Approach Detection and Warning Using BLE and Image Recognition at Construction Sites

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***Abstract*—Ensuring the safety of workers in dangerous areas is an important issue at construction sites. In particular, fatal accidents at construction sites often involve falls or traffic accidents, and tend to occur around hazardous areas. In this paper, to prevent such accidents, a proximity detection and warning system based on image recognition and Bluetooth Low Energy (BLE) technology is proposed. This system mainly uses image recognition to detect workers approaching dangerous areas, and uses BLE beacons as an auxiliary to achieve continuous detection even under occlusion conditions. A master-slave operation model is adopted, with image recognition serving as the main detection method and BLE beacons as an auxiliary. When a worker approaches a dangerous area, a real-time warning is issued via a wireless earphone connected to a smartphone, allowing immediate recognition and response. This has made it possible to reach the stage of detecting intrusion into dangerous areas. However, there are still some challenges remaining for this system. The first challenge is individual re-identification. In order to issue a warning to the relevant worker when an intrusion into a dangerous area is detected, the worker needs to be recognized individually. The second challenge is adapting to changes in the structure of the construction site. Since the environment of a construction site changes over time, it is necessary to consider the appropriate placement of cameras. Experiments show that the proposed method works well to locate workers approaching and entering dangerous areas. The proposed system also detects intrusion into dangerous areas through bone conduction wireless earphones from a distance of 115 meters and issues a warning to the corresponding workers.**

***Keywords*—Construction site; safety management; intrusion detection; object recognition; trajectory tracking; YOLOv8; ByteTrack; BLE Beacon**

I. Introduction

The number of industrial accidents in Japan's construction industry has been decreasing year by year, but the rate of decrease has been plateauing. According to the data for fiscal year 2023, there were 223 accidents and 281 fatal accidents in fiscal year 2022, making it the industry with the highest number of fatalities among all industries according to the trends in fatal accidents published by the Ministry of Health, Labor and Welfare [1]. Falls are the most common fatal accident in the construction industry, with 204 of the 223 fatal accidents in fiscal year 2023 being due to falls. Construction sites are often dangerous environments where workers are prone to falling, such as rooftops, edges, openings, and scaffolding. Various factors lead to accidents, including a decrease in attention and concentration due to excessive work and a lack of safety awareness among workers due to insufficient safety and health education.

In recent years, the introduction of AI and IoT devices has begun to improve worker safety. For example, systems that attach sensors to construction machinery to detect approaching people and prevent collisions between machinery and workers, and systems that predict intrusions into dangerous areas from the movements of workers wearing sensor devices such as RFID (radio frequency identification) are being implemented and researched. In addition, construction site monitoring systems that utilise UAVS (unmanned aerial vehicles) and image recognition are also being implemented and researched.

In this study, a system that detects intrusions into dangerous areas more accurately and efficiently, and monitors them in real time, is proposed. This system operates the image analysis of a fixed camera as the main intrusion detection process, specifies the rough area using RSSI (Received Signal Strength Indicator) by a BLE (Bluetooth Low Energy) device, and performs image recognition focusing on that area. BLE is small and low-cost, so it can be deployed in large numbers, and rough location information can be obtained for a wide area. While image recognition-based intrusion detection is highly accurate, it requires computational resources such as GPUs and is dependent on lighting and viewing conditions. By using BLE as an auxiliary to roughly specify the location and performing image recognition only within that area, unnecessary overall processing can be avoided and the computational load can be reduced. In this way, the accuracy of position measurement and the reliability of intrusion detection can be improved by utilizing multiple data sources.

In worker tracking using image recognition, two algorithms, YOLOv8 (You Only Look Once) and ByteTrack, are used to detect workers who enter dangerous areas on construction sites. This has reached the stage of detecting intrusions into dangerous areas. However, this method still has some challenges. The first challenge is individual re-identification. When an intrusion into a dangerous area is detected, the worker needs to be recognized individually in order to issue a warning to the relevant worker. The second challenge is adapting to changes in the structure of the construction site. Since the environment of a construction site changes over time, appropriate camera placement needs to be considered.

For detection using the radio wave strength of BLE beacons, AtomS3-Lite, based on the ESP32-S3 manufactured by M5Stack, was used. The RSSI from beacons installed around the danger zone is received by the worker's smartphone, and if the RSSI value is above a threshold value, it is determined that the worker is approaching.

Furthermore, an alarm sounds when the user approaches the designated area detected by the proposed method. This is an experiment on the Bluetooth communication distance of bone conduction wireless earphones that do not block the ears. The user gradually moves away from the audio transmission device and measures the distance at which audio cannot be received. Three types of bone conduction wireless earphones were used: made by Anker, Sony, and SHOKZ. An Apple Macbook Air M2 chip was used for the audio transmission device.

Section II discusses related work, research objectives are given in Section III. Experimental methods and results are then described in Section IV, and the paper concludes with a discussion in Section V.

II. Related Research Works

A. Object Recognition Model YOLO

YOLOv8 is an algorithm announced by Ultralytics on January 10, 2023. Compared to previous models in the YOLO series, YOLOv5 and YOLOv7, YOLOv8 is a cutting-edge model that achieves higher detection accuracy and speed. Fig. 1 shows a performance comparison from YOLOv5 to YOLOv8 [2].

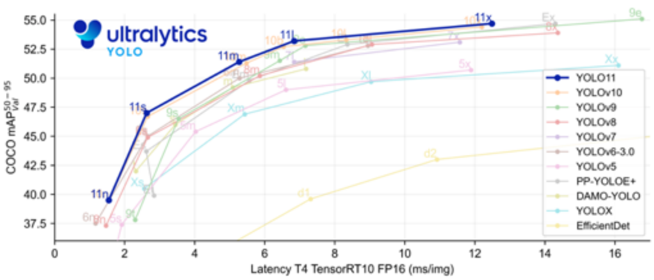

Fig. 1. List of YOLOv8 models and performance comparison [2].

The latest version, YOLOv12, was announced in February 2025. It breaks away from the traditional CNN-based approach and adopts an attention mechanism while maintaining real-time inference speed. This architectural change improves the accuracy of object detection. In this system, integration with Bytetrack, detection accuracy, resources, and speed were considered, and it was determined that YOLOv8 was sufficient to meet the requirements.

B. Tracking Algorithm ByteTrack

ByteTrack [3] is an algorithm published by Zhang et al. in 2021 that achieved the state of the art (SOTA) in the field of multi-object tracking. It tracks objects by matching IDs based on the overlap of bounding boxes estimated by object detectors such as YOLO and bounding boxes in the current frame. In addition, it utilizes a Kalman filter to predict the object's position in the next frame, allowing it to handle nonlinear movements. Fig. 2 shows a performance comparison table of tracking algorithms. In terms of MOTA and FPS, ByteTrack was selected for this study.

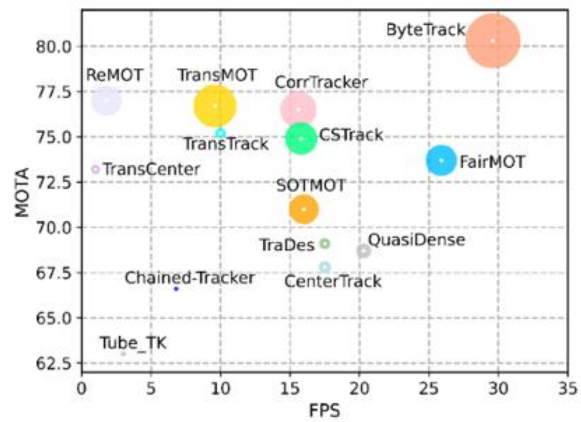

Fig. 2. Performance comparison table of tracking algorithms [3].

C. Safety Management System Using RFID

Ding et al. proposed a location detection system for workers and machinery on construction sites using RFID technology [4]. RFID tags are highly portable and do not require a power source, so they can be easily attached to various construction machinery and workers. However, there are also disadvantages. Fixed RFID readers must be installed around the construction site, which is not suitable for large-scale sites. Also, for the system to function, workers must carry RFID tags with them at all times.

D. Monitoring of Construction Sites Using UAVs

Kim et al. presented a methodology using image recognition to estimate the location of construction machinery and workers using UAVs [5]. Using the YOLOv3 object detection model, a method was developed to measure the location and distance of objects in 2D images. The advantage of this method is that all construction workers and equipment captured in UAV images can be detected by converting the UAV images into orthogonal images using orthogonal projection transformation techniques. However, this method is only viable in environments where UAVs are available, making it difficult to implement in small construction sites.

Related research on object detection includes the following papers.

Embedded object detection from radar echo data using wavelet analysis (MRA: Multi Resolution Analysis) has been proposed [6]. Meanwhile, a method for determining the support length of wavelet basis functions for edge and line detection, and for moving object and change detection has been proposed [7]. Furthermore, visualisation of 3D object shape complexity using wavelet descriptors and its application to image retrieval have been proposed and verified [8].

A method for recognizing 3D objects using multiple parts of 2D images from different viewpoints acquired by an imaging scope built into a fiber retractor has been proposed [9]. Meanwhile, a method for estimating object motion characteristics based on wavelet multi-resolution analysis (MRA) has been proposed and verified [10]. Meanwhile, a 3D rendering method based on cross-image display that can represent the internal structure of a 3D object has been proposed [11].

On the other hand, a Monte Carlo ray tracing (MCRT) based knowledge-based system for estimating height and texture mapping using object shadows using high spatial resolution remote sensing satellite image data has been attempted [12]. An object motion characteristic estimation method based on wavelet MRA has been proposed [13]. Meanwhile, a modified seam carving method that resizes the object in the time and spatial domains according to its size has been proposed and verified [14].

An object detection system has been created to assist the visually impaired in navigation [15]. Meanwhile, object detection using Haar cascades for counting the number of people implemented in OpenMV has been proposed [16]. Meanwhile, a YOLO-based object detection performance evaluation for an automatic target "Aimbot" in a first-person shooter game has been proposed and created [17].

III. Research Objective

This study aims to develop a system that utilizes both image recognition and BLE beacons to track the trajectory of workers, detect when they enter a dangerous area, and warn them about nearby hazards. This system uses YOLOv8 and bytetrack as image recognition technologies. YOLOv8 enables high-precision and high-speed object detection, and identifies the location of field workers and equipment in real time. On the other hand, by using bytetrack, it is possible to track detected objects and track their individual movement history. This makes it possible to instantly detect workers approaching dangerous areas. In addition, location estimation is performed simultaneously using BLE beacons. By coordinating these two technologies, the accuracy of intrusion detection into dangerous areas has been further improved. As a result, even if blind spots or signal interference occur in image recognition, the other technology functions complementarily, ensuring high reliability. The system configuration is shown in Fig. 3.

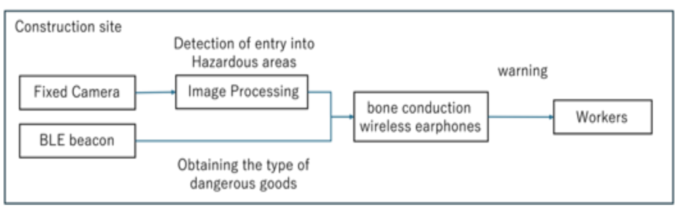

Fig. 3. System configuration diagram.

Furthermore, while most conventional hazard warning methods use rotating warning lights or buzzers to warn the entire work area, this system proposes a system that issues warnings directly to individual workers by having them wear wireless bone conduction earphones that do not interfere with their work.

Person tracking is performed using the object detector YOLOv8 and the tracking algorithm ByteTrack. As shown in Fig. 4, the worker is surrounded by a red bounding box, and its movement can be tracked.

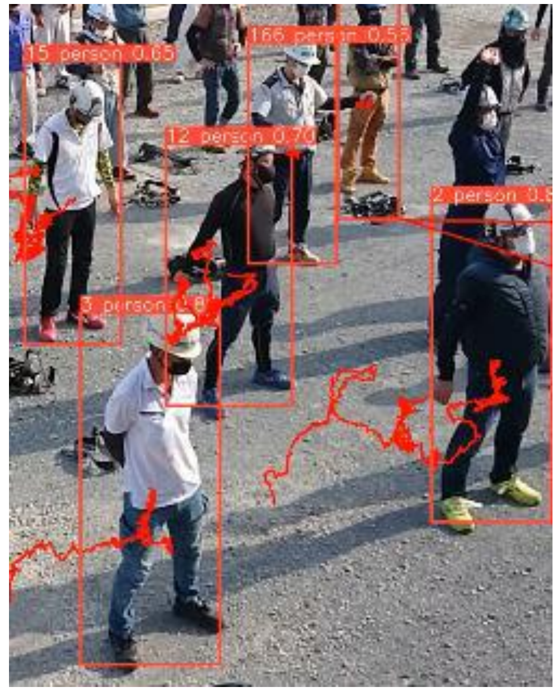

Fig. 4. Detected and tracked workers using the object detector YOLO v8 and the tracking algorithm ByteTrack.

IV. Experiment

A. Experimental Method

Experiments were conducted within the premises of Kurume Institute of Technology. The first experiment involved capturing videos in the courtyard where a new building is currently under construction. In this experiment, areas covered with red cones and blue sheets were designated as simulated hazardous zones, and intrusion into these zones was detected within the videos. For person tracking, the YOLOv8 object detector and the ByteTrack tracking algorithm were utilized.

B. Data Collection

An experiment was conducted using YOLOv8 to track individuals and detect intrusion into hazardous areas. Fig. 5 shows a frame from the video footage captured for this purpose. The collected videos were divided into images to use as training data, with a total of 300 images used for training. Of these, 210 images (70%) were allocated as training data, and 90 images were set aside for validation data.

To ensure recognition as workers, the individuals who assisted with filming wore helmets. Three types of individuals were included as “workers” in the training data, as shown in Fig. 6. Ideally, the dataset should contain individuals wearing helmets, harnesses, and safety shoes to better simulate real construction sites. However, due to the unavailability of harnesses and safety shoes at Kurume Institute of Technology, only helmets were included in the dataset for this study.

Fig. 5. A frame from the video captured at Kurume Institute of Technology.

Fig. 6. Types of individuals used in the training data.

C. Training Model

The learning model is trained using YOLOv8. YOLOv8 is a model capable of detecting humans even without training because it is pre-trained. However, since helmets are mandatory in construction sites, relying solely on a pre-trained model that has not been trained on individuals wearing helmets may result in unstable detection accuracy. Therefore, to stabilize the detection accuracy, Training was performed using data in which individuals wearing helmets were regarded as workers.

The collected videos were divided into images and used as training data, and 300 images were used for learning. Of these, 210 images, or 70%, were divided into training data and 90 images as verification data. An iPhone 13 mini was used to shoot the videos.

Object recognition involves tagging data called annotation to train an object recognizer. Generally, software is used to interactively frame a desired object on an image using a mouse cursor, etc. The coordinates of the four points are given and rectangular area information is tagged to the original image. In this research, Roboflow is used as an annotation tool. Robloflow is an image annotation tool provided by Roboflow inc. An example of annotation of worker is shown in Fig. 7.

The smallest and fastest YOLOv8 model (see Fig. 1) was used for training, making it suitable for real-time image processing tasks such as this experiment. Additionally, YOLOv8 automatically performs augmentation to increase the dataset. The results of the training process are shown in Fig. 8.

Fig. 7. Example of annotation of a worker.

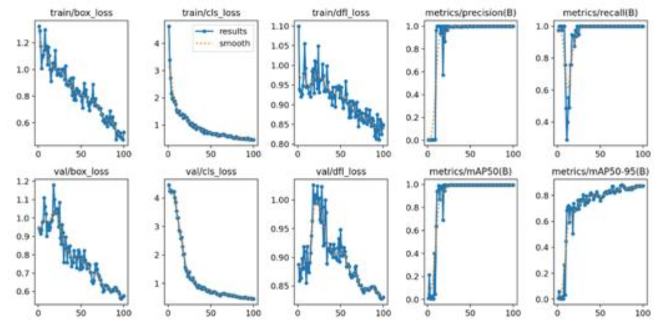

Fig. 8. Learning performance of YOLOv8.

Both train and validation box_loss are converging, indicating that the training is complete.

D. Tracking and Detection of Workers Who Enter the Designated Hazardous Areas

Fig. 9 illustrates the tracking process applied to a video captured using the YOLOv8 model as the object detector and ByteTrack as the tracking algorithm. In the center of Fig. 9, there are red-bordered rectangles representing the detected objects, along with black-bordered rectangles with yellow-striped patterns. The former denotes regions for assessing proximity to hazardous areas, while the latter signifies the hazardous zones themselves.

The two white rectangles in the bottom right of Fig. 9 are intended for displaying warning texts regarding approaching or entering hazardous areas.

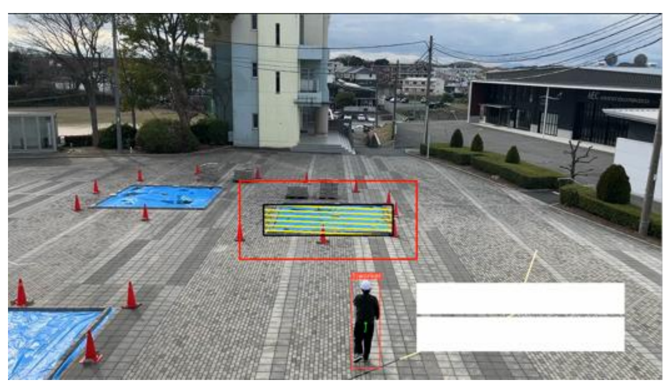

Fig. 9. Situation when not entering the region.

Additionally, green lines, originating from the center of the bounding boxes at waist level of individuals, depict their trajectories, confirming the tracking of people. The yellow-striped rectangles represent the predefined hazardous regions.

Fig. 10 illustrates the image when approaching the hazardous area. The text "detect approaching" is displayed at the bottom right of the screen, indicating that the system has detected approaching within the specified area. The timing for determining the approach is when the center coordinates of the bounding box enter the area.

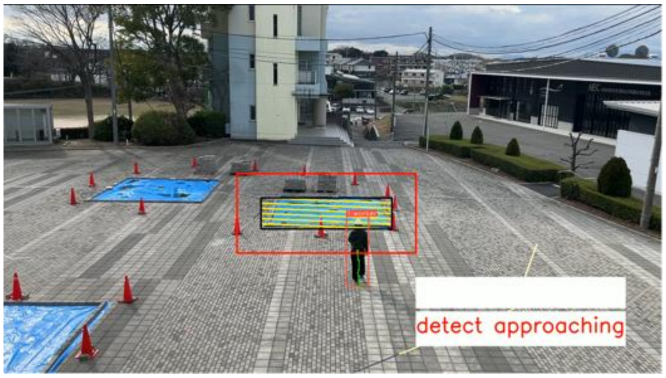

Fig. 10. Situation when approaching the hazardous area.

Fig. 11 depicts the image when entering the hazardous area. The text "Intrusion Detected" is displayed at the bottom right of the screen, indicating that the system has detected entry into the specified area. Similar to approaching, the system determines intrusion when the center coordinates of the bounding box enter the area.

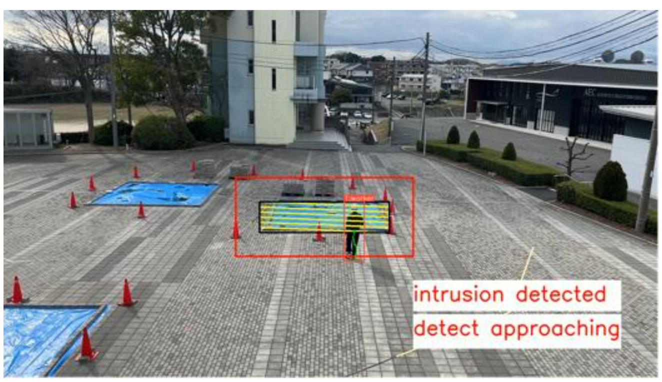

Fig. 11. Situation when entering the hazardous area.

E. Experiment on the Bluetooth Communication Distance of Bone Conduction Wireless Earphones

This research is limited to wireless earphones that do not block the ears, as it is considered important for workers at construction sites to be able to hear surrounding sounds directly. Earphones that obstruct hearing may interfere with work and pose safety concerns. There are three Bluetooth standards: Class 1, Class 2, and Class 3. The connection distance is defined as 100 m for Class 1, 10 m for Class 2, and 1 m for Class 3. However, the actual communication distance of wireless earphone devices varies depending on the product, manufacturer, and version, and even wireless earphones of the same Class 2 standard have different communication distances.

Although Class 1 wireless earphones with longer communication distances are preferable for issuing warnings, commercially available bone conduction wireless earphones are typically specified to have a communication distance of 10 meters in catalog specifications. Therefore, bone conduction models such as Anker's Soundcore AeroFit Pro (Bluetooth 5.3) and Sony's Float Run (Bluetooth 5.0), both of which list a communication distance of 10 meters, were considered. A communication distance evaluation experiment was conducted using SHOKZ's OPENRUN PRO, which is also specified to have a 10-meter communication range under Bluetooth standard Class 1.

As a result of the experiment, it was confirmed that audio could be received from the transmitting device at distances of up to 115 meters. The experimental results showed that Anker Soundcore AeroFit Pro had the longest communication distance, with Anker soundcore AeroFit Pro having a communication distance of 115m, Sony Float Run having a communication distance of 90m, and SHOKZ OPENRUN PRO having a communication distance of 83m. The experimental results are shown in Table I.

TABLE I. PERFORMANCE OF BONE CONDUCTION WIRELESS EARPHONES FOR COMMUNICATION DISTANCE

Bone conduction wireless earphones	Com. Distance
Anker Soundcore AeroFit Pro	115m
Sony Float Run	90m
SHOKZ OPENRUN PRO	83m

From this, it was found that although the specifications of the wireless earphones stated that the communication distance was 10 meters, the actual communication distance was close to 100 meters.

F. Proximity Detection Experiment Using BLE Beacons

Bluetooth communication distance was evaluated under two experimental conditions. The first was standing with the beacon on the ground, and the second was with the beacon and smartphone on the ground. The experiment did not take into account the effects of weather, metal, construction equipment, etc., that may occur at a construction site. The experimental results are shown in Fig. 12.

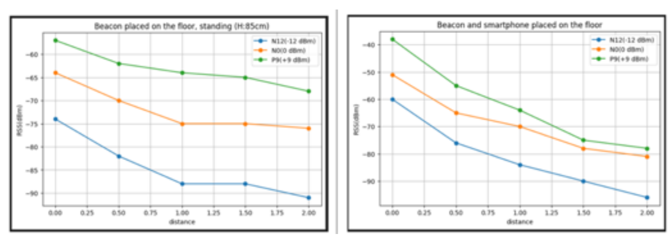

Fig. 12. Experimental results of Bluetooth communication distance when the beacon is standing on the left and when the beacon and smartphone are placed on the ground on the right.

Experimental results show that the RSSI tends to decrease overall as the distance increases, so it is possible to simply set a threshold such as "if the RSSI is greater than a certain value, it is close, and if it is smaller, it is far away." However, in reality, there is a large variation due to directivity, obstacles, and reflections and interference from the surrounding environment, and it is not uncommon for there to be fluctuations of several dB to several tens of dB even at the same distance. Therefore, in this research, BLE beacons are used only as auxiliary location estimation.

G. Discussions

1) The necessity of manually setting the hazardous area by human intervention. Currently, coordinates of four points are provided to variables within the program. However, considering potential users beyond engineers, it would be advantageous to allow interactive modification of coordinates through a user interface.

2) Decreased or undetected object recognition model accuracy due to occlusion from obstacles.

3) Limitations of a single fixed camera. To accurately assess entry into hazardous areas, it is necessary to capture and evaluate the targeted hazardous region from multiple cameras. This is because judging entry into hazardous areas is done in a two-dimensional manner; hence, for three-dimensional assessment, multiple cameras are required.

4) Identifying the worker who has entered the hazardous area. To detect intrusion and issue warnings via wireless earphones only to the relevant worker, it is necessary to register individuals captured by the camera into a database after instance segmentation, and then individually re-identify workers when needed (Person Re-Identification). Previous studies have proposed deep learning-based person re-identification methods such as distance learning and self-supervised learning to address this issue. However, it is currently considered a challenging problem due to factors like viewpoint variations, changes in lighting conditions, and occlusions of individuals.

V. Conclusion

This paper demonstrated that applying YOLOv8 and the ByteTrack algorithm enables the detection of intrusions into predefined dangerous areas, and that bone conduction wireless earphones are capable of transmitting warning sounds over a distance of approximately 115 meters. However, several challenges remain when considering practical deployment, such as developing methods to set the coordinates of hazardous areas, improving the accuracy of object detection models, and implementing and experimenting with person re-identification algorithms to determine the identity of individuals who have entered hazardous areas.

VI. Future Research Works

In this study, a system was developed to detect intrusions into hazardous areas and issue warnings to the relevant workers. For practical deployment, a method was also implemented for setting the coordinates of dangerous areas. However, several challenges remain, including improving object detection accuracy and integrating a person re-identification algorithm to determine the identity of individuals entering hazardous zones. Addressing these issues will be the focus of future work.

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