INTELLIGENT HUMAN RESCUE ROBOT: AN AI-DRIVEN APPROACH WITH FPGA TECHNOLOGY

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ABSTRACT

This study introduces an innovative AI-driven robotic system designed to enhance search and rescue operations in disaster-stricken areas, including earthquakes, floods, and conflict zones. The system integrates a multi-modal sensory framework combining RGB and thermal imaging, processed through a robust pipeline: raw sensor data undergoes validity checks and noise filtering to ensure input integrity, followed by human detection via the You Only Look Once (YOLOv8) algorithm. Concurrently, ultrasonic sensors relay environmental data to a Field-Programmable Gate Array (FPGA) module, enabling real-time obstacle avoidance and dynamic path planning for rapid, precise navigation. Experimental results demonstrate a 96% accuracy rate in survivor detection, outperforming comparable AI-FPGA hybrid systems—particularly in identifying partially obscured humans. The system also exhibits superior response times and operational safety, as quantified in the results section. Future work will focus on expanding sensory modalities, adaptive learning mechanisms, and multi-robot coordination to further enhance mission efficacy.

KEYWORDS

1. INTRODUCTION

Recent advancements in robotics have significantly enhanced capabilities for emergency response and human rescue operations. Modern systems leverage semi-autonomous or fully autonomous robots to navigate disaster scenarios—including earthquakes, fires, and structural collapses—enabling efficient victim detection and assistance. The effectiveness of these systems hinges on three critical factors: robust real-time perception, reliable decision-making algorithms, and rapid response execution. Such capabilities are indispensable in high-risk environments where human intervention is either impractical or perilous. Over 522 significant earthquakes in the 21st century have caused over 430,000 fatalities globally, primarily due to building collapses trapping victims under rubble (U.S. Geological Survey, 2017; AlShemmary, 1999).

Due to the limited time in the air supply, temperature, and victims' health condition the survival rates are sharply dropped from 48 hours with a chance of 80% to beyond 72 hours. All these factors can be considered as critically time sensitive (Huo et al., 2011). To reduce the fatalities, rapid and accurate survivor identification is essential. subjective assessments of survivor locations and debris stability are very useful for the traditional rescue and search methods, including video cameras and canine teams (Riya et al., 2020; Kiriazis et al., 1999). The rescuers may suffer from significant risks as a result from this method, such as psychological stress and aftershocks (Berger et al., 2012). Therefore, to locate survivors efficiently and safely, advanced technologies are needed. The implementation of object detection algorithms on resource-constrained embedded systems presents a notable challenge for AI-powered rescue robotics platforms. To overcome computational limitations while preserving detection accuracy, an optimized Tiny-YOLO architecture was implemented to enable real-time human recognition within the robotic system's onboard processing capabilities (Alaa et al., 2024).

Recent advancements in rescue robotics have employed integrated FPGA and AI architecture to address these operational challenges. Modern implementations leverage computer vision and deep learning algorithms to facilitate autonomous navigation through complex environments, human detection, and context-aware decision-making. Notably, YOLO-V8 architecture has gained prominence in such applications due to their optimal balance of real-time processing capabilities and high object detection accuracy.

The integration with FPGA technology offers distinct advantages for time-critical applications. These reconfigurable computing platforms enable low-latency execution through parallel processing architectures, particularly valuable in rescue robotics where real-time response is paramount. Unlike conventional processing units (CPUs/GPUs), FPGAs permit hardware-level

customization to meet precise timing and performance requirements, ensuring immediate execution of sensor-derived decisions.

This approach presents an innovative rescue human robot by using (AI) and (FPGA) technology. Combining the AI algorithm with FPGA Technology will provide low power consumption and increase the accuracy of detecting objects in addition to the use of cellular texting messages instead of the internet to locate the survivor location. This method has given our robot design an advantage over other robot designs.

The robotic system's compact design and AI-enhanced navigation capabilities facilitate safe operation in confined and unstable environments. Through integration of the YOLO-V8 architecture, the platform demonstrates precise detection of motion patterns, human presence, and thermal signatures. This approach significantly enhances operational efficiency in rescue missions while improving safety parameters and response times, effectively reducing risks for both rescue personnel and potential survivors.

The principal contributions of this work are as follows:

1. Development of AI robotic system to rescue humans in disasters with accurate results.

2. Using YOLO-V8 to detect humans precisely.

3. Using FPGA Technology to assist in navigation as an autonomous system to avoid obstacles.

4. Abandon the use of the Internet and rely on mobile phone network coverage.

Finally, the paper has been organized as follows: Section 2 shows selected papers that are related to our design. Section 3 represents methods, approaches, and AI algorithms. Section 4 presents the implementation of the proposed design and experimental results. Section 5 discusses results and the main findings of the robot. While Section 6 includes the conclusion and the future research directions.

2. RELATED WORKS

AI and FPGA technology have been used in human rescue robots to represent an important advancement in emergency response capabilities. These types of systems improve the safety of rescue operations and efficiency by using unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) equipped with AI algorithms and sophisticated sensors. To allow real-time processing and improved detection accuracy, the integration of FPGA technology was very important to use, which is crucial in hazardous environments.

The work by (Lopez et al., 2025) implements an FPGA-based control system for sensor integration while employing AI for human detection through thermal imaging and LiDAR fusion. However, this approach encountered significant technical challenges in the FPGA-AI

model integration process (Lopez et al., 2025).

(Huang et al., 2024), used FPGA technology and AI-driven method for rescue and search, and integrated UGVs and UAVs with a neural engine to detect survivors achieving 90% accuracy. His work also enhanced the performance through data fusion of various inputs.

(Pallapothu et al., 2024), in this paper a human rescue aid robots have been examined for emergency situations and tested their capabilities such as environmental monitoring, data transmission, and user control. However, it does not specifically mention FPGA technology or AI-driven approaches in the context of human rescue robotics.

(Murali et al., 2024), discussed AI-driven solutions in robotics, focusing on autonomous systems and smart machines, but does not specifically address intelligent human rescue robotics or the use of FPGA technology in this context .

(Saengsint et al., 2023), worked on autonomous hexapod robots with AI for human tracking and detection, using a DeeplabV3+ architecture with accuracy rate of 94% in identifying human body parts, but does not use FPGA technology specifically.

(Kim et al., 2022), this study presents an AI-powered object detection system for disaster response, leveraging edge-computing-enabled UAVs with YOLOv5 architecture. The system achieved 91% detection accuracy while demonstrating real-time processing capabilities in field deployments. However, performance was constrained by obstructed environments and low-light conditions, and the dependence on edge TPUs introduced additional hardware complexity. Despite these limitations, the results highlight the significant potential of edge AI in enhancing the efficiency of rescue operations.

(Huang et al., 2021), presented an edge AI-based robot system utilizing FPGA technology in multi-legged robots for search and rescue applications, integrating Tiny-YOLO for real-time survivor detection and delivering GPS information to rescuers via an edge server.

(Allam et al., 2021), this work did not discuss FPGA technology or an AI-driven approach for intelligent human rescue robotics. A four-wheeled robot implemented for manual and autonomous operation, using sensors for environmental monitoring and obstacle avoidance was a focal point in his work.

Table 1 shows a summary of the related works, pointing out the accuracy, methods, key findings, and limitations for each work. Challenges remain in ensuring reliability and safety in unpredictable environments while advancements in AI-driven rescue robotics are promising. To overcome these obstacles, continuous improvements and enhancements in AI and hardware integration are essential.

Table 1. Summary of AI-driven rescue robotics

| Author/Year	Method	ACC. %	Key Findings	Limitations
(Lopez et al., 2025)	FPGA-based sensor fusion and multimodal AI rescue system combining LiDAR, thermal imaging,	96%	High-accuracy human localization using real-time sensor fusion algorithms that optimized for FPGA	Integration complexity with existing hardware platforms and high energy consumption
(Huang et al., 2024)	AI-driven approach for search and rescue using FPGA technology, integrating UAVs & UGVs	90%	Enhanced performance through data fusion of various inputs	High computational cost due to lacks real-time obstacle avoidance, extensive sensor integration.
(Pallapothu et al., 2024)	Human rescue aid robots for emergency situations	N/A	Data transmission, environmental monitoring, and user control	Does not address AI-driven approaches or FPGA technology
(Murali et al., 2024)	AI-driven solutions in robotics	N/A	Focuses on autonomous systems and smart machines	Does not address intelligent human rescue robotics or FPGA technology
(Saengsint et al., 2023)	Autonomous hexapod robot with AI for human detection and tracking	94%	Utilizes DeeplabV3+ architecture for identifying human body fragments	Does not discuss FPGA technology
(Kim et al., 2022)	Edge-computing-enabled UAVs and AI (YOLOv5 + edge TPU)	91%	Combines UAVs with AI for fast and real-time detection in field missions	Struggles with obstructed environments or detection under low-light
(Huang et al., 2021)	Edge AI-based robot system utilizing FPGA technology in multi-legged robots	N/A	Integrates Tiny-YOLO for real-time survivor detection and GPS information delivery	GPS technology could be challenging in the places where the coverage is weak.
(Allam et al., 2021)	Four-wheeled robot for manual and autonomous operation	N/A	Utilizes sensors for obstacle avoidance and environmental monitoring	Does not discuss FPGA technology or AI-driven approach

3. MATERIALS AND METHODS

In this part, the methods, components, and materials that are used to build intelligent human rescue robots for searching and detecting missions. By combining actuation technologies, sensing parts, and high-speed processing, robots can detect survivors, navigate in complex environments, and communicate with rescue teams to protect survivors' lives. All tables and figures in this section illustrate the functionalities of each component, and the system architecture, showing the robots' effectiveness in the disaster areas.

3.1.   System architecture overview

A robust framework was used to operate the robot. This framework consists of sensory, computational, and actuation units. To enable real-time decision making and coordinating sensor data. depict the robot's overall architecture and image-processing workflow, emphasizing key components in the Input and Output sections. General architecture employs a

Raspberry Pi as the primary control unit and the FPGA as the secondary control unit, which processes inputs from various sensors and sends commands to the output devices as shown in Fig. 1.
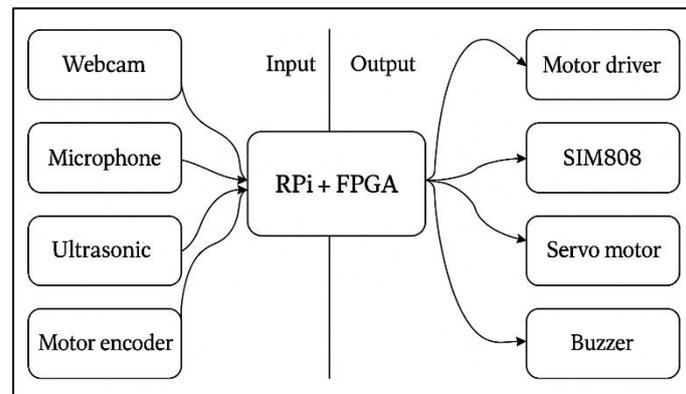
Fig. 1. General architecture of the project

This architecture is organized as follows:

1- Raspberry Pi 4: This unit works as central control unit, which is used to coordinate the inputs and outputs, managing all operational aspects of the robot.

2- FPGA(DE0-Nano): This unit coordinates obstacles avoidance by taking the data from the ultrasonic sensor and passing it to Finite State Machine (FSM) that gives order to the motors.

3- Input Section:

• Webcam: Captures real-time video, enabling visual monitoring of the surroundings.

• Microphone: Records audio signals, enhancing the robot's ability to detect sounds in the environment.

• Ultrasonic Sensor: Measures distances to detect obstacles and avoid collisions by sending the data to the FPGA which sends the decision to the Servo motor.

• Motor Encoder: Monitors motor speed and position, aiding in precise navigation.

4- Output Section:

• Motor Driver: Controls motor direction and speed based on commands from the Raspberry Pi and the FPGA

• SIM808 Module: Provides GSM, GPRS, and GPS capabilities, enabling remote communication.

• Servo Motor: Enables fine control of specific movements, such as camera angle adjustments.

• Buzzer: Produces audio alerts for signaling.

Fig.2 details the steps involved in handling visual data. A flowchart guides the decision-making process, starting with data input from the webcam and the AI module.
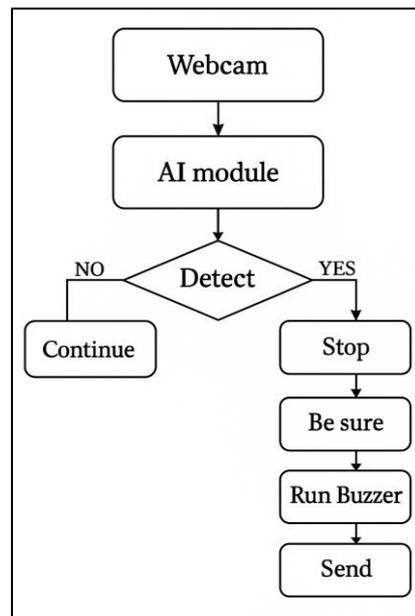
**Fig. 2. Image processing workflow**

The following sequence highlights the robot's visual processing methodology:

1. Initial Decision: Checks if the captured data is valid.

- If No: The workflow proceeds without further processing.

- If Yes: The workflow advances to subsequent actions.

2. Verification Step: Confirms the accuracy and reliability of the data.

3. Buzzer Activation: If the data is accurate, the buzzer produces a signal.

4. Data Transmission: The processed data is sent to the appropriate storage or output device.

For the object detection part, the implemented robot uses the YOLOv8 model as the main component for object detection and data validation. The input data are typically in the form of images or video frames. These frames are passed through a preprocessing stage where it is prepared for analysis by YOLOv8 model. The YOLOv8 model classifies and detects within the input. A validation module evaluates the output from YOLOv8 against predefined criteria, such as object class constraints and confidence thresholds, to distinguish valid data from invalid detections to ensure the reliability of detections. Once the validation process is completed, only validated outputs are forwarded for more processes such as deciding to send a message that contains the location of the survivor. Invalid inputs or uncertain detections are flagged for review. The model was predefined with more than 2000 images with different parts of human bodies and classified each image with object class such as hand, head, leg etc. with a confidence threshold set to 0.85.

For obstacle avoidance, the robotic system integrates multi-modal sensors that dynamically adapt during search operations. These sensors enable real-time environment mapping and

collision-free navigation while locating survivors in complex disaster environments (Zahid et al., 2025). The robotic navigation system implements a finite state machine (FSM) controlling movement in three primary directions: forward, right, and left as shown in Fig. 3.
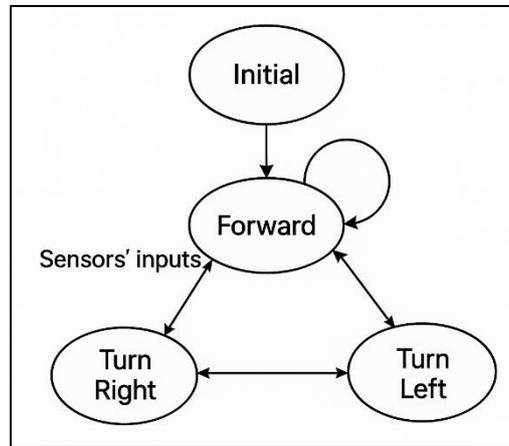
Fig. 3. FPGA obstacle avoidance FSM

 The FSM operates on the following logic:

1. Forward Movement: When no obstacles are detected (indicated by absent sensor signals in the forward direction), the robot maintains forward motion.

2. Directional Turning:

• If obstacle-free conditions are detected to the right (no right-direction sensor signal), the robot executes a right turn

If obstacle-free conditions are detected to the left (no left-direction sensor signal), the robot executes a left turn

This deterministic state-based control architecture enables efficient obstacle avoidance while maintaining navigation continuity in constrained environments.

Finally, the object detection and obstacle avoidance models are working separately. While the object detection model is working to detect objects and give a signal to the servo motor to move the ultrasonic sensor angel (Raspberry Pi part), the obstacle avoidance model is working to avoid obstacles by sending signals to the motors (FPGA part). This approach will ensure a simultaneous process to increase the efficiency of the robot and integrate all parts together.

3.2.   Hardware components of the rescue robot

The rescue robot consists of carefully selected physical components designed for effective performance in challenging environments. These components enable the robot to navigate debris, locate survivors, and communicate during emergencies:

1.   Raspberry Pi 4 (8GB): operates as the main processor, managing complicated algorithms.

2. DE0-Nano FPGA Board: provides a reconfigurable computing platform that enables low-latency execution and parallel processing. The FPGA receives the data from the ultrasonic

sensor, then makes the required processing and sends the result to the four-motor encoder.

3. Mecanum Wheel robot: used for precise positioning and movement with feedback for accurate navigation. The robot has four wheels that use motors with encoders. Each wheel requires one motor that is attached to one encoder to move the robot. The encoders are required to interpret the data from the FPGA to ensure smooth maneuvering by controlling motor power and direction. The robot needs to use the four motors at the same time to ensure accurate turns (right and left).

4. Webcam: used for survivor identification and visual monitoring by capturing real-time video.

5. Servo Motor: used for camera adjustments and object manipulation which provides precise movement control.

6. Ultrasonic Sensor: used for navigation and safety to measure distances and detect obstacles.

7. Lithium Batteries (4): Offer lightweight, reliable power for extended operation.

8. 3D-Printed Structure: Customizable and lightweight, it ensures durability and system support.

9. SIM808 Module: Facilitates remote communication for real-time monitoring and coordination.

10. Microphone: Captures audio signals to detect survivors.

11. LEDs (2): Indicate operational status and provide visual alerts.

12. Metal 4WD Vehicle Chassis: Provides a durable, stable base for traversing rough terrains. Each component contributes to the robot's effectiveness in rescue operations, ensuring reliability and adaptability in disaster scenarios. The components work together to form a reliable system, allowing the robot to locate and assist survivors in disaster areas. Table 2 summarizes the physical components, detailing their roles in the robot's functionality.

Table 2. Physical components of the rescue robot

No.	Component	Quantity
1	Raspberry Pi 4 8GB	1
2	DE0-Nano FPGA Board	1
3	Motor with encoder	4
4	Webcam	1
5	Servo motor	1
6	Ultrasonic	1
7	lithium Battery	4
8	3D printing structure	1
9	SIM808 module	1
10	Microphone	1
11	LED	2
12	Metal 4WD Vehicle Chassis	1

4. PROPOSED METHOD

The intelligent rescue robot is designed with carefully chosen materials and methodologies to optimize its performance in search and rescue operations. Key features include:

- YOLO-V8 for Object Detection: Enables real-time identification of human bodies and critical elements in disaster zones, ensuring swift and accurate responses to survivors.

- Raspberry Pi 4 as Core Processor: Powers navigation and decision-making by integrating data from sensors.

- 3D-Printed Structure: Offers a customizable, lightweight, and durable design for effective movement over uneven terrain.

- SIM808 Module for Communication: Facilitates real-time data exchange and command transmission with rescue teams.

- Precision-Controlled Motors: Four motors with encoders provide accurate movement in confined or unpredictable environments.

These components work together to create a robust and efficient framework, enhancing the robot's ability to navigate, detect, and assist during emergencies. The implementation details of the proposed model, including data pre-processing, model architecture, and training procedures, are publicly available on GitHub (AlShemmary, 2025). System validation included real-world performance tests (see Supplementary Video S1) (AlShemmary, 2025).

4.1.   YOLO-V8

YOLO-V8 represents a significant leap in the field of computer vision, offering advanced object detection capabilities. Using YOLO-V8 as the main core detection system has increased the efficiency of the robot in the dynamic environment (Aidi Sharif et al., 2025). In contradistinction to known approaches that divide images for analysis, YOLO-V8 predicts class probabilities and bounding boxes directly from entire images in a single pass, making unmatched speed and efficiency, especially for real-time applications such as surveillance and autonomous driving (Da Silva et al., 2012). One of the most important novelties of YOLO-V8 is its adaptation through customized types tailored to certain needs. For instance:

- YOLO-V8 Tiny prefers processing speed over precision, which makes it perfect for resource-constrained scenarios that needs fast responses.

- YOLO-V8 Small balances accuracy and speed, catering to different applications.

- YOLO-V8 Standard strikes a balance between precision and speed for tasks of object detection.

- YOLO-V8 Large achieves a great performance, for applications that demand processing

speed and high accuracy (Norman, 2002).

YOLO-V8 has been enabled to excel in object detection regardless of their lighting, position, or orientation by taking advantage of the technological advancements in training methodologies and network architecture. It demonstrates reliability in real-world scenarios and performs robustly even with partially visible or occluded objects. In addition, YOLO-V8 optimally uses specialized accelerators and Graphics Processing Units (GPUs), reducing enhancing resource efficiency and inference time (Cheng et al.,2022). The movement from previous YOLO models to YOLO-V8 is not just an additional upgrade but a transformative step, accuracy, blending speed, and adaptation across different scenarios. This major update has paved the way for endless opportunities in computer vision and artificial intelligence, pointing out YOLO-V8 as an important achievement in object detection technology. Fig 4 shows a summary of the YOLO-V8 work map.
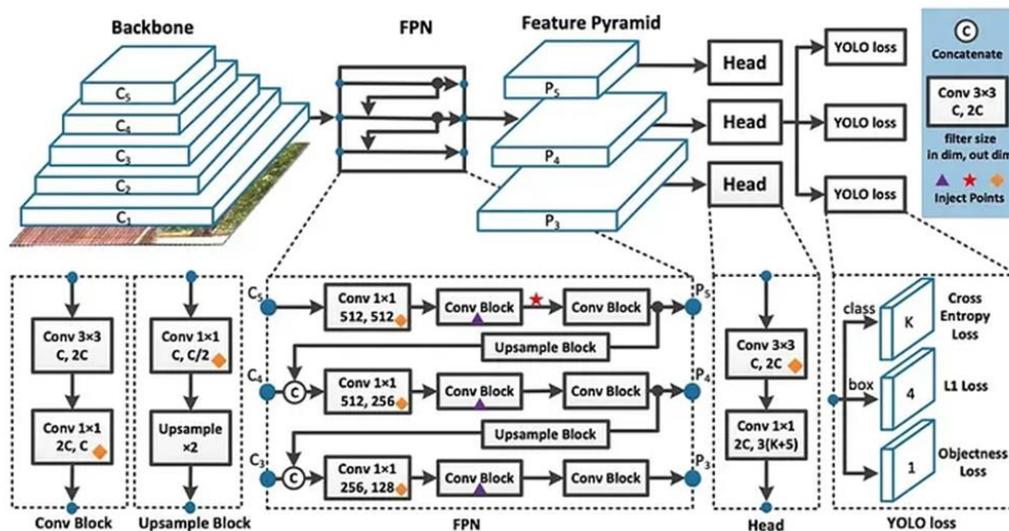

Fig. 4. YOLO work Plan (Atiqur et al., 2020).

4.2.   Raspberry Pi

Single Board Computers (SBCs) like Raspberry Pi devices have become popular due to their energy efficiency, versatility, and affordability across many different applications. This paper introduces a novel comparative comparison of five Raspberry Pi 4 models (Raspberry Pi 4Zero 2 W, Raspberry Pi 4 Zero W, Raspberry Pi 4 3B, Raspberry Pi 4 3B+, and Raspberry Pi 4 4B) to evaluate their performance under various real-world scenarios. The results of implementing the robot highlighted the super performance of the Raspberry Pi 4 4B, establishing it as the most important capable model. Notably, the Raspberry Pi 4 Zero2W, when operated at over speed, demonstrated performance comparable to Raspberry Pi 4 3B+ and Raspberry Pi 4 3B, providing a significant enhancement over its previous versions, the Raspberry Pi 4 Zero W.

This makes Raspberry Pi 4 Zero 2 W a perfect upgrade choice because of its improved capabilities and identical hardware dimensions, authorizing for seamless alternative.

This paper produces significant guidance and insights for enthusiasts and researchers in choosing the most suitable Raspberry Pi 4 model for their works as shown in Fig. 5.
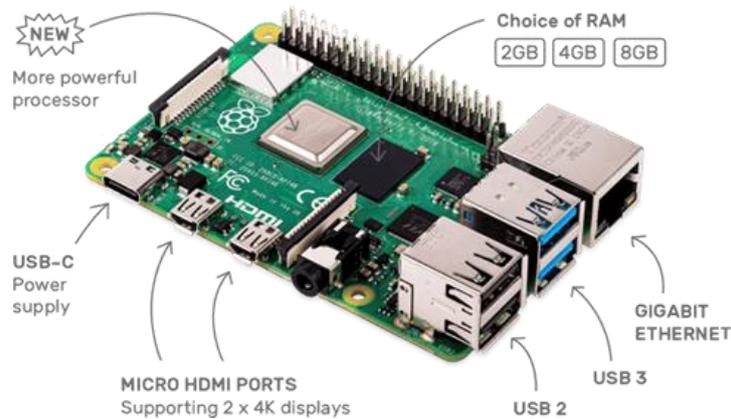

Fig 5. Raspberry Pi components (Niu et al., 2023).

4.3. 3D printing Structure

In this section, a custom 3D-printed external structure was built using a 3D printer to perform as secure houses for the hardware component of the robot while optimizing their arrangement for functionality. This design helps to enhance the robot's observational and navigational capabilities by making an optimal viewing angle for sensors and cameras, ensuring accurate tracking and detection. The main advantage of the 3D printing process is allowing customizable structures to be tailored, lightweight, and durable to the robot's working needs, withstanding environmental challenges, and critical for maintaining balance during rescue and searching missions. Modular components further facilitate easy maintenance and part replacement. Fig. 6 illustrates the design and printing stages, showcasing considerations like weight distribution, stress points, and sensor alignment for a robust and efficient design.
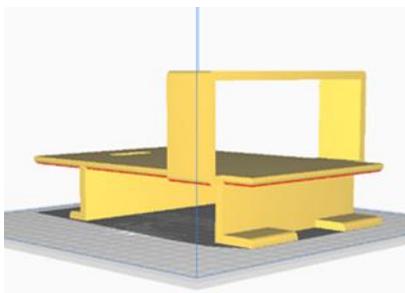
| Design and planning | (b) 3D Printing and assembly | (c) Testing and refinement |

Fig. 6. Phases of design and 3d printing of the external structure

4.4.   SIM808 Module

The SIM808 module integrates GSM, GPRS, and GPS functionalities, supporting Quad-Band networks and satellite navigation, as shown in Fig. 7. It features ultra-low power consumption in sleep mode and includes a charging circuit for Li-Ion batteries, making it suitable for long-term, rechargeable applications. With high GPS sensitivity (22 tracking and 66 acquisition channels), it is controlled via AT commands over UART and supports 3.3V/5V logic levels. The module enables real-time tracking by transmitting GPS coordinates to a web server through HTTP or SMS, viewable via platforms like Google Maps. It connects easily to Arduino or Raspberry Pi via TX/RX ports and is powered by a 5V or Li-Ion battery (SIMCom, 2014).

Fig. 7. SIM808 components (SIMCom, 2014).

4.5.   Motor with encoder

Within the domain of intelligent human rescue robotics, the Gear Motor with Encoder DC 12V 201RPM plays a pivotal role in enabling precise and reliable motion control. These motors, integrated into FPGA-driven robotics, significantly enhance the performance and efficiency of rescue operations. The use of Gear Motors with Encoders in rescue robotics allows for enhanced maneuverability and precision. They are instrumental in controlling robotic arms, wheels, and other actuators, enabling the robot to navigate through debris, lift objects, and perform life-saving tasks with high accuracy. The feedback provided by the encoders ensures that the FPGA-based control system can make real-time adjustments, adapting to the dynamic and unpredictable environments typically encountered during rescue missions. By incorporating these advanced motors into the design of intelligent rescue robots, we can achieve a higher level of operational efficiency and reliability, ultimately improving the effectiveness of human rescue efforts. Fig. 8 shows the components of motors with encoder (Suntaxi, 2024).

4.6.   Finite State Machine

A finite state machine has been used to avoid obstacles. The data from the ultrasonic sensor is saved in memory. The servo motor is moving in three angles: 0, 90, and 180 degrees which

means the following directions for the ultrasonic sensor: left, forward, and right. For instance, if the input value of the sensor is 101, that means the robot has detected obstacles on the right and left and should move forward (Forward State).

Fig. 8. Motor with encoder components (Atiqur et al., 2020).

The other two states follow the same procedure. Table 3 shows more analysis for the procedure of avoiding obstacles. DE0-Nano Altera FPGA board and Quartus Prime Software were used to implement the finite state machine that is used to drive the motor encoder. Fig. 9 shows the finite state machine diagram that is used to avoid obstacles and the FPGA circuit design with RTL schematic that controls the movements of the motors.

Table 3. Input values of the ultrasonic sensor based on the servo motor angel

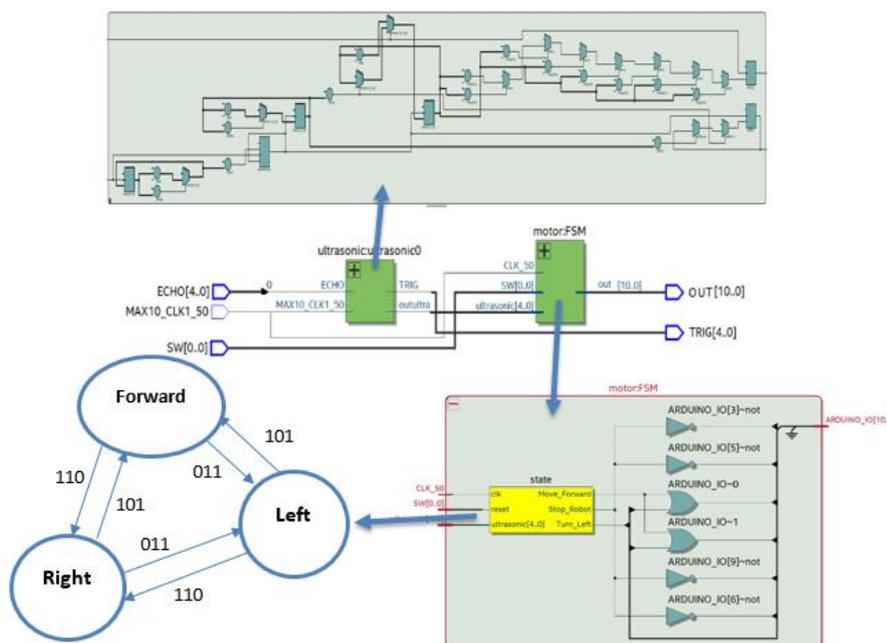| State	Ultrasonic values		
	Servo angle = 0	**servo angle = 90**	**servo angle = 180**
Forward	1	0	1
Right	1	1	0
Left	0	1	1

Fig. 9. FSM, RTL level, and hardware Circuit

5. RESULTS AND DISCUSSION

5.1.   Evaluation and performance metrics

The final design of the robot, as shown in Fig. 10, exemplifies a compact, functional, and modular structure optimized for disaster response scenarios. The proposed robot shows 96% accuracy to detect survivors. The usage of FPGA as alternative processing unit for navigation and obstacle avoidance (e.g., TPU, GPU, edge AI) has improved the power consumption efficiency and reduced the cost of the robot and enable the ability to use the robot for swarm systems because of its architecture. The robot integrates multiple advanced components to achieve seamless navigation, obstacle avoidance, object detection, and communication capabilities. The top view (left image) showcases the layout of the electronic components, including the Raspberry Pi microcontroller, FPGA, motor drivers, and communication modules. This robot has been organized and structured in a way to ensure easy accessibility for system upgrades and maintenance while minimizing interference among its hardware components. The front view, which is an image in the middle, points to the integration of an ultrasonic sensor, camera system, and mounting hardware. The camera system, used for the YOLO-V8 to detect objects by using several algorithms to ensure accurate detection of objects, including any visible humans' parts in disaster areas. The ultrasonic sensor is attached to the FPGA to enhance real-time obstacle avoidance and detection to ensure safe navigation in hard environments. The side view (right image) illustrates the robot's mobility properties, including the equipped encoders that are attached to the motorized wheels. These hardware components enable precise control movement and adaptability to unstable terrains. Additionally, the SIM808 module for communication can be seen, making real-time data exchange between the rescue teams and the robot.

| (a)Top View | (b) Front View | (c) Side View |
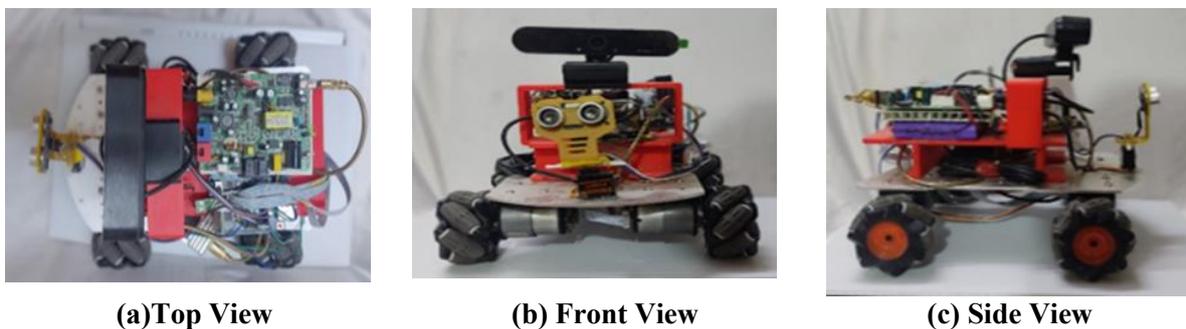
Fig. 10. Final Robot design with all its hardware components.

Robot design ensures robustness and reliability during field operations and facilitates the integration of different sensors and actuators. This prototype of robots demonstrates how a mix of advanced AI algorithms and compact hardware can significantly improve the effectiveness and efficiency of rescue robots in dangerous   scenarios. This developed robot has gone through

and subjected to rigorous testing to evaluate its real-world applicability and was compared to another real robots and AI systems to rescue humans. YOLO-V8 is the primary AI driven model which is used to implement this work and provides a significant improvement over past versions such as YOLO-V5 in terms of object detection, accuracy, computational efficiency, and inference speed. These achievements are essential for improving the robot's ability to work in complicated and risky environments. To justify the choice of YOLO-V8, it offers faster inference speeds, superior mean Average Precision (mAP)which is more than 0.96, and advanced techniques like Context Aggravation and Wasserstein Distance Loss. Even under challenging conditions such as partial obstructions or cluttered environments these features contribute to their exceptional ability to detect objects with high precision and recall. Table 4 illustrates a comprehensive comparison between YOLO-V5 and YOLO-V8, showing YOLO-V8's is suitable for disaster response tasks.

Table 4. Comparison between YOLO-V5 and YOLO-V8

Feature	YOLO-V5	YOLO-V8
Release Date	June 2020	Likely late 2023 or early 2024
Focus	Balance between accuracy and speed	Improved accuracy over previous models
Reported Advantages	Faster inference speed	Potentially higher mAP (mean Average Precision)
Techniques	Focus module, Path Aggregation Network (PAN)	Wasserstein Distance Loss, FasterNext, Context Aggravation
Model Sizes (Examples)	YOLO-V5s (small)	YOLO-V8s (smaller/similar size)
Reported FPS (Examples)	YOLO-V5s: ~60 FPS (on specific GPU)	YOLO-V8s: Potentially higher FPS
Reported mAP (Examples)	YOLO-V5s: ~0.45 (on specific dataset)	YOLO-V8s: Potentially higher mAP

The improved FPS and the higher mAP values highlight YOLO-V8's real-time applicability and robustness. Fig. 11 shows the training process of YOLOv8 which revealed several noteworthy trends. An extensive analysis of the key performance indicators, including classification loss, box loss, and recall has been done. The classification losses and steadily decreasing boxes signify the model's growing ability to predict classify objects and bounding boxes accurately. In the same way, the increasing recall values and precision demonstrate its effectiveness in reducing false negatives and false positives, critical for life-saving missions in the disaster areas. Validation metrics mirrored the training metrics, suggesting that the model generalizes well to unseen data. The robot performs reliably across various environments and situations due to its consistency. The metrics mAP50-95 and mAP50 further show the AI model's strength. Higher mAP values across a range of IoU thresholds indicate the model's

superior detection capabilities, especially in distinguishing subtle features of objects such as human body parts, even when partially obscured.

To compare the system with existing approaches, our proposed system shows high performance across key object detection metrics. Achieving a recall of 97%, precision of 98%, and mAP@50 of 96%, the proposed system shows achievement over several current studies. For Example,
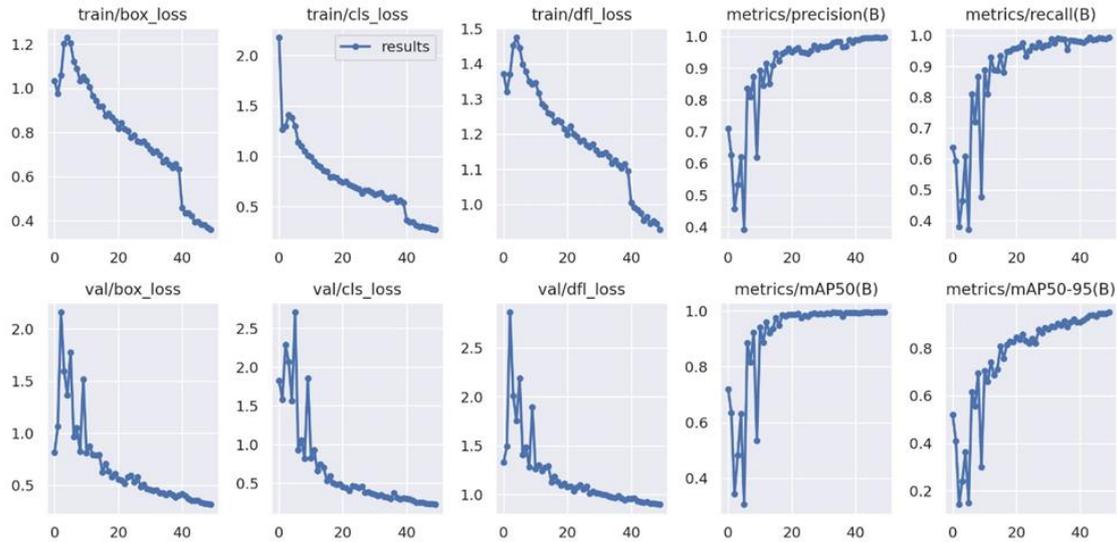
Fig. 11. AI training module results

(Huang et al., 2021) implemented a Tiny-YOLO-based FPGA platform, but did not report recall metrics or precision, mentioning only qualitative improvements in GPS-assisted detection. Like, (Lopez et al., 2025) provided a multimodal AI rescue system with a mAP of 96%, matching the current work's performance but at a system complexity and higher energy cost. (Kim et al., 2022) introduced a precision of 91% using an UAV approach, while (Saengsint et al., 2023) achieved 94% accuracy using a hexapod robot with DeepLabV3+ for human detection. In other hand, (Allam et al., 2021) and (Pallapothu et al., 2024) improved a rescue platform without deep AI integration, providing in limited performance data and no reported accuracy metrics. Therefore; our proposed model stands out not only for its metric-driven validation but also for its efficiency in using FPGA technology with AI for real-time rescue operations.

5.2.   Recent research comparative analysis

It is important to compare the proposed approach with the latest works in disaster response robotics to better understand the advancements of this study. To identify potential areas for future improvements, providing a thorough understanding of their contributions, this comparison underscores the strengths of the current work. Table 5 shows a comparison of recent developments in the field with the contributions to this study.

Table 5. Recent research compared to the proposed method.

Author/Year	Methods	Acc. (%)	Hardware Complexity	Time Complexity	Tradeoff Analysis
(Charmaine et al., 2024)	YOLO-V5 for object detection	~91	Moderate	Moderate	Lacks the precision and speed improvements provided by YOLO-V8.
(Zhao et al., 2024)	LiDAR and infrared sensor fusion with ML models	~93	High	High	Complex hardware design; integration with simpler modular systems needed.
(Aboualola et al., 2023)	Lightweight models like MobileNet for edge computing	~87	Low	Low	Lower detection accuracy compared to YOLO-V8.
(Drew et al., 2021)	Swarm robotics with inter-robot communication	N/A	High	High	Focused on swarm coordination, with limited emphasis on individual robot precision.
Proposed Method	YOLO-V8, ultrasonic sensors, Raspberry Pi, SIM808	96	Moderate	Low (Real-time)	Integration of thermal imaging sensors, multi-agent communication, and advanced autonomy needed for future work.

## 5.3. Real-world performance and Field testing

The robot demonstrated exceptional operational efficiency in the testing field. As shown in Fig.12, the AI algorithm accurately detects humans, including partially obscured human limbs, with minimum error rates. This capability is critical in disaster scenarios where survivors may be trapped partially hidden or under debris. For all those challenges such as same color patterns in the environment, the AI algorithm differentiated humans effectively, reinforcing its robustness. TensorFlow Lite was integrated to enable real-time application in resource-constrained environments, giving the model the chance to run efficiently on TPUs. This adaptation assures that the robot can process complicated and confused tasks with minimum latency, which can be considered as a critical factor in rescue missions. As illustrated in Fig.13, the smooth integration of software and hardware was a crucial aspect of the robot's functionality. The synchronization between hardware, such as sensors and communication systems, and AI modules enabled the robot to navigate obstacles, detect objects, and transmit data to the rescue teams. For example, the robot halted and transmitted precise location coordinates to the teams upon detecting a potential survivor, ensuring timely assistance.

The outcomes of this study highlight the transformative potential of rescue robotics in disaster management to rescue humans' lives. The YOLO-V8 powered robot minimizes risks to human rescuers and enhances the efficiency of search operations. By combining advanced AI with

hardware, the robot could navigate in uneven terrains, identifying survivors, and relaying important information to rescue teams.

The results also highlight the adaptability and scalability of this technology. Future iterations of this hardware module of robots could incorporate additional features like real-time decision-making algorithms, thermal imaging, and swarm robotics capabilities with ongoing upgrades in AI and FPGA technology. These improvements would further amplify the robot's efficacy in diverse disaster actions. Certain limitations warrant discussion while the robot's performance is commendable. The dependence on consuming high computational power, mitigated through TPUs and TensorFlow Lite, may still pose challenges in highly resource-constrained environments. In addition, environmental circumstances like dense smoke or extreme weather could impact detection performance and sensor accuracy. Addressing these limitations through advanced AI training techniques and robust hardware design is a great topic for future research. Results demonstrate scalable adaptability, with Video S2 confirming stable navigation in complex terrain (. While future versions could integrate swarm robotics and enhanced thermal perception (leveraging AI-FPGA advances), current limitations include computational intensity (despite TPU optimization) and environmental susceptibility - both suggesting valuable research directions in edge AI and robust sensing (AlShemmary, 2025). Conclusion

   This paper represents important progress in disaster response technology through an AI-driven exploration robot. The robot offers a reliable solution for assisting and detecting survivors in disaster areas by combining YOLO-V8 with a compact and efficient hardware design. The use of developed hardware components such as Raspberry Pi, FPGA, SIM808 module, and motor encoders which enhances its communication, navigation, and obstacle avoidance capabilities. These hardware and software integrations making it suitable for real-world applications. The results show the superior performance of YOLO-V8 in detecting objects accurately, including individuals in challenging scenarios like obstruction. This capability, combined with effective obstacle navigation and real-time data transmission, underscores the practicality of the robot in search and rescue operations. Features like webcams, ultrasonic sensors, and communication modules further enable seamless interaction with rescue teams, enhancing its operational efficiency. This research suggests that AI-powered rescue robots can revolutionize emergency response efforts by minimizing risks to rescuers while maximizing the chances of locating survivors. As technology advances, future enhancements to such systems will undoubtedly play a pivotal role in improving the effectiveness and efficiency of disaster response strategies.
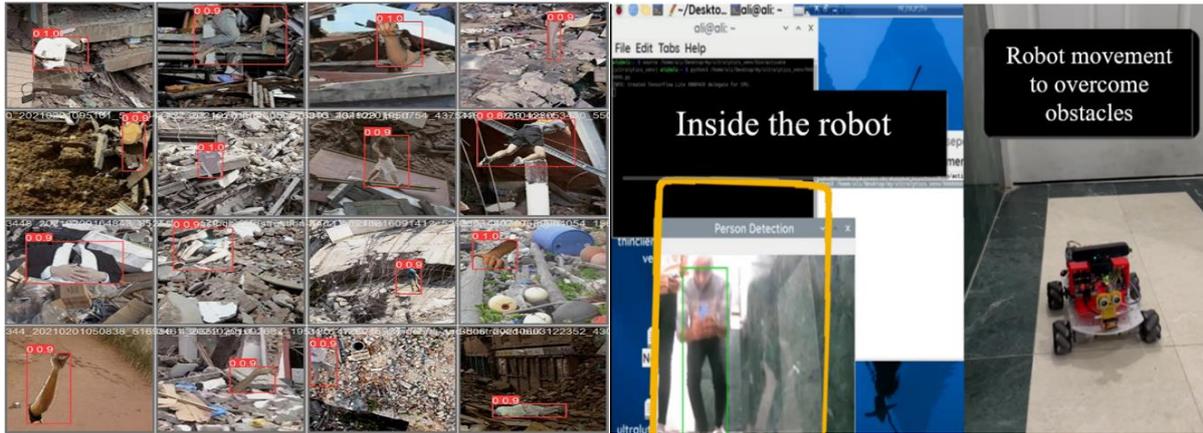
Fig. 12. Testing results for the AI module   **Fig. 13 Robot operation in real-world testing**

CONFLICTS OF INTEREST:

The authors declare that there are no conflicts of interest regarding the publication of this paper. All authors have contributed to the work reported, have read and approved the final manuscript, and have agreed to be accountable for all aspects of the work.

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