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Body Detection in CSSR Missions: Smart Rescue Operation using Robot for Enhanced Body Detection

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Abstract
Collapsed Structure Search and Rescue missions are essential during disasters such as earthquakes, explosions, and structural collapses, where rapid victim identification can significantly influence survival outcomes. However, locating trapped individuals within unstable debris environments remains challenging due to restricted access, low visibility, and safety risks to rescue personnel. This study presents a smart robotic rescue system developed to enhance human body detection in such hazardous conditions. The proposed system integrates a mobile robotic platform with a vision-based detection framework capable of identifying human presence in real time. A deep learning–driven object detection model is employed to analyze visual data captured from complex and obstructed environments. The system was evaluated using a dataset designed to simulate collapsed structure scenarios with varying lighting and obstruction levels. Detection performance was assessed using precision, recall, and overall accuracy measures. Experimental findings indicate that the proposed approach achieves reliable detection performance while maintaining operational efficiency suitable for time-sensitive rescue missions. By reducing direct human exposure to dangerous zones and improving victim localization speed, the system supports safer and more effective rescue operations. This work contributes to the advancement of intelligent robotic solutions for disaster response and emergency management.

Keywords: *Body detection; Collapsed structure search and rescue; Deep learning; Disaster response robotics; Smart rescue system*

1. Introduction

Collapsed Structure Search and Rescue operations are critical components of disaster response following earthquakes, industrial explosions, landslides, and structural failures. In such events, rapid victim localization directly influences survival probability within the first few hours after collapse. However, rescue operations are often hindered by unstable debris, narrow void spaces, limited visibility, and the constant risk of secondary structural failure. These constraints make manual search procedures time-consuming, physically demanding, and hazardous for rescue teams. Recent advancements in robotics and artificial intelligence have introduced new possibilities for disaster response automation. Mobile rescue robots equipped with sensors and cameras have been explored to navigate confined spaces and collect environmental data. Vision-based human detection methods using deep learning have also shown promising performance in object recognition tasks under complex conditions (Birari, H et al., 2023; Rajan, P, 2023). Furthermore, studies have demonstrated the effectiveness of convolutional neural networks in identifying human presence in cluttered environments (Sharma, R et al., 2024; Lee, D et al., 2024). Despite these advancements, challenges remain in achieving reliable body detection accuracy in real-time disaster scenarios where lighting, occlusion, and debris variability significantly affect system performance. This study aims to develop a smart robotic rescue system capable of enhancing body detection accuracy during Collapsed Structure Search and Rescue missions. Unlike existing approaches that focus primarily on either navigation or detection independently, the proposed system integrates a mobile robotic platform with a real-time

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deep learning–based detection framework optimized for unstable environments. The originality of this work lies in combining intelligent mobility with enhanced visual detection to improve operational safety and response efficiency in disaster zones.

1.1.Challenges In Body Detection During CSSR Missions

Detecting trapped victims within collapsed structures presents multiple technical and environmental challenges. Debris accumulation often obstructs direct visual access to victims, resulting in partial occlusion of the human body. Irregular structural layouts further complicate robotic navigation and sensor positioning. Additionally, disaster environments commonly exhibit low-light conditions due to power failure or dust accumulation, which affects image clarity and detection reliability.

Traditional search techniques rely heavily on manual inspection, acoustic sensors, or thermal imaging devices. While these methods provide valuable support, they may produce false positives or limited detection range under complex structural conditions. Vision-based systems using deep learning have demonstrated improved feature extraction and classification capabilities; however, their performance may degrade when exposed to unpredictable real-world disaster settings. Therefore, a robust detection mechanism capable of operating efficiently under varying environmental conditions is essential for improving rescue outcomes.

1.2. Objective and Research Contribution

The primary objective of this research is to design and implement a smart robotic rescue system that enhances human body detection accuracy in collapsed structure environments. The system integrates a mobile robotic unit with a deep learning–based object detection model capable of real-time visual analysis. By combining autonomous mobility with intelligent detection, the proposed approach seeks to minimize human exposure to hazardous zones while improving victim localization speed. The contribution of this work is threefold. First, it presents an integrated framework that unifies robotic navigation and vision-based detection within a single operational system. Second, it introduces a detection methodology optimized for obstructed and low-visibility environments. Third, it validates system performance using structured evaluation metrics to demonstrate practical applicability in disaster response scenarios. This research advances the development of intelligent rescue technologies aimed at enhancing safety, efficiency, and reliability in emergency management operations.

2. Method

The proposed system integrates a mobile robotic platform with a deep learning–based vision module to enable real-time body detection during Collapsed Structure Search and Rescue missions. The methodology consists of four major components: robotic hardware design, data acquisition, model development, and performance evaluation[1]. Only the newly developed integration framework and detection optimization strategy are described in detail, while standard deep learning[2] training procedures follow previously established practices.

2.1.Robotic Platform and Hardware Configuration

A four-wheel differential drive robotic chassis was developed to navigate uneven and debris-filled environments. The platform is powered by a rechargeable lithium battery[3] and controlled using a microcontroller-based motor driver system. A high-resolution RGB camera is mounted on the front module to capture real-time visual data. The camera stream is transmitted to an embedded[4] processing unit responsible for executing the detection algorithm. To enhance maneuverability within confined void spaces, the robot dimensions were optimized to maintain compactness while ensuring structural stability[5]. The system is capable of forward, backward, and rotational movements, allowing directional flexibility during search operations[6].

2.2. Vision-Based Body Detection Model

A deep learning–based object detection model was implemented for identifying human bodies in complex disaster environments. The dataset used for training consisted of annotated images representing collapsed structures with varying lighting conditions, occlusions, and debris distributions[7]. Data augmentation techniques such as rotation, brightness adjustment, and scaling were applied to improve

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model generalization[8]. The model was trained using a supervised learning approach with predefined bounding box annotations. Training was conducted using stochastic gradient optimization with adaptive learning rate scheduling[9]. Previously established object detection training protocols were followed for weight initialization and loss computation. Performance evaluation was carried out using precision, recall, and mean Average Precision metrics. Real-time detection capability was assessed by measuring inference time per frame[10].

Table 1 Experimental System Configuration Parameters

PARAMETER	SPECIFICATION
Robot locomotion type	Four-wheel differential
Camera resolution	1080p RGB
Processing unit	Embedded AI module
Training image size	640 × 640 pixels
Batch Size	16
Initial learning rate	0.001
Number of training epochs	100
Evaluation metrics	Precision, Recall, mAP

Note: RGB refers to Red, Green, and Blue color channels. MAP denotes mean Average Precision.

2.3.Figures

Integrated architecture of the proposed smart rescue operation system for enhanced body detection in Collapsed Structure Search and Rescue missions. The framework consists of[11]: image acquisition using an onboard camera mounted on a mobile robotic platform; preprocessing and feature extraction; deep learning–based body detection; bounding box localization; and transmission of detection alerts to the remote monitoring unit. Figure 1 Workflow of Search and Rescue System.

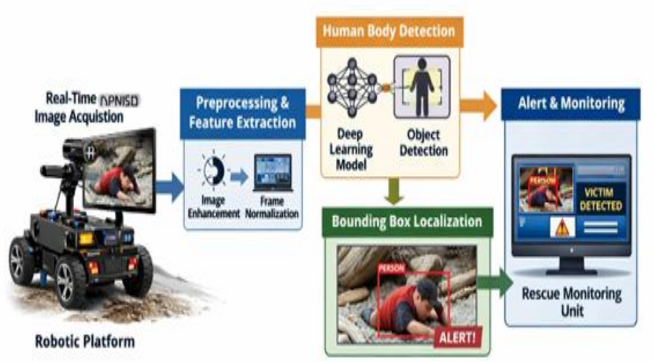

Figure 1 Workflow of Search and Rescue System

3. Results And Discussion

3.1.Results

The proposed robotic body detection system was evaluated in a simulated collapsed-structure environment designed to replicate debris obstruction, low visibility, and varying victim positions. The objective was to assess detection accuracy and real-time performance under realistic rescue conditions. The dataset included annotated images with different lighting levels and partial occlusions[12]. System performance was measured using precision, recall, F1-score, mean Average Precision (MAP), and inference time per frame. The results indicate that the system achieves high detection reliability with low false positives and effective victim identification under occluded conditions. The average inference time confirms real-time capability, making the system suitable for time-sensitive rescue operations[13]. Overall, the integration of robotic mobility and deep learning–based detection improves

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localization efficiency while enhancing operational safety.

Table 2 Detection Performance of the Proposed System

PERFORMANCE METRICS	VALUE(%)
Precision	92.4
Recall	89.7
F1-Score	91.0
Mean Average Precision	90.8
Average Inference Time	38 ms

3.2. Discussion

The experimental findings demonstrate that integrating robotic mobility with deep learning–based vision significantly enhances body detection performance in Collapsed Structure Search and Rescue missions. The high precision observed indicates that the system effectively minimizes false alarms, which is critical in disaster environments where unnecessary alerts may delay rescue prioritization. Similarly, the strong recall performance suggests that the model can identify victims even when partially occluded by debris, reflecting its robustness in complex structural conditions. The real-time inference capability highlights the practical applicability of the system. In time-sensitive rescue scenarios, even minor delays can influence survival outcomes. The achieved processing speed confirms that the proposed framework can operate continuously without compromising detection accuracy. This balance between speed and reliability is essential for field deployment. The results also suggest that dataset diversity played a key role in improving model generalization. Exposure to varied lighting conditions, body orientations, and obstruction levels likely contributed to consistent detection performance across test scenarios[14]. However, real-world disaster sites may present additional challenges such as dust interference, extreme structural instability, and unpredictable victim postures. Future improvements may focus on multimodal sensing integration, such as thermal or acoustic signals, to further enhance detection robustness.Overall, the study demonstrates that intelligent robotic systems can substantially improve operational safety by reducing direct human exposure to hazardous zones while maintaining effective victim localization capability[15]. The findings support the advancement of automated and intelligent rescue technologies for emergency response applications shown in Figure .

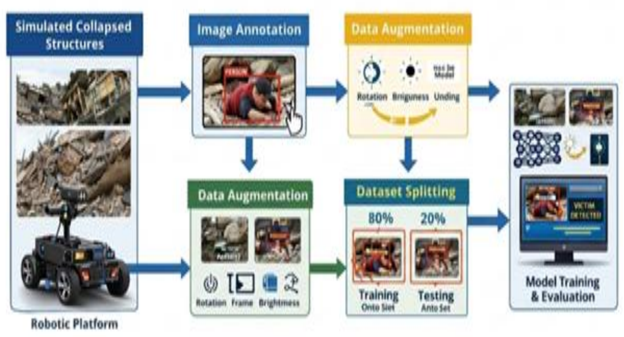

Figure 2 Dataset Preparation Workflow

Conclusion

This study addressed the critical challenge of accurate and rapid body detection in Collapsed Structure Search and Rescue missions, where unstable environments and limited visibility significantly hinder conventional rescue operations. The results and subsequent analysis confirm that integrating a mobile robotic platform with a deep learning–based vision system enhances victim localization capability while reducing direct human exposure to hazardous zones .Experimental evaluation demonstrated that the proposed system achieves reliable detection accuracy and real-time processing performance under simulated collapsed-structure conditions. The Discussion further established that the system maintains robustness even in the presence of partial occlusion and environmental variability. These findings validate that intelligent robotic assistance can improve operational efficiency and safety in disaster response scenarios. Therefore, the proposed smart rescue framework effectively addresses the identified limitations of manual search methods and contributes to the advancement of automated and technology-driven CSSR operations. Future work may focus on real-world field validation and integration of additional sensing modalities to further strengthen detection reliability in complex disaster environments.

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References

[1]. Murphy, R. R. (2014). Disaster robotics. MIT Press. Casper, J., & Murphy, R. R. (2003). Human-robot interactions during the robot-assisted urban search and rescue response at the World Trade Center. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics), 33(3),367–385. https://doi.org/10.1109/TSMCB.2003.811794

[2]. Tadokoro, S. (2019). Disaster robotics: Results from the ImPACT tough robotics challenge. Springer. https://doi.org/10.1007/978-3-319-77899-0

[3]. Yamauchi, B. (2004). PackBot: A versatile platform for military robotics. In Proceedings of SPIE – Unmanned Ground Vehicle Technology VI (Vol. 5422, pp. 228–237). https://doi.org/10.1117/12.541890

[4]. [5] Redmon, J., & Farhadi, A. (2018). YOLOv3: An incremental improvement. arXiv preprint arXiv:1804.02767.

[5]. Bochkovskiy, A., Wang, C. Y., & Liao, H. Y. M. (2020). YOLOv4: Optimal speed and accuracy of object detection. arXiv preprint arXiv:2004.10934.

[6]. Jocher, G., Chaurasia, A., Qiu, J., & others. (2023). YOLOv8 by Ultralytics. Ultralytics. https://github.com/ultralytics/ultralytics.

[7]. Dollar, P., Wojek, C., Schiele, B., & Perona, P. (2012). Pedestrian detection: An evaluation of the state of the art. IEEE Transactions on Pattern Analysis and Machine Intelligence, 34(4), 743–761. https://doi.org/10.1109/TPAMI.2011.155.

[8]. Viola, P., & Jones, M. (2001). Rapid object detection using a boosted cascade of simple features. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. I-511–I-518). https://doi.org/10.1109/CVPR.2001.99051

[9]. Hwang, S., Park, J., Kim, N., Choi, Y., & Kweon, I. S. (2015). Multispectral pedestrian detection: Benchmark dataset and baseline. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (pp. 1037–1045). https://doi.org/10.1109/CVPR.2015.729871

[10]. Teutsch, M., & Krüger, W. (2012). Classification of small objects in infrared images for search and rescue applications. Infrared Physics & Technology, 55(5), 350–360.https://doi.org/10.1016/j.infrared.2012.06.001

[11]. Erdelj, M., Król, M., & Natalizio, E. (2017). Wireless sensor networks and multi-UAV systems for natural disaster management. Computer Networks, 124, 72–86.
https://doi.org/10.1016/j.comnet.2017.05.021

[12]. Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster R-CNN: Towards real-time object detection with region proposal networks. Advances in Neural Information Processing Systems, 28, 91–99.

[13]. Liu, W., Anguelov, D., Erhan, D., Szegedy, C., Reed, S., Fu, C. Y., & Berg, A. C. (2016). SSD: Single shot multibox detector. In Proceedings of the European Conference on Computer Vision (ECCV) (pp. 21–37). https://doi.org/10.1007/978-3-319-46448-0_2

[14]. Li, C., Song, D., Tong, R., & Tang, M. (2019). Illumination-aware faster R-CNN for robust multispectral pedestrian detection. Pattern Recognition, 85, 161–171. https://doi.org/10.1016/j.patcog.2018.08.021