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CCTV Integration of YOLOv8 for Human Detection and Safety Enhancement in Forklift Work Environments

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ABSTRACT

Workplace accidents caused by collisions between workers and forklifts represent one of the most significant safety risks in manufacturing environments. Limited workspace often forces forklift operational paths to intersect with pedestrian walkways, creating hazardous zones that require proactive mitigation strategies. This study investigates the implementation of the You Only Look Once version 8 (YOLOv8) method on existing CCTV systems for real-time human detection as an effort to reduce forklift-related incidents. The methodology includes the development of an optimized YOLOv8 architecture tailored for industrial settings, model training using Roboflow with a dataset consisting of photos collected directly from the factory area, and integration with the facility's speed-door system that governs forklift entry and exit. Detection performance testing demonstrated that the model achieved 100% accuracy across 55 test images, with precision, recall, and F1-score each reaching a perfect value of 1. These findings indicate that YOLOv8 is highly reliable for real-time person detection in industrial environments and can be effectively deployed using existing CCTV infrastructure. It is expected that workplace accidents can be minimized by preventing the door-open mechanism activated when the CCTV system detects the presence of a person. Integrating the detection system with automated door control offers a promising safety enhancement, helping to restrict unsafe access to forklift pathways and reduce the risk of collisions in manufacturing settings.

1. INTRODUCTION

Occupational Safety and Health (OSH) is one of the key priorities that must be addressed in work environments with potential hazards that may lead to workplace accidents. Such accidents can occur at any time and affect anyone within the working area. The government has responded seriously to this issue through Government Regulation No. 50 of 2012, this regulation is mandatory for employers and sets minimum OSH standards to ensure a safe work environment and improved productivity [1].

However, in practice, many companies particularly those in the manufacturing sector lack adequate workspace, resulting in machine movement areas such as forklift lanes overlapping with pedestrian pathways used by workers to access their respective plants. This condition increases the risk of accidents caused by direct interaction between transport equipment and workers [2]. Therefore, proper workspace arrangement, engineering control applications, and strict supervision are needed to minimize potential hazards and cultivate a safety-oriented culture throughout operational activities.

In the era of Industry 4.0, advancements in digital technology have driven the rise of automation and system integration across various industrial sectors. Conventional equipment can now be enhanced into smarter and more adaptive devices, including Closed-Circuit Television (CCTV) systems used for workplace monitoring [3]. One important innovation is the use of CCTV programmed to detect the presence of pedestrians in forklift operational areas, thereby reducing the risk of accidents due to direct interactions between transport equipment and workers. Such enhanced detection capabilities can be achieved through the application of Artificial Intelligence (AI) and machine learning technologies, particularly in the field of computer vision [4].

In this context, deep-learning–based object detection methods are preferred due to their ability to process visual data in real time with high accuracy. One of the most widely adopted object detection architectures is You Only Look Once (YOLO), which integrates feature extraction and object classification into a single processing step, allowing fast and efficient detection [5]. Its latest version, YOLOv8, offers significant improvements in detection accuracy, inference speed, and computational efficiency. YOLOv8 is supported by a lighter network architecture and improved generalization capabilities under various lighting and environmental conditions [6]. These advancements make YOLOv8 one of the most effective computer vision technologies for safety applications, including pedestrian detection in forklift operational areas within industrial settings. By integrating conventional CCTV systems with YOLOv8-based object detection models, companies can develop an intelligent surveillance platform interconnected with various supporting devices. This system is capable of identifying human presence in hazardous areas in real time through deep-learning based visual processing, providing a much higher level of detection reliability compared with conventional methods.

Furthermore, the YOLOv8-based human detection module can be directly integrated with speed doors or automatic doors in industrial facilities. When a forklift is about to pass through a doorway and the CCTV system detects a worker in the danger zone, the door control mechanism will automatically lock the door, preventing it from opening. This ensures that workers crossing in front of the door are protected from potential collisions or incidents involving forklifts and pedestrians. The implementation of this technology not only enhances Occupational Safety and Health (OSH) standards through proactive accident prevention but also contributes to establishing a safer, more adaptive, and more responsive working environment toward potential hazards.

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2. METHODS

We have illustrated the system in this study requires several steps that are illustrated in the figure 1.

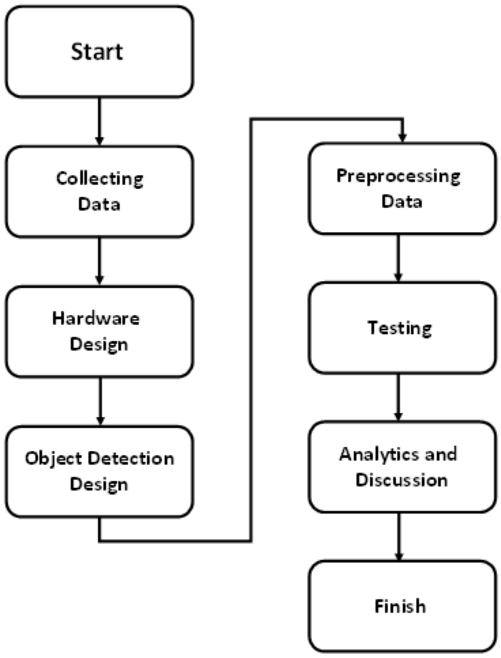

Figure 1. Diagram Flow of Research Step

In the initial stage, we identified the shortcomings found in previous studies and reviewed relevant scientific references as the foundation for developing the research. The next step involved designing the hardware according to the needs of the human-presence detection system. This detection system applies an object detection method to automatically identify human objects. After the hardware design and method selection were established, the next step was preprocessing the dataset using the Roboflow software. At this stage, all images containing human objects or factory workers were uploaded, annotated, and processed to produce a clean, structured dataset ready for use in training the detection model. The following step was system testing, which is essential for evaluating the detector's performance under various operational conditions. Upon completing the testing phase, a comprehensive analysis of the results was conducted, followed by discussion and comparison to determine the effectiveness of the developed system.

2.1. Material

For this study, proposed system to detect human presence as a means of mitigating workplace accidents, particularly the risk of forklift collisions. This implementation process required strong scientific references to justify the selection of methods, algorithms, and technical approaches used, ensuring that the system operates optimally, accurately, and in accordance with occupational safety standards.

2.1.1 CCTV

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Human-presence detection using cameras has been widely implemented to assist humans in monitoring an area. The camera shown in the figure was selected because it can capture images and videos that can be recorded. One of the devices capable of detecting humans is the Closed-Circuit Television (CCTV) [7] (Figure 2). In recent years, computer vision technology has advanced significantly, especially in the widespread application of detection systems and facial recognition. Facial recognition plays a vital role in systems specifically designed for identifying individuals. This technology has been widely used across various domains, which is primary focus of these applications is providing functional and reliable identification capabilities [8].

Figure 2. Closed-Circuit Television

2.1.2 Raspberry Pi 5

The Raspberry Pi 5 is powered by a quad-core 64-bit processor based on Arm architecture. It uses an ARM Cortex-A76 processor running up to 2.4 GHz, offering a 2–3× increase in CPU performance compared with its predecessor, the Raspberry Pi 4[9]. The Raspberry Pi 5 is also equipped with the 800 MHz Video Core VII GPU, making it a solid choice for tasks such as object detection, in which it processes and outputs the detected object coordinates. In this study, the researcher used the 8 GB RAM variant of the Raspberry Pi 5 (Figure 3).

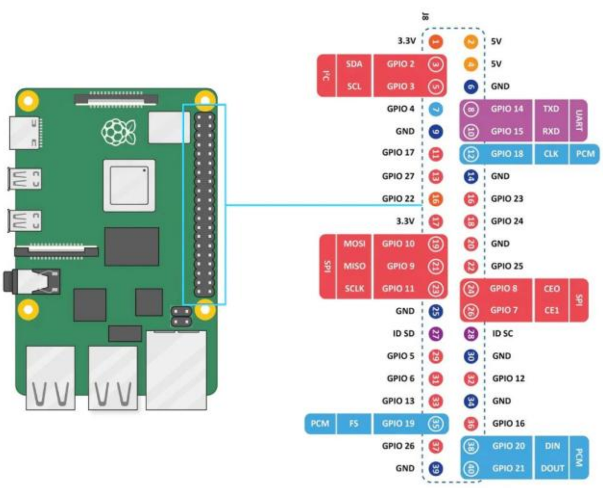

Figure 3. Raspberry Pi 5

2.1.3 Relay

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A relay is an electronically or electromagnetically controlled mechanical switch. The relay switches from OFF to ON when electromagnetic energy is applied to its armature. Essentially, a relay consists of two main components: a mechanical switch and an electromagnetic generator system (iron-core inductor). The switch or contactor of the relay is controlled by electrical voltage supplied to the magnetic coil, which pulls the armature lever to change the contact position (Figure 4) [10].

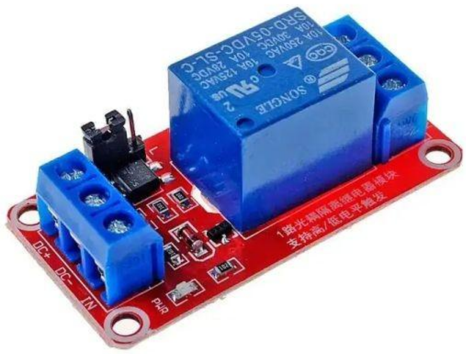

Figure 4. Relay

2.1.4 Speed Door

A speed door is an automatic door designed to open and close rapidly, commonly used in production areas, warehouses, or loading docks. Compared with conventional doors, high-speed doors offer faster response times, reducing delays for vehicles or workers in operational zones (Figure 5). Busy industrial environments require intelligent solutions to manage high activity levels and maintain operational efficiency. One innovation widely adopted across industries is the high-speed door. This automatic door is specifically engineered to meet the demands of modern factories, offering speed, safety, and efficiency in every process [11].

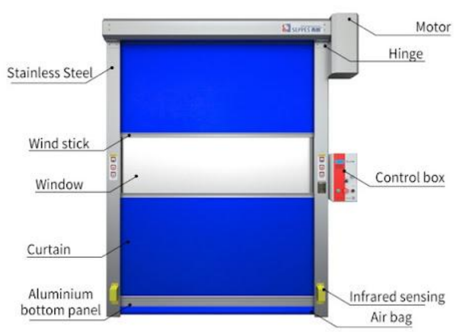

Figure 5. Speed Door

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2.2 Method

2.2.1 Artificial Intelligence

Artificial Intelligence (AI) is a field of computer science that aims to replicate human behavior [12], [13]. AI represents a human innovation embedded into machines, enabling them to understand and perform tasks typically carried out by humans [14]. In this process, computers are trained to behave in ways that resemble human thinking patterns. AI is a broad domain that includes Machine Learning (ML) and Deep Learning (DL) [15], [16].

2.2.2 YOLO

A single-stage object detection network was introduced in 2016. Under identical testing configurations, this network demonstrated the ability to process 45 frames per second (fps) and perform real-time object detection without difficulty. Its speed and unique approach inspired its creators to name it YOLO (You Only Look Once) [17]. There are many types of pretrained models, such as R-CNN, SSD, YOLO, ImageNet, COCO, PASCAL VOC, BDD100K, and DOTA v2.0 [18]. YOLO has become popular due to its accuracy and performance in detecting multiple objects or classes [19].

2.2.3 YOLOv8

YOLO v8 introduced by Ultralytics has been used by academics and practitioners especially in object detection [20]. YOLO v8 is an improvement and development of YOLOv5, this causes YOLOv8 to have several advantages [21], [22]. The enhanced YOLOv8 algorithm removes the original feature fusion Neck structure and adopts the lightweight Slim-Neck as its feature fusion network, which significantly outperforms other lightweight networks such as Xception and ShuffleNet in terms of inference latency and accuracy [23], [24], [25]. Through these lightweight enhancements, the number of parameters in YOLOv8 is significantly reduced.

2.2.4 Hardware Design

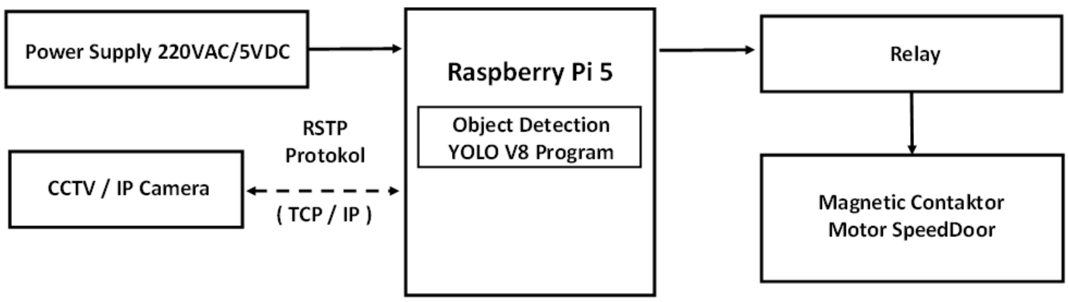

Figure 6. Diagram of the System Implementation on CCTV Camera

Figure 6 presents the block diagram of the system implemented on a CCTV camera for human-presence detection integrated with a speed-door system. The system uses a 5V power supply as the energy source for the Raspberry Pi 5. The Raspberry Pi 5 functions as an auxiliary processing module that connects to the CCTV camera via the RTSP protocol to perform image acquisition and person detection. When the CCTV camera detects a person, the program sends a signal to the Raspberry Pi. The Raspberry Pi then activates a 5V digital output connected to

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a relay module. The relay contacts switch to the ON state, sending a signal to the magnetic contactor of the speed-door electric motor, preventing the door from opening even if the forklift operator presses the remote button. This mechanism is designed to prevent potential accidents between pedestrians passing through the doorway and forklifts operating in the area.

2.2.5 System Design

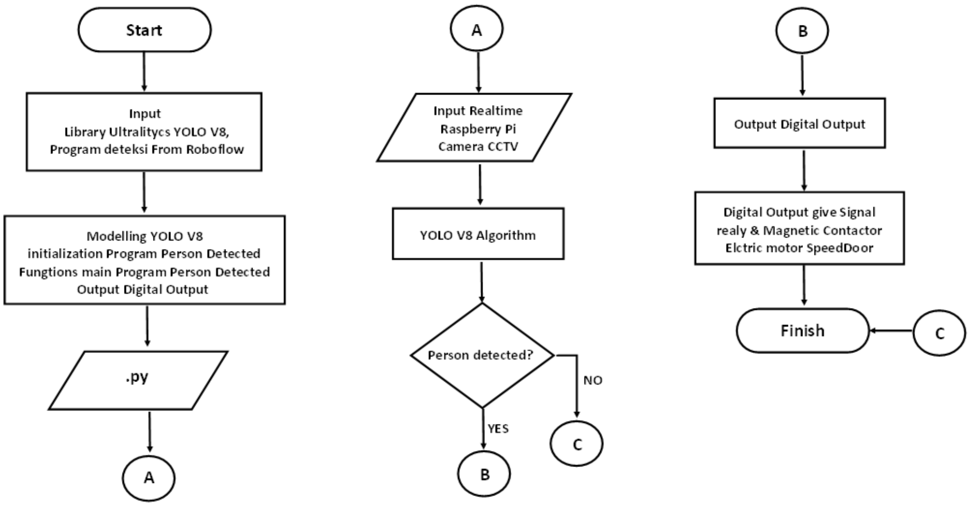

Figure 7. Detailed Steps of the Experimental Procedure

This study uses Python programming on the Raspberry Pi 5 through Visual Studio Code, where Python is applied for person-detection tasks. The vision sensor uses a CCTV camera configured to stream video to the Raspberry Pi 5 via the RTSP protocol. The Raspberry Pi runs a Python program (YOLOv8) to perform object detection and generate output signals to the relay. The flowchart in Figure 7 illustrates the detailed steps of the experimental procedure. Initially, a dataset consisting of employee photos is created and annotated using the Roboflow platform. This dataset is then processed using the YOLOv8 algorithm to produce an object-detection model (person detector) implemented in the Visual Studio Code environment. Next, on Visual Studio Code, the YOLO model and the Roboflow dataset are integrated through the Ultralytics library. Once all data are configured, the modeling and programming stages apply if–else logic to determine the required digital output. This process produces a final program file with a .py extension, ready to be deployed on the Raspberry Pi 5.

2.3 Evaluation Methods

2.3.1 Accuracy

Accuracy measures the proportion of correct predictions generated by the model, including both true positives (TP) and true negatives (TN), relative to the entire dataset. It is calculated by dividing the sum of TP and TN by the total number of samples [26]. *(Figure 8: Accuracy)*

$$Accuracy = \frac{TP + TN}{TP + FN + FP + TN} x100\%$$

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Figure 8. Accuracy Evaluation

2.3.2 Precision

Precision indicates the percentage of positive predictions that are correct. It is obtained by dividing the number of true positives (TP) by the total predictions classified as positive, namely true positives (TP) plus false positives (FP) [26] *(Figure 9: Precision)*

$$Precision = \frac{TP}{TP + FP}.$$

Figure 9. Precision Evaluation

2.3.3 Recall

Recall, also referred to as sensitivity or the true positive rate, represents the proportion of actual positive instances correctly identified by the model. It is calculated by dividing the number of true positives (TP) by the total actual positives, which is the sum of true positives (TP) and false negatives (FN) [26]. *(Figure 10: Recall)*

$$Recall = \frac{TP}{TP + FN}$$

Figure 10. Recall Evaluation

3. RESULTS AND DISCUSSION

3.1. Results

In this experiment, a confusion matrix was used to evaluate the performance of the trained object detection model. The test data consisted of a 30-minute video recording containing the movements of 55 individuals as well as several vehicles. The confusion matrix provides a detailed overview of the model's prediction outcomes, enabling a clear assessment of accuracy and error rates in detecting and classifying objects as "person" or "not person" based on the trained dataset.

Table 1. Confusion Matrix

Actual Category	Predicted: Person	Predicted: Non-Person	Total Actual (%)
Person	55 (TP)	0 (FN)	55 (100%)
Non-Person	0 (FP)	0 (TN)	0

Based on the confusion matrix presented in Table 1, it is known that out of the total 55 individuals detected, the model achieved a True Positive (TP) count of 55, indicating that all individuals were correctly identified. Both the False Negative (FN) and True Negative (TN) values were 0, demonstrating that there were no missed detections and no misclassification of

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non-human objects. These results indicate that the model achieved perfect accuracy in this testing scenario.

Test of F1 was done with formulas:

$$\text{Accuracy} = \frac{TP+TN}{TP+FP+TN+FN} = \frac{55+0}{55+0+0+0} = 1 = 100\%$$

$$\text{Precision} = \frac{TP}{TP+FP} = \frac{55+0}{55+0} = 1 = 100\%$$

$$\text{Recall} = \frac{TP}{TP+FN} = \frac{55+0}{55+0} = 1 = 100\%$$

$$F1 = 2 \text{ x } \frac{\text{Precision x Recall}}{\text{Precision+ Recall}} = 2 \text{ x } \frac{1 \text{ x } 1}{1+1} = 1 = 100\%$$

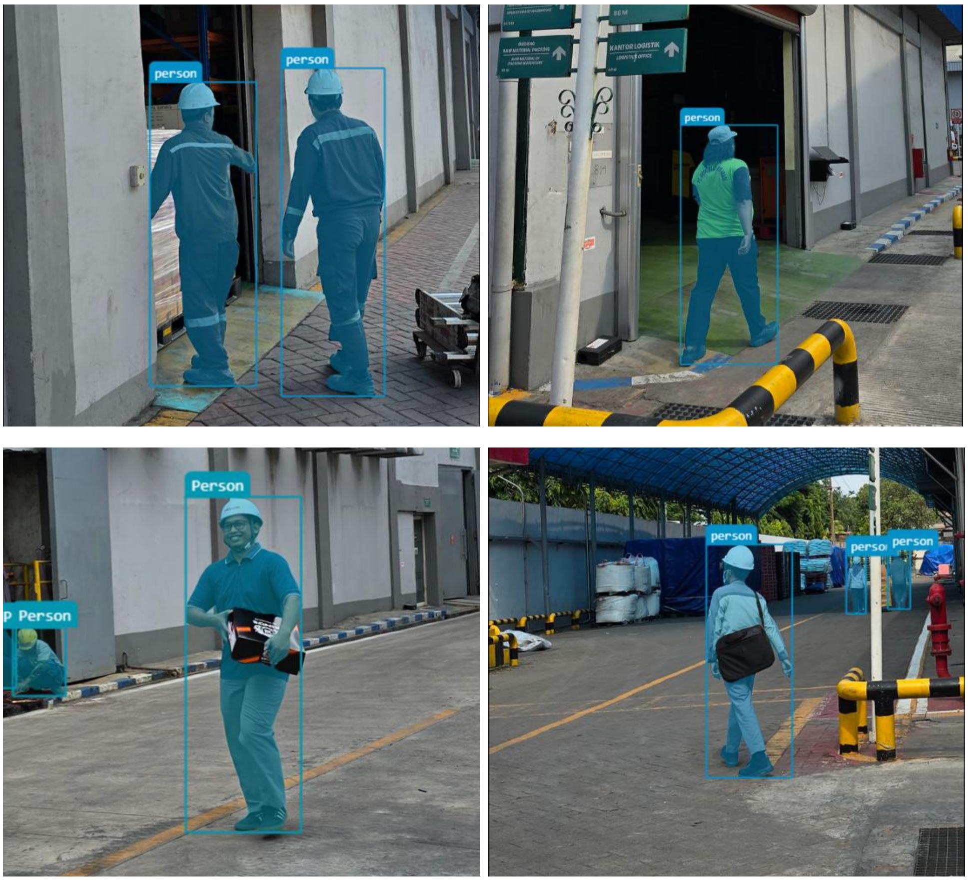

Figure 11. Result of Testing

YOLOv8 demonstrates strong performance in detecting humans, as shown in Figure 11. The model can accurately identify and localize human objects within the scene, indicating its reliability for human detection tasks [5]. It is expected that workplace accidents can be minimized by preventing door-open mechanism activated

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when the CCTV system detects the presence of a person. By linking the detection capability with the door's response, the system can prevent unauthorized or unsafe entry into restricted areas, thereby enhancing overall safety and reducing the risk of incidents in the workplace.

4. CONCLUSION

The person-detection system using CCTV cameras was successfully designed and implemented using the YOLOv8 object detection method. This success was demonstrated through the confusion matrix results, which showed perfect scores for accuracy, precision, recall, and F1-score. YOLOv8 is highly suitable for low-power devices such as the Raspberry Pi due to its lightweight architecture. Despite being optimized for efficiency, YOLOv8 demonstrated excellent performance in object detection, as evidenced by achieving an accuracy of up to 100%. Furthermore, integrating this person-detection system with safety mechanisms such as preventing door-open mechanism when a person is detected can help minimize workplace accidents and enhance overall operational safety.

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6. AUTHORS' NOTE

The authors declare that there is no conflict of interest regarding the publication of this article. The authors also confirm that this paper is free from plagiarism.

7. AUTHORS' CONTRIBUTION/ROLE

AD: Conceptualization, Methodology, Writing Original Draft, and Investigation, while LA: Formal Analysis and Supervision.

8. AI USE AND DECLARATION OF GENERATIVE AI USE

During the preparation of this work, the authors used Grammarly in order to improve the readability and language of the manuscript. After using this tool/service, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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