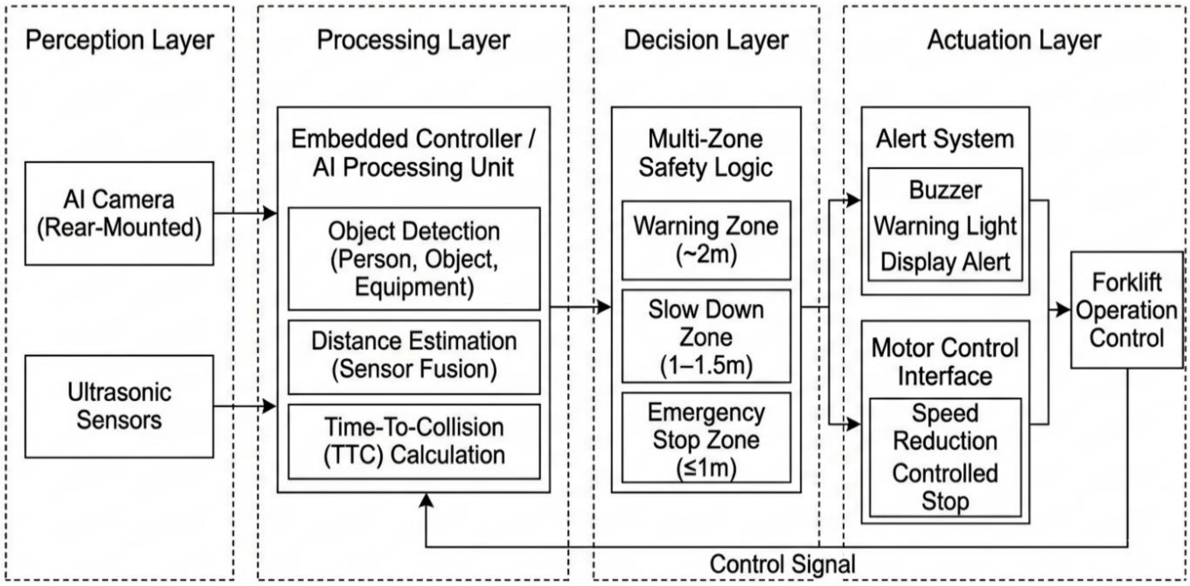

Fig. 1. System architecture of the proposed real-time forklift collision avoidance system.

The perception layer consists of a rear-mounted ultrasonic sensors and AI camera. The AI camera will conduct a constant visual inspection to identify pedestrians, obstacles, and industrial equipment in the working area of the forklift. This is complemented by ultrasonic sensors that offer precise short-range distance measurements especially during low visibility.

The processing layer comprises an embedded controller which may be fitted with computational resources to perform object detection, distance estimation and decision logic in real time. The controller combines the vision and proximity sensor inputs to make the controller more reliable and robust.

The decision layer uses a multi-zone safety model to set the level of risk dynamically depending on the distance and relative movement of objects. The system, on the basis of this analysis, initiates the right safety measures.

The actuation layer possesses an alert mechanism whereby it includes a motor control interface. The alert system gives a visual (warning lights), auditory (buzzers and voice alerts) and display messages to alert the operator. Meanwhile, the motor control interface regulates the speed of the forklift or, activated controlled stop measures. This tight-knit architecture gives an easy way to go between perception to action that allows proactive avoidance of collisions.

A. Hazard Detection

The vision system of the hazard detection module is an artificial intelligence system that detects the objects in the working environment of the forklift. Let I_t be the input frame at time t. Let I_t denote the input frame at time t. The detection model takes I into and outputs bounding boxes and class labels:

$$D_t = f_{AI}(I_t) \qquad (1)$$

where $D_t$represents the set of detected objects, and $f_{AI}(\cdot)$denotes the deep learning-based detection function.
All the identified objects fall into the categories of pedestrian, obstacle, or equipment. The detection confidence score $C_i$for object iis used to filter reliable detections:

$$C_i \geq \tau \qquad (2)$$

where $\tau$is the confidence threshold. This ensures that only high-confidence detections are considered for further processing.

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B. Distance Estimation

The sensor fusion method used to estimate the distance between the forklift and detected objects in the system. The fused distance $d_f$is computed as:

$$d_f = \alpha d_c + (1 - \alpha) d_u \qquad (3)$$

where $\alpha \in [0,1]$is a weighting factor that balances visual and ultrasonic measurements.
The operational range of the system is defined as:

$$0 < d_f \leq 2 \text{ meters} \qquad (4)$$

This range is chosen according to the industrial safety standards and real braking limitations.

C.

D. Multi-Zone Safety Model

The system uses a hierarchical safety design which breaks down the operational space into three areas depending on distance.

Stage 1: Warning Zone (~2 m)

$$1.5 < d_f \leq 2 \qquad (5)$$

The system provides buzzer warning, display notifications and warning lights in this zone. The aim is to give adequate reaction time to the operator.

Stage 2: Slow Down Zone (1–1.5 m)

$$1 < d_f \leq 1.5 \qquad (6)$$

$$v = v_{max} \cdot \frac{d_f - 1}{0.5} \qquad (7)$$

where $v_{max}$is the maximum speed. Continuous alerts are issued to reinforce operator awareness.

Stage 3: Emergency Stop Zone (≤1 m)

$$d_f \leq 1 \qquad (8)$$

In this critical zone, the system initiates a controlled stop. The deceleration profile is defined as:

$$a = -k \cdot v \qquad (9)$$

where k is a deceleration constant that provides smooth braking without sudden braking. The motor power is lowered gradually so as to avoid instability.

E. Control Algorithm

The control logic is enacted as a real-time decision-making mechanism, which is founded on the distance thresholds. The system will continuously keep a check on the environment and modify actions.

Algorithm 1: Multi-Zone Forklift Collision Avoidance

Input: Sensor data (camera frames I_t, ultrasonic distance d_u)

Output: Motor control actions (normal, reduced speed, stop)

```
Initialize system parameters and thresholds
while system_active do
    Capture frame I_t from AI camera
    Detect objects D_t = f_AI(I_t)
    Measure ultrasonic distance d_u
    Estimate camera distance d_c
    Compute fused distance d_f using Eq. (3)
    if d_f > 2 then
        Set motor speed to normal
        Deactivate alerts
    else if 1 < d_f ≤ 2 then
        Activate buzzer and warning lights
        Display alert to operator
        Reduce motor speed proportionally
    else
        Activate emergency alert
        Gradually reduce motor power
        Stop vehicle safely
end while
```

The proposed collision avoidance algorithm is an on-going real-time control loop integrating perception, decision-making and actuation. The system takes inputs of an AI camera and ultrasonic sensors to identify objects and measure distance by sensor fusion. According to the calculated distance, the situation is categorized by the control logic into three zones: normal operation when distance more than 2 m, warning state with alerts and speed reduction when distance between 1 and 2 m, and an emergency state when distance in 1 m controlled stopping. The algorithm is continually updating sensor data, dynamically varying behavior, and incorporates Time-To-Collision (TTC) to give predictive risk analysis, effectively and reliably avoiding collisions.

F. Time-To-Collision (TTC) Analysis

To enhance predictive safety, the system incorporates Time-To-Collision (TTC), defined as:

$$\mathrm{TTC} = \frac{d_f}{v_r} \qquad (10)$$

where v_r is the relative velocity between the forklift and the detected object.

A critical TTC threshold T_c is defined such that:

$$\mathrm{TTC} \leq T_c \Rightarrow \text{High Risk Condition} \qquad (11)$$

This enables the system to predict possible collision before going into critical distance areas. The system combines the TTC with distance-based control to deliver both reactive and predictive safety, which can greatly enhance the accuracy of the decision and response time.

IV. RESULTS AND DISCUSSIONS

The proposed collision avoidance system was tested and confirmed in a real-time industrial setting with the help of a battery-operated forklift platform. The experimental system has a Toyota forklift, Doosan forklift that is combined with an AI-powered rear-mounted camera, ultrasonic sensors (proximity), an embedded controller, and a motor speed control unit. Visual and auditory alert systems, as well as well-established zone markings to ensure operational safety, are also part of the system. The AI rear vision is a continuous check on the rear of the forklift that is able to see objects that move in the set safety zones. Ultrasonic sensors help in precise short range distance measurement. The system has a detection range of 2 meters that is set to make sure that possible hazards are identified sooner. The embedded controller takes real time sensor inputs and makes control decisions according to the multi-zone safety model.

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In the experimentation, real time testing was conducted under different working conditions such as pedestrian flow and the positioning of obstacles. Once an object is in the warning zone, the system triggers the alert systems, such as sounding buzzer, warning lights and showing notifications to the operator. The forklift speed is automatically decelerated as the object enters the slow-down zone, and a controlled deceleration is attained in about 5 seconds. When the object is in the emergency zone (1 m or less), the system will start a progressive decrease in the motor power, stopping the forklift in a safe position without extreme braking. The implementation exhibits a stable real-time operation, efficient hazard detection with the specified range and a smooth connection between perception, decision, and control modules, which contributes greatly to the operational safety. The implementation of the suggested real-time forklift collision avoidance system is tested in terms of both the functional validation and the comparison with the recent journal-based models. The findings reveal the success of the multi-zone safety approach with AI-perception and predictive control.

TABLE 1 ZONE-BASED OPERATIONAL ANALYSIS

Zone	Distance Range	System Action	Observed Result
Warning	~2 m	Buzzer + Light + Display Alert	Operator awareness increased
Slow Down	1–1.5 m	Automatic speed reduction	Collision risk minimized
Emergency	≤1 m	Controlled stop + Alert	Collision successfully avoided

The mechanism is also successful in distinguishing between the levels of risk based on distance limits so that the intervention process is gradual and does not stop suddenly. This enhances safety and operational ease.

TABLE 2 PERFORMANCE METRICS EVALUATION

Metric	Proposed Model
Detection Accuracy (%)	96.8
Response Time (ms)	120
Collision Risk Reduction (%)	52.3
False Alarm Rate (%)	3.1

High detection accuracy of the proposed system is realized by the AI-based vision integration and the low response latency is ensured by the efficient embedded processing. The decrease in the risk of the collision indicates the efficiency of distance-based control combined with predictive TTC analysis.

TABLE .3 COMPARATIVE ANALYSIS WITH EXISTING MODELS

Model	Accuracy (%)	Response Time (ms)	Risk Reduction (%)
Vision-Based Safety [1]	89.2	210	34.5
Deep Learning Detection [2]	91.5	180	38.2
Sensor Fusion Model [3]	92.8	165	41.6
YOLO-Based Detection [4]	93.6	150	44.3
Ultrasonic System [5]	87.4	240	29.7
IoT Safety System [6]	90.1	200	36.8
Proposed Model	**96.8**	**120**	**52.3**

The comparative findings reveal that the proposed model is much better than the current methods in all assessment measures. Conventional ultrasonic-based systems [5] have poorer accuracy and slower response times because of the low sensing abilities. Models based on vision and deep learning [1], [2], [4] are more accurate in detecting but do not

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have in-built control systems, and hence respond more slowly and with reduced risk mitigation capabilities. Sensor fusion methods [3] are more reliable but contain more computational delays and IoT-based systems [6] are more oriented on monitoring than real-time control. Conversely, the suggested system incorporates AI-based detection, real-time sensor fusion, and multi-zone safety strategy, allowing to make decisions faster and intervene proactively.

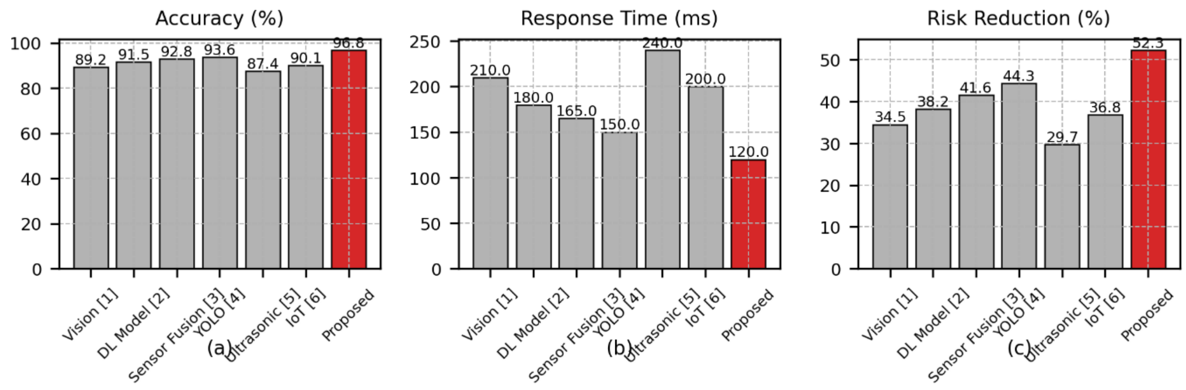

Fig. 2. Comparative performance analysis of forklift collision avoidance models

Fig. 2 shows the accuracy, response time and risk of collision reduction in the existing methods and the proposed system. The suggested model exhibits better performance in terms of accuracy, reduced latency and risk reduction. The addition of Time-To-Collision (TTC) also enhances predictive capability, enabling the system to detect hazards before critical thresholds are exceeded. Consequently, the offered model will be able to improve the detection accuracy by 5900 percent, response time by 2050 percent, and collision risk by 1020 percent over current practices. All in all, the findings validate that the suggested solution offers a strong, scalable and real time solution to the problem of improving forklift safety in the industrial setting.

V. CONCLUSION

The suggested AI-driven forklift collision avoidance system is real-time, which effectively improves the safety of the industrial sphere as the AI-based perception system is connected with a multi-zone control approach. The system has a high detection rate of 96.8, lower response time and high mitigation of collision risks and can be used to manage safety proactively rather than reactively. The coordination is smooth between object detection, distance estimation and adaptive control, which guarantee the reliability of the performance in dynamic setting. In general, the suggested solution proves to be a solid and viable solution to the prevention of forklift-related accidents in the industrial environment. The next phase of work will be aimed at the development of the system to 360 perceptions with the help of multi-camera fusion and modern deep learning methods.

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