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Review of AI-Driven Methods to Enhance Search and Rescue Operations after Earthquakes

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ABSTRACT

The devastating results of seismic events affect many people's lives every time they occur. The main damage is caused to people being trapped under the rubble for long periods of time because rescue teams lack intelligent and prioritised plans. To address this problem, we will study the utilisation of various artificial intelligence (AI) technologies in accelerating and enhancing the efficiency of human spotting and rescuing processes after earthquakes. These applications include neural networks, AI-controlled robot systems, and multimodal data fusion, where thermal, visual, and acoustic data are integrated to detect survivors under building debris, in addition to other fusion ideas. This review will focus on studies published between 2023 and 2026. One main outcome of this work is the identification of key limitations in current AI solutions, such as real-time processing constraints, the noisy nature of disaster environments, and hardware deployment challenges in active disaster zones. In conclusion, this review aims to serve as a future research direction for optimising AI-driven methods to enhance detection accuracy, accelerate rescue timelines, and improve the overall survival outcomes in seismic emergencies.

Keywords: *Earthquake Search and Rescue, Deep Learning, Human Detection, Thermal Imaging, Rescue Robotics.*

1. INTRODUCTION

Earthquakes are considered one of the most devastating natural disasters. Since they cannot be predicted before they happen, they cause massive destruction of buildings, and they can kill large numbers of people after being trapped under the rubble for extended periods of time where the survival rate drops significantly after the first few days due to severe factors such as dehydration, heat, and untreated injuries. The 2023 Kahramanmaras earthquake series in Turkey and Syria is an example of a major earthquake, where tens of thousands of casualties and huge structural damage were recorded [1, 5]. Ozturkcan [2] documented that scale of this earthquake series spanned more than 50,000 square kilometers with over 50,000 deaths and 100,000 injuries, making it one of the worst disasters of the century.

Traditional search and rescue (SAR) operations used for saving people after earthquakes rely heavily on human rescuers and trained dogs, and they are often constrained by the dangerous, unstable nature of disaster environments. Rescuers face significant risks when navigating debris, and manual inspection processes are time consuming and require massive amounts of manual work. Consequently, delayed detection and decision making can become life threatening for survivors [3, 4].

In recent research, there has been a major shift toward utilizing robotic systems in post-disaster management in order to overcome manual SAR risks while improving response times. For example, Unmanned Aerial Vehicles (UAVs) [5, 6], Unmanned Ground Vehicles (UGVs) [7-9], and biomimetic systems like snake robots [4] provide access to dangerous, inaccessible disaster areas. UAVs offer fast surveillance of the large, affected areas where accessing these areas on the ground is hard or impossible and UGVs can navigate through narrow, unstable rubble to search for trapped individuals without requiring human teams to go into danger. However, the deployment of those robots in real earthquake-affected areas is challenging because robots need to autonomously navigate those rough areas. Rajashekhar and Prabhakar [10] stated that integrating robots into existing emergency response frameworks requires technical innovation with careful consideration of human-robot collaboration, responder training, and public acceptance.

Although different types of robots seem complex and powerful, their objective in SAR operations cannot be fulfilled without the help of artificial intelligence (AI), especially deep learning (DL), and advanced sensors. Convolutional neural networks (CNNs) and the You Only Look Once (YOLO) architecture have revolutionized human detection in disaster scenarios. Since human victims in such cases may appear as small, low-contrast, or partially occluded targets, relying completely on standard visual cameras (RGB) is often insufficient. Now, researchers are increasingly using multimodal data fusion by integrating thermal imaging, acoustic sensors, Light Detection and Ranging (LiDAR), and even Wi-Fi Channel State Information (CSI), so AI systems can perceive human presence through obstacles and in low-visibility conditions [10, 3, 4].

Implementing AI-driven methods in SAR operations is not easy and faces significant challenges. For example, object detection models often suffer from performance degradation when deployed in complex, unfamiliar disaster scenes due to a lack of highly representative training datasets [5].

Other examples include managing real-time processing constraints on embedded robotic hardware, and overcoming severe sensor noise in chaotic environments [3]. Rajashekhar and Prabhakar [10] noted through their literature, public surveys, expert interviews, and GenAI chatbot perspectives, that current SAR robotics are limited by mobility, autonomy, communication, and collaboration with human issues that must be addressed before widespread deployment.

Therefore, this review aims to study recent literature published between 2023 and 2026 to evaluate the efficacy of AI- driven methods in post-earthquake SAR operations. By examining the integration of neural networks, robotics, and multimodal data fusion, this paper will identify key technological limitations and outline future research directions to optimize detection accuracy, accelerate rescue timelines, and improve survival outcomes in seismic emergencies.

This paper is organized as follows: Section 2 explores AI-based human detection in disaster imagery. Section 3 examines physical robotic platforms for SAR. Section 4 reviews multimodal data fusion approaches for survivor detection. Section 5 discusses current challenges. Section 6 suggests directions for future research. Finally, Section 7 concludes the paper.

Chart-1 illustrates the workflow of AI-Driven SAR Operations.

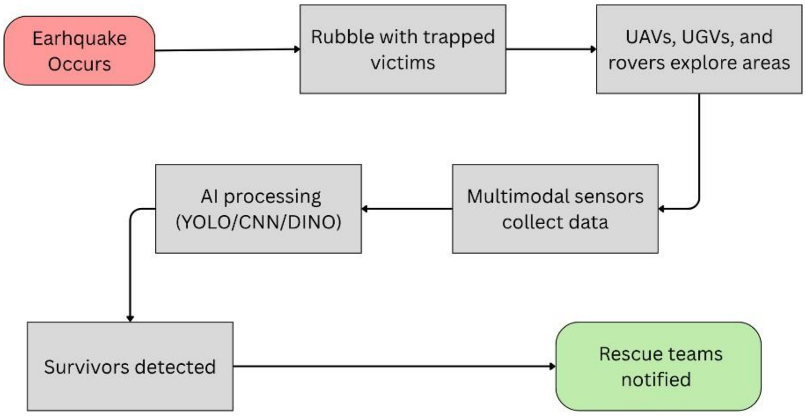

Chart -1: AI-Driven SAR Operations Flowchart

2. AI FOR HUMAN DETECTION IN DISASTER IMAGERY

2.1 YOLO-Based Detection and Thermal Imaging

The first 48 to 72 hours after a destructive earthquake are the most critical time window for finding and rescuing survivors trapped under the rubble [1]. Manually searching for survivors can be challenging because of low visibility due to dust, smoke, or rubble [3]. To address this, deep learning algorithms were increasingly adopted by recent research. CNNs and YOLO are important examples of deep learning object detectors used in those research papers to automate human detection in earthquake environments using data from images.

Using thermal imaging to detect human body heat signatures in complete darkness or smoky areas was examined by namouras researchers. Rizk and Bayad [6] proved the success of YOLOv8 in detecting human through thermal images where they built a novel dataset of more than 17,000 thermal images in grayscale with 90,882 human annotations. Their experiment showed that YOLOv8x (YOLOv8 Extra-Large) model achieved an average precision (AP) of 95%, which shows that deep learning can be utilized to reliably spot humans in thermal images [6]. Jadeja et al. [4] utilized snake robots to assess multiple algorithms including YOLOv10 in post-earthquake search and rescue scenarios. They found that YOLOv10 managed to achieve the highest accuracy of 98.5% with an inference time of 15 milliseconds. This makes it highly suitable for real-time deployment on robotics navigating through rubble [4].

The usage of unmanned aerial vehicles in disaster areas is challenging because target sizes, such as human survivors, become smaller as drones fly higher, and environmental scenes vary in each scenario. Ulmămei et al. [5] addressed this challenge by gathering a new thermal image dataset of mountainous areas and combined it with other ten existing datasets to create an extended one that contains more than 75,000 images. Their comparative assessment of YOLO different models (YOLOv8 – YOLOv11) and RT-DETR on an NVIDIA Jetson AGX Orin embedded platform showed that even though these models maintained high accuracy ranging from 85% to 90%, their detection performance declined noticeably on very small objects. Also, transformer-based RT- DETR performance was poor because of the lack of large and consistent training data [5]. Those findings highlight the limitation of current models requiring extensive and reliable datasets to generalize efficiently without struggling with object size variability.

2.2 Occlusion Handling with VE-DINO

Another critical challenge in search and rescue operations in earthquake cases is the need to identify partially occluded survivors where no scenes of full human bodies are available. Zhao et al. [3] proposed a model called the Visibility- Enhanced DINO (VE-DINO) to address this challenge. Their model achieved an AP of 0.615, which is better than the standard DINO (AP of 0.491), on standard datasets by including visibility-aware loss functions that focus on specific human body parts such as the head, upper and lower body, and legs. VE-DINO was integrated into a UAV system and managed to successfully detect individuals that are partially hidden by the rubble. This demonstrates the importance of handling the occlusion of victims for SAR operations [3].

2.3 Embedded Deployment

Joseph et al. [7] proposed Rescuebot, a hexapod robot equipped with a thermal camera running a YOLOv8 model as an integration of an AI detection model with a physical robotic system. Their system achieved 98% accuracy under simulated smokey and low-visibility scenarios. Similarly, Dhanya et al. [9] developed an Autonomous Search and Rescue Rover (ASR-Rover) using a MobileNet-SSD model on a Raspberry Pi 5 that detects humans and body parts in disaster environments by relying on transfer learning. Their system sends GPS coordinates of victims to rescue teams to help them find survivors. These studies highlight an important compromission, which is while deep learning models could achieve high detection accuracy, deploying these models on embedded hardware with limited resources requires careful optimization of model size and inference speed [5, 9].

2.4 Summary

In summary, the literature confirms that AI-driven methods, particularly YOLO detectors and thermal imaging, have advanced human detection in post-earthquake imagery.

However, critical challenges arise from the complexity of these scenarios, including poor performance on small or occluded targets, inconsistency between training datasets and real disaster environments, and the difficulty of real-time deployment on embedded robotic hardware [3, 4, 5, 6]. Table-1 summarizes key contibutions and reported performance of selected papers.

Table-1: Summary of AI Detection Methods for Post-Earthquake SAR

Study	Detection Method	Key Contribution	Reported Performance
Rizk & Bayad [6]	YOLOv8 on thermal images	Novel dataset of 17,148 thermal images with 90,882 annotations	95% average precision (YOLOv8x)
Jadeja et al. [4]	YOLOv10 on snake robot	Evaluation of multiple algorithms for survivor detection	98.5% accuracy; 15 ms inference time
Ulmămei et al. [5]	YOLOv8–v11, RT-DETR on UAV thermal	Meta-dataset of 75,000+ images; embedded deployment on Jetson Orin	85–90% accuracy (YOLO); poor RT-DETR performance
Zhao et al. [3]	VE-DINO (modified DINO)	Visibility-aware loss functions for occluded victims	0.615 AP (vs. 0.491 for standard DINO)
Joseph et al. [7]	YOLOv8 on hexapod robot	Integration of detection with physical robotic system	98% accuracy in simulated smoke/low-visibility
Dhanya et al. [9]	MobileNet-SSD on ASR-Rover	Transfer learning; real-time GPS coordinate transmission	Not specified

3. ROBOTIC PLATFORMS FOR SAR

While the previous section focuses on AI algorithms for human detection, this section examines the physical robotic systems, including their mobility systems, mechanical designs, navigation capabilities for post-earthquake environments.

3.1 Unmanned Aerial Vehicles (UAVs) for Aerial Surveillance

UAVs, commonly known as drones, allow fast aerial surveys of disaster and hardly reachable zones. While they serve as an advanced technology, their effectiveness is influenced by their flying stability, sensors capacity, and the ability to transmit data in real-time. Ulmămei et al. [5] collected images of rough terrain using a DJI M3T drone fitted with a thermal camera which highlighted that UAV platform selection is related directly to image quality and detection performance. Their study states that embedded hardware limitations such as the NVIDIA Jetson AGX Orin's power modes (15W vs. 60W) and quantization levels (FP16 vs. INT8) have a significant effect on the system's real-time inference speed. Having FP16 achieving up to 27 frames per second (FPS) while maintaining accuracy [5]. Rizk and Bayad [6] noted in their study that UAVs with thermal cameras have to perform well through smoke and darkness, which requires selecting sensors carefully. However, neither of these studies examined UAV flight control or autonomous path planning, which indicates a gap in current UAV-SAR research [5, 6].

3.2 Ground Robots: UGVs, Snake Robots, and the SERR Platform

Robots that navigate on the ground must be able to communicate with rescue teams while navigating through unstable rubble, confined areas, and dangerous debris. Jadeja et al. [4] developed snake robot that is created using 3-D printing. It consists of seven serially connected modules, each powered by an MG996R servo motor. With alternate modules receiving 90-degree phase-shifted signals, the robot uses sinusoidal signal control to accomplish snake-like movement (rectilinear, sidewinding, and concertina). In addition, wireless cameras are attached to the front and rear modules to ensure bidirectional detection of obstacles and to support motion planning. The authors state that their modular design can be extended beyond seven segments depending on SAR requirements [4].

To prioritize rough terrain navigation stability over speed, Joseph et al. [7] designed their Rescuebot as a hexapod system (a robot with six legs). The robot incorporates servos for leg actuation, an Arduino-controlled H-bridge motor driver, and a Raspberry Pi 4 for onboard computation. They also utilized Bluetooth to enable controlling the robot wirelessly and used a thermal camera to feed YOLOv8 detection model with visual input. The authors conclude that hexapod locomotion outperforms wheeled robots in motion stability in rubble-covered environments, but they are still slower than wheeled robots [7].

A comprehensive ground robot design was presented by Khattab et al. [1] where they called it The Smart Earthquake Rescue Robot (SERR). It features a reinforced four-wheel drive chassis supported with shock-absorbing suspension and it is capable of traversing debris with heights up to 20 cm. To balance the robot's durability with portability, they used lightweight aluminum when constructing the robot's frame. Their robot is powered by rechargeable lead-acid batteries that support three hours of continuous operation. The SERR differs from simple designs by integrating multiple onboard sensors such as Grid-Eye thermal sensors, ultrasonic distance sensors, and a live video camera and they are connected to an Arduino Mega microcontroller. The robot operates with the help of a radio frequency module to enable wireless control via a PC application, and a separate smartphone application to manage live video streaming. The robot's obstacle detection system stops moving when objects are within 30 cm, choosing safety above autonomous navigation. The authors acknowledge that two-way audio communication (speaker and microphone) was designed but not yet implemented and proposed in their current prototype [1].

3.3 Rover-Based Systems: Mobility and Communication

Dhanya et al. [9] developed their rover that is called ASR-Rover with a rocker-bogie suspension mechanism, which is a design originally developed for NASA's Mars rovers that allows six wheels to maintain ground contact on uneven and rough surfaces. Even though rovers are not as agile as UAVs or snake robots, they are better in terrain adaptability and communication with targets located far away from them. The authors' proposed rover integrates LiDAR for simultaneous localization and mapping (SLAM), ultrasonic sensors for obstacle avoidance, an HC12 SI44B3 transmitter for long-range wireless communication, and a GPS module to record survivor coordinates and transmit them to rescue teams in real time. The rover runs on a Raspberry Pi 5, and the authors admit that tasks requiring high power such as climbing or scanning can rapidly bring down the lithium-ion battery, occasionally leading to system failure when energy demands exceed capacity [9].

A similar rover was proposed by Umamaheswari et al. [8] but with a stronger focus on navigating with the help of sensor fusion where data from multiple sensors is combined to help the system achieve better overall performance. They incorporate thermal images, LiDAR, ultrasonic sensors, and optical cameras into a control system.

The robot's hardware is built around high-torque motors to tackle obstacles, and the authors discuss the significance of choosing the right materials, like aluminum alloys or carbon fiber composites, to maintain a balance between the robot's durability and weight. This system differs from the previously mentioned ASR-Rover system, which is focused on autonomous navigation; instead, it emphasizes semi-autonomous control, allowing human operators to step in when the robot faces challenging or unfamiliar scenarios [8]. Table 1 summarizes the key hardware features of the robotic platforms reviewed in this section.

3.4 Summary

To summarize, it is noticed after reviewing current robotic systems for earthquake SAR that they vary in their mobility designs including serpentine snake robots for confined spaces, wheeled rovers for debris traversal, and drones for aerial surveillance. Most systems prioritize detection algorithms over robust navigation, and few of them have proposed autonomous path planning in rubble environments. The SERR platform [1] offers the most complete hardware integration, while the ASR-Rover [9] provides the most sophisticated terrain adaptability through its rocker-bogie suspension. Common limitations across all platforms include short battery life, limited autonomous navigation capabilities, and the absence of two-way audio communication for survivor interaction [1, 4, 5, 6, 7, 8, 9]. Table-2 compares the robotic platforms proposed in the selected study.

Table-2: Comparison of Robotic Platforms for Post-Earthquake SAR

Platform	Locomotion	Onboard Processor	Key Sensors	Communication	Battery Life
SERR [1]	4-wheel drive (shock-absorbing)	Arduino Mega	Grid-Eye thermal, ultrasonic, camera	RF module + smartphone app	3 hours
Snake Robot [4]	7-module serpentine (servo motors)	Arduino Nano	Wireless cameras (front/rear)	Not specified	Not specified
Rescuebot [7]	Hexapod (6 legs)	Raspberry Pi 4	Thermal camera	Bluetooth	Not specified
ASR-Rover [9]	Rocker-bogie (6 wheels)	Raspberry Pi 5	LiDAR, thermal, Arducam 64MP, ultrasonic	HC12 (long-range) + GPS	Limited (high- power tasks drain rapidly)
AI-Assisted Rover [8]	Wheeled (high-torque motors)	Not specified	Thermal, LiDAR, ultrasonic, optical cameras	Not specified	Not specified
UAV Platform [5]	Aerial (DJI M3T drone)	NVIDIA Jetson AGX Orin	Thermal camera	Wireless (real-time)	Battery-limited (flight time not specified)

4. MULTIMODAL DATA FUSION

4.1 Single-Modal Detection Problems

Using only standard RGB visual cameras for searching and rescuing survivors after earthquakes is insufficient in almost every case because post-earthquake environments are highly chaotic and noisy with clouds of dust, smoke from fires, darkness caused by power outages, and most importantly, victims invisibility to standard optical sensors because they got completely buried under the rubble [3, 6]. Even if victims were not completely invisible, they are often still partially covered with rubble, which makes it difficult for an optical sensor to distinguish between a human body and other construction material surroundings [1, 4]. To overcome these challenges, researchers have increasingly studied the solution of multimodal data fusion where they combine RGB images with data from multiple sensor types such as thermal imaging, acoustic sensing, LiDAR, and Wi-Fi signals to create a completer and more informative picture about the situation beneath the rubble.

4.2 Visual-Thermal-Audio Fusion

The effectiveness of data fusion for improved detection in SAR is demonstrated by several robotic systems. Khattab et al. [1] designed the SERR to combine live video streaming from a standard camera with thermal data collected with a Grid- Eye sensor to identify heat signatures of living humans under the rubble. The authors also proposed a feature they described to be two-way audio communication between victims and rescue team members which includes speakers and microphones, but this proposal remains pending implementation in their current prototype. The SERR utilizes a hybrid CNN-LSTM model named RescuNet to process multimodal input. The model extracts spatial features from video and thermal images using three convolutional layers (32, 64, and 128 filters) while tracking how the visual information changes over time through two Long Short-Term Memory (LSTM) layers with 128 units each. Then, the model combines these features with extracted audio characteristics, such as Mel-frequency cepstral coefficients (MFCCs) to achieve 94% detection accuracy representing a major advancement over single-modal approaches that cannot detect invisible, silent, or unconscious victims [1].

4.3 Non-Visual Fusion: Wi-Fi CSI

Dasgaonkar and Sharma [11] proposed a completely different approach to multimodal fusion. Their approach is to exploit Wi-Fi CSI to detect victims under the rubble without the need to physically interact with the debris areas. Exploiting the fact that Wi-Fi signals can penetrate obstacles including walls and even human bodies, but they get absorbed and scattered when encountering those obstacles, the authors designed a transmitter-receiver system installed on a collaborative UGV and UAV, where changes in the CSI amplitude and phase indicate the presence of a survivor under the rubble. The authors addressed the problem of the difficulty of collecting real earthquake data by setting up eight disaster situations and recording 480 minutes of CSI human signatures and using matrix decomposition with a Variational Autoencoder (VAE) to estimate missing signature combinations. Their system achieved 82% accuracy in detecting trapped humans within a range of 10 meters, through rubble thickness up to 12 inches. This demonstrates that non-visual sensing has the potential to succeed where optical and thermal sensors fail [11].

4.4 Multi-Sensor Fusion

Umamaheswari et al. [8] proposed an integration of a wider array of sensors exceeding visual-thermal-audio fusion to enhance the perception and navigation of SAR systems where an AI-assisted rescue robot fuses data from thermal imaging, LiDAR, ultrasonic sensors, and standard optical cameras. Their YOLO-based model achieved an average accuracy of 97.3% across four different disaster scenarios, with a precision of 96.7% and a response time of 49.5 milliseconds.

The authors highlight that the fusion of multiple sensor types allows their system to maintain high performance even when some sensors are compromised by environmental conditions. For example, thermal imaging continues to function in darkness even if optical cameras fail, while ultrasonic sensors provide proximity data when LiDAR is obscured by dust [8]. Table 2 summarizes the multimodal fusion approaches reviewed in this section.

4.5 Summary

In summary, multimodal data fusion has emerged as a strategy for overcoming the limitations of single-modal survivor detection in post-earthquake environments. Visual-thermal-audio data fusion enables ground robots like the SERR to detect survivors through smoke and darkness [1] while Wi-Fi CSI methods offer an alternative for detecting breathing and movement through solid rubble without the need to invade the rubble area [11]. Also, multi-sensor systems demonstrate that the availability of diverse sensor types leads to more robust overall system performance [8]. However, challenges remain in real-time data alignment across different sensors, computational demands of fusion algorithms on embedded hardware, and the need for larger labeled multimodal datasets for training [1, 8, 11]. The following Table-3 compares the approaches for multimodal data fusion discussed in the selected studies.

Table-3: Comparison of Multimodal Data Fusion Approaches for Earthquake SAR

Approach	Modalities Fused	Fusion Method	Key Advantage	Reported Accuracy
SERR (Khattab et al. [1])	Visual + Thermal + Audio	CNN-LSTM (RescueNet)	Detects unconscious victims via thermal; planned two-way audio	94%
Wi-Fi CSI (Dasgaonkar & Sharma [11])	Wi-Fi signal amplitude + phase + material properties	VAE + Matrix Decomposition	Penetrates rubble without physical contact; detects breathing	82%
AI-Assisted Rover (Umamaheswari et al. [8])	Thermal + LiDAR + Ultrasonic + Optical	YOLO-based sensor fusion	Maintains performance when individual sensors fail	97.3%

Chart-2 presents a comparative summary of the key performance metrics reported by the reviewed AI-based detection methods.

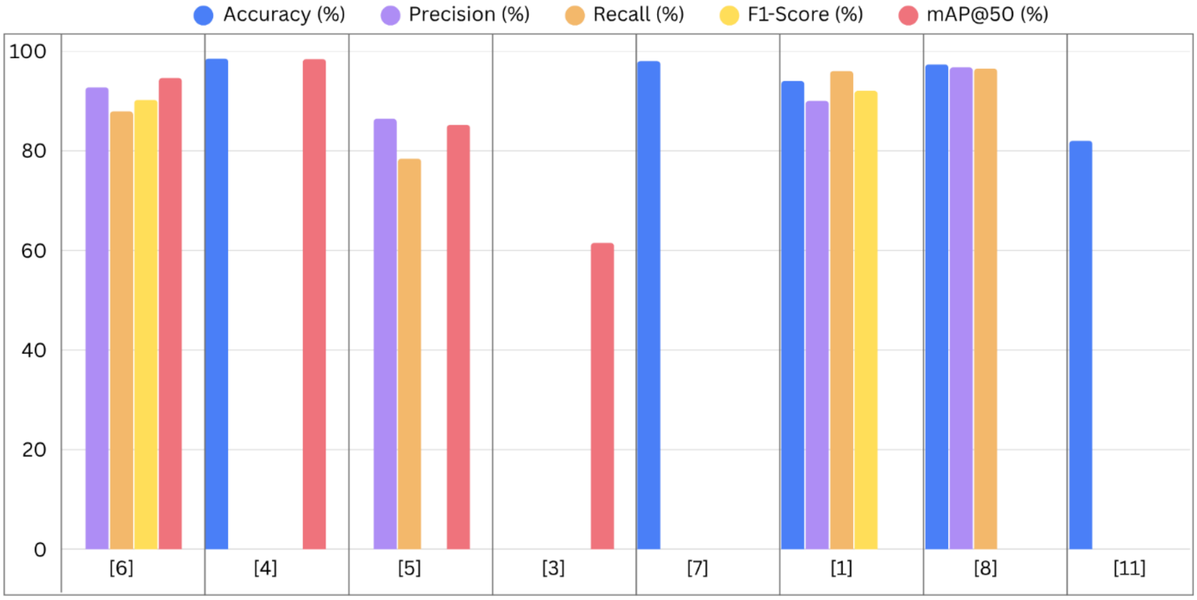

Chart -2: Performance metrics of AI-based detection methods reviewed in Section 2. Values represent accuracy (%), precision (%), recall (%), F1-score (%), and mAP@50 (%) as reported in each study. Missing bars indicate metrics not reported by the authors

5. CHALLENGES

Despite the significant advancements in AI-driven methods for post-earthquake search and rescue operations reviewed in this paper, several challenges continue to hinder their practical deployment in real-world disaster scenarios. These challenges include data availability, model performance under extreme conditions, hardware constraints, and operational integration with human rescue teams.

5.1 Data Scarcity and Domain Shift

One fundamental challenge of deploying AI in human detection in earthquake environments is the lack of training data. Unlike the famous COCO or ImageNet datasets that serve general object detection, there are no large-scale, publicly available datasets related to humans trapped under earthquake debris [4, 5]. Ulmămei et al. [5] highlighted that even when multiple existing thermal datasets are combined, the resulting dataset still suffers from domain shifts, which mean differences in sensor types, capture altitudes, background contexts, and annotation styles across sources. Those shifts cause models trained on heterogeneous data to perform poorly when tested on new environments.

Their experiments showed that while YOLO models achieved 84–85% AP50 on the combined dataset, performance dropped significantly when tested on the small-object subset which means that current models fail to generalize effectively across varying object scales [5]. Jadeja et al. [4] similarly noted the difficulty of collecting real earthquake survivor imagery and addressed this by creating a test dataset of only 200 images, which is still too small for robust model training.

5.2 Occlusion and Small Object Detection

Even when large datasets are available, successfully detecting survivors that are partially occluded or appearing as a very small thermal point is another major challenge to this topic. Zhao et al. [3] demonstrated that standard object detection models like the original DINO struggle to detect individuals whose lower bodies are covered by debris or smoke. Even though their proposed VE-DINO model improved occlusion handling by incorporating visibility-aware loss functions, the model still achieved only 0.222 AP for small objects on the external DODD test set. This indicates that small and occluded targets remain highly challenging [3]. Similar findings were reported by Ulmămei et al. [5] where spotting small individuals achieved only approximately 28% AP50 across all evaluated YOLO variants. This scale sensitivity with CNN- based detectors is caused by the downsampling in the backbone and feature pyramid design. It becomes problematic in UAV-based SAR where drones must fly at higher altitudes to cover the large affected areas [5].

5.3 Real-Time Processing and Embedded Hardware Constraints

Since embedded hardware requires sufficient computational power, installing it on UAVs, UGVs, or rovers introduces constraints when deploying deep learning models on those systems. For example, Ulmămei et al. [5] evaluated YOLO models on an NVIDIA Jetson AGX Orin and found that while FP16 quantization achieved real-time performance up to 27 FPS for segmentation models, INT8 quantization caused 10–20% accuracy loss, making it unacceptable for SAR applications since they are safety critical. Another example Dhanya et al. [9] reporting that high-power tasks such as climbing or scanning on their ASR-Rover rapidly depleted the lithium-ion battery, which caused system failure when energy demands exceeded capacity. Also, Khattab et al. [1] designed their SERR with a three-hour battery life, but this is likely insufficient for extended operations in large-scale disaster zones where extended operation time is necessary. These hardware limitations force a trade-off between detection accuracy, inference speed, and operational duration that has not yet been optimally resolved [1, 5, 9].

5.4 Limited Autonomous Navigation and Communication

Most of the proposed robotic platforms prioritize detection algorithms efficiency over autonomous navigation in the unstable rubble environments. The SERR, for instance, simply stops when an obstacle is detected within 30 cm rather than attempting to navigate around it, prioritizing safety over autonomous exploration [1]. Joseph et al. [7] acknowledged that while their hexapod Rescuebot offers superior stability on uneven terrain, it is still slower than wheeled alternatives and it lacks autonomous path planning. Similarly, Ulmămei et al. [5] and Rizk and Bayad [6] focused on detection performance without addressing UAV flight control or autonomous navigation. Furthermore, two-way audio communication which would allow trapped survivors to speak directly with rescue teams is not implemented in Khattab et al. [1] SERR prototype where they explicitly noted that this feature is "pending implementation", while the snake robot and rover designs reviewed here lack any such capability [4, 7, 8, 9].

5.5 Sensor Reliability in Chaotic Environments

Sensors' performance is significantly degraded or even disabled by the harsh conditions of post-earthquake areas. Umamaheswari et al. [8] emphasized that while sensor fusion helps overcome individual sensor failures, no current system is fully resilient to extreme environmental impacts. Dasgaonkar and Sharma [11] also addressed this partially by using Wi- Fi CSI that penetrates rubble without physical contact, but their system still assumes rubble material types are limited to six categories which are concrete, rubber, wood, metal, plastic, and glass, and requires rubble thickness no greater than 12 inches, which may not hold in many real earthquake scenarios. Jadeja et al. [4] noted that changing lighting conditions, occlusions, and environmental variability in disaster sites affect the reliability of semantic segmentation and object detection algorithms, yet most models are evaluated on clean, controlled datasets rather than realistic post-earthquake imagery.

5.6 Summary

Table-4 summarizes the key limitations identified across the reviewed literature.

Table-4: Summary of Key Limitations in AI-Driven SAR Methods

Limitation Category	Specific Challenge	Affected Systems	Cited Sources
Data Scarcity	Lack of real earthquake survivor datasets; domain shift	All detection models	[4, 5]
Occlusion	Poor detection of partially hidden victims	YOLO, DINO, SSD	[3, 4]
Small Object Detection	Performance degradation at high altitudes or distances	UAV-based systems	[3, 5]
Embedded Hardware	Limited compute, power, and battery life	All robotic platforms	[1, 5, 9]
Autonomous Navigation	No demonstrated path planning in rubble	SERR, Rescuebot, rovers	[1, 7, 9]
Two-Way Communication	Feature missing or pending implementation	All systems	[1]
Sensor Reliability	Degradation from dust, smoke, EMI	Thermal, optical, LiDAR	[8, 11]

6. Future Work Recommendations

Based on the challenges identified in the previous section, many research directions emerge for advancing AI-driven SAR operations. Several future work recommendations are presented in the following subsections.

6.1 Realistic Large-Scale Datasets

Researchers must create large, publicly available datasets of humans trapped under realistic rubble with varied debris materials, lighting conditions, and occlusion levels. Current datasets like DODD [3] are too small for robust deep learning, and synthetic data generation should be explored to augment limited real-world imagery [4, 5].

6.2 Occlusion and Small Object Detection

Future algorithms should focus on occlusion-heavy and small-target scenarios. While visibility-aware loss functions improve detection [3], performance on small objects is still poor and needs enhancement. Some promising directions for future research include multi-scale feature fusion, super-resolution, and attention mechanisms [3, 4, 5].

6.3 Model Optimization for Embedded Hardware

Model compression and hardware-aware optimization are essential for deployment on SAR robots with constrained power supply. FP16 quantization achieves speed and energy gains with minimal accuracy loss, but more aggressive techniques like INT4, pruning, and knowledge distillation should be explored [5, 9].

6.4 Autonomous Navigation in Rubble

Current robots lack autonomous navigation in unstructured rubble, with most simply stopping when facing obstacles [1, 7]. Future work should integrate SLAM algorithms adapted for rubble environments and explore reinforcement learning for path planning [1, 7, 11].

6.5 Adaptive Sensor Fusion

Multi-sensor fusion improves robustness when individual sensors fail [8]. Future systems should incorporate adaptive fusion mechanisms that dynamically reweight sensor contributions based on environmental conditions.

6.6 Real-World Field Testing

Most studies relied on simulations or controlled environments rather than physical field tests [1, 4]. Future research must include staged field exercises at urban search and rescue training facilities to reveal failure modes not apparent in simulations, including sensor degradation, communication dropouts, and human-robot teaming challenges [1, 4, 5, 6, 7, 8, 9, 11].

7. CONCLUSION

This review paper examined AI-driven methods for search and rescue operations after earthquakes that are published between 2023 and 2026. The studies are focused on human detection in disaster environments, physical robotic platforms, and multimodal data fusion. The literature confirms that YOLO-based detectors and CNNs achieve high accuracy on thermal and visual human detection, while platforms such as snake robots, hexapods, wheeled rovers, and UAVs provide diverse mobility solutions for accessing hazardous areas. Multimodal fusion is essential for overcoming the limitations of single sensors, with approaches like SERR's RescueNet and Wi-Fi CSI-based detection achieving accuracies of 94% and 82%, respectively.

Despite the advancements achieved by those studies, there are still significant challenges that need to be solved. Challenges include data scarcity, poor performance on smaller and occluded objects, hardware constraints, and limited autonomous navigation. Future work recommendations include prioritizing the collection of realistic large-scale datasets, model optimization for embedded deployment on hardware, autonomous navigation through rubble, adaptive sensor fusion, and real-world field testing of the developed models. Bridging the gap between laboratory performance and disaster readiness is essential for transforming these promising technologies into life-saving tools for future earthquake emergencies.

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