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RESEARCH PAPER

Human Body Detection in Disaster Environments: A Review of Framework Design and Development Strategies

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***Abstract*—The developments in intelligent systems and emerging technologies have greatly affected the disaster management processes by making the rescue operations quick, safe, and effective. Accuracy in detecting the human body in critical situations is crucial for minimizing response time and saving human lives. Various methods have been developed, including infrared and radar-based techniques, acoustic analysis, unmanned aerial vehicles, and robotics. These systems have been further enhanced with the incorporation of cloud computing, artificial intelligence (AI), and the Internet of Things (IoT), which enable real-time monitoring and decision-making, regardless of scale, as they can be easily deployed in changing, dynamic environments. In this study, deep learning (DL) frameworks and machine learning (ML) models have enhanced the accuracy of detection, particularly in complex or obstructed environments where conventional tools tend to fail. Combining dissimilar strategies for sensing creates a multimodal system, which is more reliable. The use of drones also expands to areas that are not accessible. A comprehensive review of existing approaches highlights the growing shift toward intelligent, adaptive, and cooperative frameworks in disaster response. This work emphasizes the importance of developing integrated detection technologies that not only improve efficiency and resilience but also contribute to sustainable and robust strategies for future disaster preparedness and management.**

Keywords—Human Detection, Disaster Management, Infrared Imaging, IoT, Drones, Radar.

I. INTRODUCTION

Although nature can inspire awe, it also poses enormous threats to human health through natural disasters. Natural disasters, such as earthquakes, tsunamis, floods, forest fires, aircraft accidents, and viruses, are occurring more often and posing significant challenges to both the general public and government organizations in charge of disaster management and preparedness [1]. To perform good disaster management, a series of rational, coordinated, and the Disaster Management Cycle, which is a cycle of progressive activities, should be implemented. This cycle includes different phases, including reaction, rebuilding, mitigation, and readiness [2]. The response phase is considered to be one of the most crucial stages in the life cycle of disaster management. Under some conditions, the necessity for a prompt response and the high number of potential victims make the disaster response task more complicated. To manage response operations, four primary managerial duties should be performed: planning, organising, directing, and controlling. Disasters can impact a person's physical and mental health both immediately and over time, in addition to the direct consequences, such as evacuation, social unrest, financial loss, lifestyle changes, damage to medical facilities, and changes in the broader political and socioeconomic context [3]. Natural disasters are inevitable and destructive, including earthquakes and building collapses. It is often difficult to locate and rescue those who are imprisoned beneath the debris [4].

The application of AI in disaster risk management (DRM), which include recognizing, evaluating, addressing, overcoming, and lowering the dangers brought on by natural disasters, has made it possible for disaster and emergency responses to be more accurate, efficient, and successful. The ability to foresee and handle upcoming disasters and the risks connected with them has increased because to AI-powered technologies including early warning systems, decision support systems, and predictive analytics [5]. Real-time surveillance footage containing the detection of human bodies poses a challenging issue for computer vision, necessitating the use of a complex system capable of tracking and identifying human bodies on-site while also overcoming numerous hurdles. The issues include scale variations, which need the system to recognize human beings regardless of their size in the frame [6][7]. In an image, object detection is the process of finding and recognizing things of interest. Object detection may also be used to find people in a catastrophe during rescue operations [8][9]. Computer vision research is advancing due to the development of new real-time observation systems, which necessitate academics to conduct innovative research on a range of topics. One branch of computer vision that is applied to locate specific objects is also used to recognize real-world objects, animals, and humans.

A. *Structure of the Paper*

The paper is organized as follows: Section II discusses the basics of human body detection in disaster situations. Section III describes the design of frameworks in disaster settings. Section VI presents a literature review of key works, and Section V outlines development strategies. Section VII is the conclusion of the paper, which presents the results and develops future research directions.

II. HUMAN BODY DETECTION IN DISASTER ENVIRONMENTS

Human body detection is crucial for disaster management, where disaster management agencies need to identify survivors as soon as possible so as to reduce the number of casualties and aid fast rescue missions. Natural calamities like earthquakes, floods, landslides, fires, and collapses can make the environment complicated, affecting visibility, effective communication, and accessibility. In this case, conventional methods of rescue may not be effective, and therefore, there is a need to introduce intelligent human detection devices that can operate in unfavorable environments [10].

One of the major challenges in disaster environments is the diversity of conditions in which detection must operate. Factors such as occlusion due to debris, variable body postures of trapped individuals, fluctuating crowd density, adverse weather conditions, and lighting variations significantly affect detection accuracy. Furthermore, the urgency of real-time detection requires computationally efficient systems capable of analyzing continuous data streams without delay.

A. Nature of Disaster Environments

A natural catastrophe is defined as an event that is brought on by the planet's natural processes and causes serious damage to the environment and local population [11]. A disaster's intensity is often defined in terms of fatalities and economic losses. Natural disasters occur worldwide every year. Depending on the intensity, a variety of calamities might claim life. Among the deadly outcomes are falling structures, trees, dying in the winter, being swept away, and heat exhaustion. Figure 1 displays the catastrophe environment system.

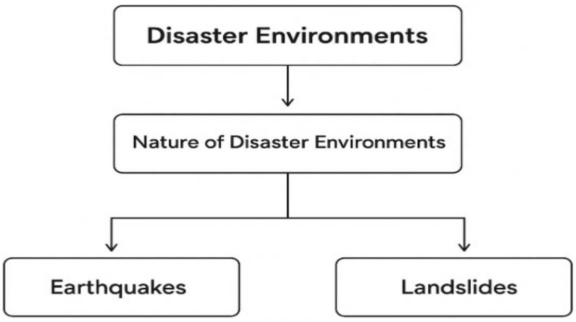

Fig. 1. Disaster Environment

- **Earthquakes:** An earthquake happens when the Earth trembles due to the release of stored energy. The Earth's surface is composed of many incredibly large land masses called plates. The majority of earthquakes happen when these plates collide. The exact time of an earthquake is impossible to anticipate. Most earthquake-related deaths are caused by buildings collapsing. Construction methods have a significant impact on earthquakes and fatalities.
- **Landslides:** The pressures of seismic waves do not just affect buildings. Rock and dirt patches slide downhill as a result of the earthquake. Unstable portions of mountains or slopes frequently collapse. Along with the obvious risks of large landslides, non-fatal slides can also be problematic when they block highways. Non-fatal landslides might be difficult or complicated. Emergency and rescue activities.

B. Challenges and Difficulties in Human Detection and Counting

In vision-based human identification and counting applications, attaining constant accuracy across various situations is extremely challenging [12]. Factors such as camera orientation, crowd density, occlusion, lighting, and computational demands significantly affect performance. The major difficulties and existing approaches can be summarized as follows:

- **Variation in Camera Orientation** – Different camera angles capture human objects from distinctive perspectives, requiring diverse implementation methods to maintain accuracy.
- **Changing Crowd Density** – The accuracy of detection fluctuates with variations in the number of people, as higher density increases complexity.
- **Occlusion of Human Objects** – Overlapping individuals create difficulties in distinctly detecting and counting each person. To address this, three methods are employed:
  - ***Trajectory Clustering*****:** Tracks individuals over time for better separation but is computationally expensive.
  - ***Feature-Based Regression*****:** Utilizes background subtraction and feature extraction followed by regression modeling for improved accuracy.
  - ***Individual Pedestrian Detection*****:** Detects and counts full bodies individually, though with lower computational efficiency.
- **Environmental Factors** – Lighting variations, weather conditions, and issues such as glare or blur reduce image quality, impacting detection performance.
- **Computational Efficiency** – Real-time applications require processing multiple image frames simultaneously, demanding high-speed algorithms and optimized resource usage.

C. Human Body Detection Techniques in Disaster Environments

In disaster response, human detection techniques are essential, utilizing cutting-edge technologies such as infrared technology, gas sensors, acoustic sensors, drones, robots, radar, artificial intelligence, and optical detection [13]. These techniques aid in identifying survivors and facilitating speedy response actions. As catastrophes pose global dangers, it is becoming increasingly crucial to develop and integrate these technologies to strengthen emergency operations' efficacy and durability. Figure 2 illustrates the Human detection techniques, displaying the section-wise layout of the work presented.

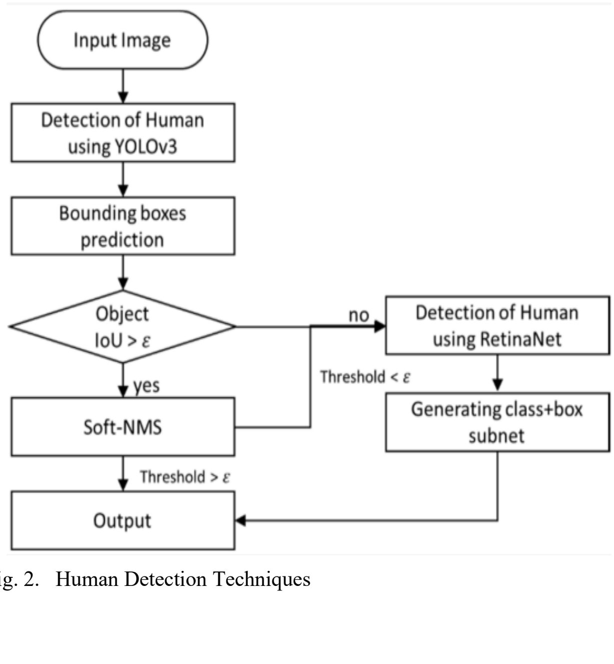

Fig. 2. Human Detection Techniques

As shown in Figure 2 is systematically organized to first highlight various human detection techniques applied in disaster response, including radar-based, AI-driven, and sensor-oriented approaches. The subsequent sections focus on the application of Synthetic Aperture Radar (SAR) in real-world scenarios, recent advancements in SAR technologies, and their strengths, limitations, and future research perspectives. This structured approach ensures a comprehensive understanding of existing methods and their potential in enhancing disaster management systems.

III. Framework Design in Disaster Environments

Disaster management in developing and underdeveloped countries. As a consequence, they offered a conceptual framework for these nations based on a public-private partnership (PPP) that is suitable for developing countries, provided that specific requirements between the public and private sectors are met. There are three conditions: mutual coordination, shared risk and benefits, and organizational management [14]. The conceptual framework was based on comparable successful ones established in developing nations such as India, Turkey, and Malawi. Furthermore, the authors advised that risk mitigation measures (i.e., insurance) be supplied to the private sector, especially in the most susceptible nations that experience repeated, severe crises. presented a cloud-based, comprehensive catastrophe management architecture. The proposed framework processes data from various sensors in a stream-processing manner. It is more suited for processing in real time as opposed to batch. The framework consists of five major stages: collection, appraisal, collation, analysis, and distribution.

A. Big Data Processing Frameworks

The most prominent large data processing frameworks have been introduced. However, nearly all of them compare processing frameworks without categorizing them based on the kind of data source that utilized (batch, stream, or hybrid). The three types of big data processing frameworks that are most commonly used are Stream-only, batch-only, and hybrid, based on the type of data they are designed to process. The discussion on big data processing frameworks can be summarized as follows [15]:

- **Modular Architecture Design -** dividing the system into independent, reusable modules
- **Layered Framework Approach -** separating sensing, processing, decision-making, and visualization layers.
- **Sensor Fusion Frameworks -** integrating data from thermal cameras, LiDAR, UAVs, and acoustic sensors.
- **AI-Driven Architecture –** leveraging deep learning, YOLO, CNN, or transformers for detection tasks.
- **Edge–Cloud Hybrid Design –** combining local (edge) processing with cloud-based analytics.
- **Scalable & Extensible Design –** ensuring the framework can adapt to new disaster scenarios and sensor types.

B. Sensor-Oriented Frameworks

The majority of environmental data is collected by the sensors employed in the pre-disaster phase. Earthquakes are frequently detected with accelerometers. In addition to accelerometers, borehole inclinometers, bar extensometers, and inertial sensors are also employed to detect landslides. Additional articles that concentrate on flood monitoring [16]. Flooding may occur more frequently in cities. One reason is that heavy and protracted rainfall frequently causes urban drainage systems to become saturated. A triaxial accelerometer, cameras, soil moisture sensors, weather sensors, drones, rain gauges, water level sensors, water pressure sensors, and others are among the sensors that researchers utilize in flood monitoring systems. Sensors are frequently powered by solar batteries. Proposed a model that selects cluster heads using an improved hybrid Particle Swarm Optimizations algorithm and a harmony search strategy to minimize sensor energy consumption. They developed a multi-hop routing system based on particle swarm optimization that has enhanced tree encoding and a revised data packet layout.

C. Key Principles and Elements of Risk Communication Framework

The success of risk communication is determined by a set of Key principles [17]. These principles ensure the information shared is understood, trusted, and acted upon:

- **Accuracy and Timeliness:** The information served must rely on credible sources, so that people are given enough time to prepare or respond. This kind of delays or failures in accuracy causes confusion, mistrust, and panic.
- **Clarity and Simple:** Complex information should be converted to simple, understandable and interpreted language without any technical terms. This translation in local languages is very important in multilingual societies such as that of India.
- **Transparency and Openness:** The openness about the nature of the risk, its possible impacts, as well as uncertainties, promotes trust. Hiding it or down-playing it complicates the task of gaining the support of the populace.
- **Two-way Communication:** Risk communication is not to be one-way. It must enable the masses to post their input, upon which the authorities may then proceed to address such issues, respond to questions in as best a manner as possible and even go a notch higher and revise strategies in as far as community needs are concerned.
- **Targeted and Inclusive:** The communication needs to be targeted at various audiences, including vulnerable persons, particularly children, older people, and disabled, who may be more vulnerable in the face of a disaster. Such approaches need to be transmitted through all possible media.

IV. Development Strategies in Disaster Environments

The process of physical and human development based on the values of sustainability and equity may preserve and enhance the quality of life in a community. The term "local economic development" encompasses this concept. Development is often "forward-focused," aiming to achieve long-term objectives and focused on improving the social and economic environment, in contrast to catastrophe reactions [18]. The connection between development and catastrophe is significant from the standpoint of sustainable development. One definition of sustainable development is "development that meets current needs without endangering the ability of future generations to meet their own needs." Another definition of it is "improving human life quality while living within the carrying capacity of supporting ecosystems." The former concept focuses on questions of fairness between current and future generations, whereas the latter definition discusses how to reconcile environmental preservation with economic development. The interest in sustainable development stems from worries about the detrimental effects of environmental issues and the inequities of economic development.

A. Hardware Integration of IoT Drone Architecture and Ecosystem

It is necessary for the IoT drone to be integrated with the IoT system. Figure 3 illustrates the components of the system, which include the drones, gateway, internet, IoT Cloud, and user interface remote [19]. Transferring data between drones and microcontrollers, the internet, IoT Cloud, and other IoT components is made possible by the Gateway. For other applications, the gateway is often installed at a permanent position. The IoT gateway in this instance can be placed anywhere, on a base station, or mounted to another drone, providing it with flexibility and mobility. As a result, the mobile gateway allows the base station and IoT drones to establish a long-range connection.

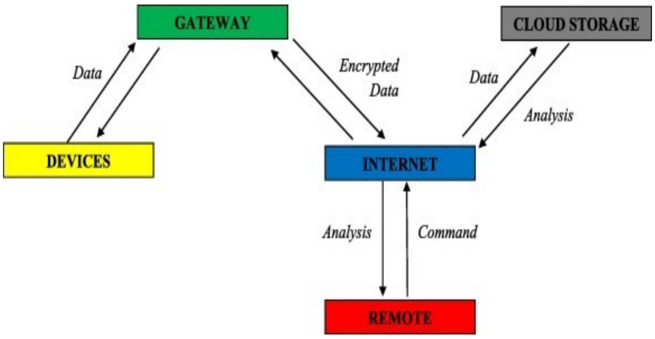

Fig. 3. IoT Drone Architecture

A. Simulation-Based Development

Simulating the operation of one system or process by mimicking the operation of another is known as simulation. It is a simplification of how a real-world system functions. It is necessary to create a model that depicts a verbal, pictorial, mathematical, or physical notion in a condensed form of reality in order to mimic. Therefore, simulation modelling is the process of creating and assessing a digital prototype of a physical model to predict how well it would work in the real world. Pro Model software is used in this project report [20]. This facilitates the measurement of the effects of environmental elements by using simulation as a tool. It provides a realistic and understandable illustration of how uncertainty can lead to project completion delays. Before being applied in the real world, simulation enables the evaluation of a model's accuracy and efficiency. Building physical systems expensive if simulation isn't used. Instead of using subjective analysis methods like the relative importance index (RII), which is based on respondents' opinions or experiences, simulation employs intelligent computer modelling elements, such as entities, locations, and processing, to demonstrate how a model operates virtually as it would in the real world.

B. Challenges in Disaster Management Systems

The issues pertaining to each category are highlighted after a broad discussion of disaster management system concerns [21].

- In crisis management, it can be difficult to allocate precious resources like staff, supplies, and money efficiently, particularly when there are several or restricted resources available.
- To address challenges including intricate networks, language hurdles, and coordination concerns across agencies and organizations, it is imperative that stakeholders ensure excellent communication and cooperation.
- It can be difficult to collect, evaluate, and distribute fast and correct information during quickly developing crises because of barriers including incomplete data, false information, and communication failures.
- It is difficult to engage local communities and help them become more resilient due to cultural differences, distrust, ignorance, and a lack of resources.
- Disaster management systems must be updated to reflect the changing nature and consequences of catastrophes, including urbanization and climate change.

V. Literature Review

The Summary literature highlights human detection innovation in disaster response, which makes use of multimodal sensing, UAVs, radar and robotics.

Ponzini et al. (2025) search and rescue for humans in the water, which depends on LiDAR and thermal imaging data were first fused. Even under extreme circumstances, the system remains quite dependable, as it identifies and classifies survivors in multi-source images using the YOLOv8 deep neural network. The framework was built specifically for this application and was planned, constructed, and tested using recently collected real-world data. To boost resilience, other data augmentation techniques create harsh operational and environmental conditions. Accuracy in detection and computing efficiency served as performance indicators [22].

Kalyan et al. (2024) propose a UAV system to enhance disaster search and rescue operations. The system utilizes an Ensemble HOG Human Detection System, based on computer vision, to identify humans in the video stream in real-time and approximate the distance between humans and UAVs. This approach enhances situational awareness for rescue teams, addressing challenges such as varying lighting conditions and occlusions. The system demonstrates high accuracy in complex scenarios, potentially expediting victim localization and improving survival rates. Future work focus on performance enhancement in diverse environments and integration with other disaster response technologies [23].

Qi and Lou (2023) suggested an effective technique for employing an RGB-D camera to identify 3D human key points while a person is lying down. First, generate 2D key points of the entire body using the existing 2D human posture estimation technique for RGB photos. Then, by combining the depth data with a coordinate transformation and passing the 2D coordinates through an invention filter, the final 3D coordinates of the human key point are acquired. Experiments demonstrate that the suggested technique is precise and quick enough for the mobile rescue robot used to detect 3D critical points of a lying human body at the casualty collection site [24].

Polepaka et al. (2023) consists of a sensor-equipped robot that recognizes victims and measures their heart rate. To detect a living human body, a passive infrared (PIR) sensor detects the infrared wavelengths produced by the body. The robot identifies a human and then uses heartbeat monitoring to determine the victim's current state of health. Furthermore, all captured data is sent to the mobile application via the prototype's Bluetooth connection. To make additional judgments, the rescue teams examine the data they have received. Along with details on the victims' health, the idea offers an effective answer to issues that arise in conflict zones and after natural catastrophes like earthquakes [25].

Patel et al. (2022) provided a method that makes use of multi-modal data to facilitate longer-range object recognition by combining the complementing capabilities of depth and vision sensors. Specifically, recommendations for objects in the environment are generated using observations of depth and intensity from sparse LiDAR returns. To find and categorize items in challenging environments, a Pan-Tilt-Zoom (PTZ) camera system utilizes these recommendations to conduct a guided search by adjusting its location and magnification level. The suggested work has been fully validated using datasets gathered during the DARPA Underground Challenge finals and an ANYmal quadruped robot in subterranean circumstances [26].

Huang, Zhang and Dong (2021) propose an approach of pre-processing the through-wall radar's human echo signal that uses the MTI fusion algorithm and extended PCA to remove background noise and wall echo interference. First, SVD is used to pre-process the simulated noise-plus-interference echo signal, and then the actual data collected confirms it. The simulation results are more satisfying, but in real-world applications, the interference from the wall cannot be totally eliminated [27].

Table I highlights diverse approaches for human body detection in disaster environments, emphasizing imaging, sensor fusion, and UAV-based methods, while addressing environmental challenges and proposing future research directions.

TABLE I. SUMMARY OF A STUDY ON HUMAN BODY DETECTION IN DISASTER ENVIRONMENTS

Author	Study On	Approach	Key Findings	Challenges	Future Directions
Ponzini et al. (2025)	Human-in-water search and rescue	Early integration of LiDAR and infrared imaging with YOLOv8	High reliability in adverse environments; robust detection and classification of survivors	Harsh environmental variations	Extend dataset diversity; refine robustness for real-world operations
Kalyan et al. (2024)	UAV-based search and rescue	Ensembled HOG Human Detection with real-time video analysis	Accurate detection under varying conditions; improved situational awareness	Lighting variations and occlusion	Enhance system adaptability and integrate with other response technologies
Qi & Lou (2023)	3D key point detection in lying posture	RGB-D camera with 2D-to-3D coordinate transformation	Fast and accurate posture recognition; suitable for mobile rescue robots	Depth noise and limited environment testing	Expand for multi-person detection and complex terrains
Polepaka et al. (2023)	Victim detection and health monitoring robot	PIR sensor for body detection + heartbeat monitoring via Bluetooth	Detects human presence and transmits health data to rescue teams	Limited to PIR sensitivity and communication range	Improve robustness in diverse disaster scenarios
Patel et al. (2022)	Object detection in underground settings	Multi-modal fusion of LiDAR and PTZ camera for directed search	Reliable detection at longer distances; tested in DARPA SubT challenge	Sparse LiDAR returns and complex terrains	Broaden applicability to outdoor and mixed environments
Huang, Zhang & Dong (2021)	Through-wall human detection	Radar echo preprocessing with PCA and MTI fusion	Suppressed noise and reduced wall interference	Wall interference not fully eliminated	Develop advanced algorithms for real-world through-wall detection

VI. CONCLUSION AND FUTURE WORK

Human body detection in disaster environments has become increasingly significant in advancing rescue operations and reducing casualties. This study explored a range of detection technologies, including infrared imaging, radar, acoustic sensors, drones, robotics, and AI-based models, each addressing specific challenges such as occlusion, density variations, and unpredictable environmental conditions. The integration of IoT, cloud computing, and big data frameworks has further enhanced the efficiency, scalability, and adaptability of these systems, enabling real-time disaster response and improved decision-making. Multi-modal approaches and intelligent frameworks have demonstrated the ability to strengthen both accuracy and resilience in complex disaster scenarios. Also, more sustainable disaster management practices are brought about by pioneering approaches to disasters like IoT-based drone ecosystems and risk communication platforms. Even with these developments, there are constraints, especially in terms of scalability, deployment cost, and the system's inability to perform reliably in unpredictable real-world settings. These issues underscore the need for further innovations and cross-disciplinary collaboration.

In future studies, emphasis should be put on the development of cost-effective, scalable, and flexible detection systems that can operate reliably across a wide range of unpredictable disaster scenarios. Multi-modal integration, fault-tolerance improvements, and leveraging machine learning will be essential in overcoming existing constraints and providing quicker, more dependable, and sustainable disaster response.

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