Proceedings of the 8th International Conference on Trends in Electronics and Informatics (ICOEI-2025)
IEEE Xplore Part Number: CFP25J32-ART; ISBN: 979-8-3315-4460-7

# 5G and Edge Computing Enabled Search and Rescue Drones

Charan Velavan
*Department of Electronics and Communication Engineering*
*St. Joseph's College of Engineering*
*OMR, Chennai, India*
charanvelavan12@gmail.com

Akshay Balamurugan
*Department of Electronics and Communication Engineering*
*St. Joseph's College of Engineering*
*OMR, Chennai, India*
akshaybr2369@gmail.com

Lingeshwaran Murugasamy
*Department of Electronics and Communication Engineering*
*St. Joseph's College of Engineering*
*OMR, Chennai, India*
radhalingesh@gmail.com

2025 8th International Conference on Trends in Electronics and Informatics (ICOEI) | 979-8-3315-4460-7/25/$31.00 ©2025 IEEE | DOI: 10.1109/ICOEI65986.2025.11013465

***Abstract*—Search and rescue operations during natural disasters like earthquakes and floods are often delayed and prove inefficient due to the unavailability and inaccessibility of the required resources. Traditional methods frequently fail to detect and rescue survivors in time. The proposed system is a revolutionary solution for search and rescue operations. This system operates with the integration of drone technology, AI, 5G communication, and edge computing. The YOLOv8 model is used for real-time inference of survivors by running it on the onboard edge device, Raspberry Pi 5, with the Hailo AI kit. The 5G network is utilized to facilitate low-latency, smooth, and secure data transmission by enabling real-time video streaming and control. This system enhances response time and thus provides a significant advantage to large-scale disaster search and rescue operations.**

***Keywords: Edge Computing, AI, YOLOv8, URLLC, eMBB, Raspberry pi 5, Cloud storage***

## I. INTRODUCTION

The consequences of earthquakes and floods not only destroy communities but also cause deaths. Traditionally, search and rescue operations have often been unsuccessful due to inadequate resources, poor response times, and decision-making. The window of opportunity to save lives is narrow; thus, rescue operations must be both fast and precise. Disaster zones are usually surrounded by damaged infrastructure, blocked paths, and inaccessible locations, making it very hard for rescuers to locate survivors quickly. To counter these challenges, new technologies, such as AI, 5G communication, and edge computing, have the potential to transform disaster response strategies.

AI and machine learning have a proven track record of efficiency in many sectors; it is no different when deployed in search and rescue operations. AI can quickly process large amounts of data, eventually suggesting fast and accurate decision-making. In search-and-rescue operations, AI models can identify survivors in images and in live video feeds, helping to pinpoint their exact locations with high precision. Drones, when equipped with these AI-powered object detection systems, can autonomously scan large areas from above, eliminating the need for manual searching. This technology is especially valuable in disaster zones that are difficult to navigate on foot or by traditional vehicles. Hence, UAVs (Unmanned Aerial Vehicles) can be used for rescue operations, thereby reducing the amount of time taken to locate survivors. Edge computing and 5G connectivity can be integrated with the AI models, enabling the drones to conduct real-time detection of victims and immediately notify teams on the ground.

In this system, the role of AI is fundamental to speeding up and simplifying search and rescue operations, making them more efficient and faster. Drones equipped with AI, such as YOLOv8, can quickly scan disaster areas and identify survivors in real time based on aerial footage. Using onboard edge devices such as the Raspberry Pi 5 and the Hailo AI kit, these drones can detect survivors at a much faster rate.

Edge computing is a distributed computing model that allows data processing to occur closer to the source of the data, rather than relying solely on cloud-based servers. This is particularly important for applications that require low-latency processing, such as real-time video analysis or object detection in drones. A large number [3] of such edge devices with computational power deployed at points close to data collection, such as onboard drones or ground stations, can reduce the time it takes to analyze and respond to real-time information. For instance, Raspberry Pi 5, in conjunction with AI acceleration kit, Hailo AI module, allows processing of high volumes of data locally, and thus not needing to send all the information to distant cloud servers. This is essential in the event of quick and accurate decision making, reducing bandwidth usage, and hence being more dependable in network aspects. Also, edge devices can continuously process data and update decisions on the fly, allowing for more dynamic and adaptable rescue operations.

The integration of 5G technology takes this a step further by establishing ultra reliable low latency communications and high-speed mobile broadband (eMBB). 5G network provides the necessary bandwidth and speed to support real time video streaming and control of drones from ground station, providing situational awareness and coordination. In disaster zones [4], where traditional communication infrastructure may be damaged or overloaded, 5G network offers a robust and resilient alternative. The low-latency communication and eMBB enabled by 5G allows control of drones and the ability to transmit high-resolution video feeds without any significant delays, less than 10ms. This capability is essential for guiding rescue ops teams to precise locations, enabling them to make informed decisions about where to deploy resources and rescue personnel. Such features of 5G communications will also make it possible to send large quantities of data at the fastest speeds. Therefore, the key information, i.e., the location of survivors, logs of flights and environmental conditions could be shared in real time with rescue teams in a jiff.

The integration of 5G, edge computing, and AI is revolutionizing search-and-rescue operations. AI-powered drone swarms, connected by 5G networks, enable disaster response teams to quickly locate survivors, cover wide areas, and increase task precision. This technique reduces dependency on traditional communication networks and centralized cloud services, which helps to mitigate network congestion and infrastructure breakdowns during emergencies. Additionally, the system's ability provides real-time data and adapt to evolving conditions ensures that rescue efforts remain agile and effective. In the long term, this technological convergence not only enhances operational efficiency but also plays a vital role in saving lives through faster and more accurate emergency responses.

This work is organized as Section II presenting a review of the literature survey. Section III describes the methodology, highlighting its key features and functionality. Section IV discusses the results, analysing the system's effectiveness. Lastly, Section V concludes with the main findings and explores future implications.

## II. LITERATURE SURVEY

The one of the most interesting applications of AI, 5G, and edge computing in search and rescue operations. It is because it will transform the whole process of disaster response. In recent years, researchers have worked on various technologies such as drone swarms, real-time data processing, and machine learning models for efficient and precise rescue missions. Specifically, object detection models such as You Only Look Once (YOLO) have the capability to detect survivors in difficult conditions. Another achievement is the deployment of 5G connectivity, resulting in low-latency communication for the coordination and transfer of information during the critical operation. Altogether, the rescue efforts are done much faster and accurately, given the improvement over the traditional operations.

Emergency situations claim millions of lives every year and can only improve if there are faster ways to isolate the victims' location difficult areas and silence cannot contribute to creating an even greater problem. By leveraging 5G technology together with drones and machine learning approaches to calculate location estimates, we can improve accuracy with less effort. The proposed system would revolutionize search and rescue operations by providing more effective ways of delivering rescue services while more reliably locating victims[6].

In drone-assisted rescue scenarios, a swam of self-managed and heterogenic units carries the advantage, though obstacles block and interfere communication with the group, affecting network coverage and causing latency with high energy expense. Addressing this [7], the RIS can be integrated to improve communication even in non-line-of-sight cases. The method of federated learning has been considered to offload computation among drones for optimal improvement in performance while communicating. Simulation results have shown significant improvements in terms of energy consumption and latency and throughput, which makes the system most efficient for real-time rescue operations.

Wireless devices, such as Bluetooth-enabled wearables, are increasingly being used by the general population and can even serve as beacons in cases of emergencies. In a rescue environment [8], the robots can identify the devices both on the ground and in the air to localize the victims. The experimental test demonstrates that Bluetooth Low Energy is a reliable means for detecting the device at 15 meters or even more distant with complex backgrounds. This can guide the robot towards the area of interest, allowing them to make efficient search paths towards the victims. This innovative system gives a hopeful answer to making rescue missions much more effective.

Search and Rescue Drone Operation (SARDO) is an autonomous drone-based system that is attempting to minimize deaths in disaster situations by accurately locating missing people by using their mobile phones. This system works independent of any infrastructural support and does not need any [9] modifications on mobile phones. It can locate mobile phones with the pseudo-trilateration technique along with machine learning with high accuracy, minimal battery consumption, and within record time. This approach marks a significant advancement over traditional infrastructure or visual-based systems, and it can operate efficiently in large, inaccessible areas.

In earthquake aftermaths, Unmanned Aerial Vehicle (UAV) can enhance direct rescue efforts by conducting aerial surveys to guide response teams more efficiently. The model proposed [10] focuses on optimizing drone coverage by determining the necessary number of UAVs and additional batteries. It also prioritizes critical areas, such as hospitals and high-risk buildings, for immediate inspection. The UAVs are programmed to work in a cooperative manner with minimal manual interference and quickens the rescue mission. This approach promises more effective and timely resource utilization in disaster situations.

In search and rescue, the detection of humans from aerial images is quite challenging due to various environmental conditions. A novel approach [11] is presented that combines ensemble learning and a convolutional neural network-based model to enhance human detection in high-resolution UAVs images. The system was trained on the Heridal dataset, which it achieved with an outstanding accuracy rate, thus being very effective in complex SAR environments. This method can handle problems such as motion blur, scale variations, and camouflaged environments, which makes it very useful for rescue missions.

This work overcomes the complexity of UAVs task schemes and optimal secure channel choice in data collecting and transmitting. A multi-domain model about secure transmission divided into physical [12] domain and social domain ensures the UAV's safety with the operation involved. A multiple-to-one stable matching problem for task allocation in UAVs and a popular matching strategy to allocate spectrum resource are proposed here. The coherent drone actions from information collection to transmission improve efficiency and security. Experimental results show considerable gains in security and revenue for UAVs and ground users, and performance improves with higher spectrum sharing limits and certain operational constraints.

This work proposes a Direction of Arrival (DoA) module for WiFi-based positioning in GPS-denied areas, especially for search and rescue operations. It uses patch antennas and a rat-race [13] coupler as receivers to estimate angles for localization. Experiments carried out in an area of 100m x 100m show the mean positioning deviation of 2m, hence with high accuracy. The pseudo-inverse algorithm best positions the antennas to minimize the fading and shadowing effects. The method provides a strong alternative for SaR missions, with confidence ranges calculated for precise localization, ensuring effective performance in environmental conditions that affect traditional GPS-based systems.

In avalanche scenarios, this study explores LoRa technology for search and rescue (SaR) operations. By collecting radio propagation data and snow profile information, the research evaluates [14] LoRa's potential under challenging conditions. Tests involved buried transmitters over a 50m x 50m area, and localization was carried out using RSSI and SNR metrics. The results suggest reliable LoRa communication even when the snow depth reaches 1 meter and has a varying liquid water content. Signal propagation through snowpack conditions is quantified to illustrate the adaptability of LoRa. This dataset helps in the improvement of localization algorithms, thereby making sure effective victim tracking is performed in adverse environments and developing wireless technologies in SaR missions.

UAVs are now increasingly deployed across a number of civil applications such as goods delivery, search and rescue, and precision agriculture. Such high mobility and flexibility at UAVs increase the [15] reliability and coverage of the wireless network. The work reviews the requirements of aerial communication systems and the dual role of UAVs as mobile terminals and aerial base stations. The work illustrates the simulation platform and future areas of research toward highlighting the improved UAV technologies critical to civil application, which therefore calls for a need for more innovative communication and networking solutions.

The study aimed at determining some optimal configurations to be used within UAV swarms in passive geolocation applications and was focused mainly on RSS localization under constraints as geographical limits and security concerns including [16] flight speed. Using the D-optimal criterion for maximizing localization accuracy, it provides optimal geometrical configurations of UAVs. Closed-form solutions based on real-world constraints improve sensor-target geometry and are validated to be practically feasible and effective. Simulation results verify that these configurations allow UAVs to perform localization with high accuracy while adhering to operational constraints, significantly enhancing their utility in applications such as wildlife tracking, rescue missions, and electronic warfare.

Interchangeable payload unit for UAVs allows real-time visual-inertial Light Detection and Ranging (LiDAR) odometry and mapping. It accommodates both small-scale drones and full-scale aircraft with monocular [17] cameras, the inertial measurement unit, LiDAR sensors, and an RTK-enabled GNSS receiver. A portable GPU integrates sensor data, which enables AI modules for obstacle detection and emergency landing zone identification. Field tests validate its performance in real-time localization and mapping, making it apt for applications such as delivery, surveillance, and search and rescue. This modular payload facilitates algorithm development and operational testing, connecting research to practical deployment with increased efficiency and precision.

For detecting small maritime objects in UAV images, a lightweight model, AB2D-YOLO, is proposed. Improvements include intra-scale feature interaction modules based on attention for robust occlusion modeling and dilation-wise residual modules for enhancing multi-scale objects. The weight-based [18] bi-directional feature pyramid network enhances smaller target features, and also, a detection layer is constructed for better position capture. AB2D-YOLO outperforms YOLOv8s with respect to the rise of 8.96 % mean average precision over the dataset SeaDroneSee. It combines high precision and lower complexity, which makes it work better for maritime UAV applications, addressing challenges like dense object distribution, scale variations, and occlusions.

This survey, therefore, deals with machine learning applications within UAVs to challenge different problems in civil and military. The UAV enhances velocity and precision through different kinds [19] of health, transportation, telecom, and rescue operations. The review classifies applications by environment, communication, and security and identifies neural networks and other ML techniques as pivotal solutions. By summarizing recurring research areas and techniques, the study points out advancements in UAV-ML integration. The findings highlight the transformative impact of ML on UAV technologies, foster innovation in autonomous systems for diverse fields, and advance the understanding of their capabilities and limitations in real-world scenarios.

Analysis of Energy-Efficient UAV Service Offloading in Cloud-Fog Architectures for Trajectory Planning and Resource Allocation Underlying [20] the optimization framework is cost minimization for power consumption, flight distance, and processing demands. The study has shown impressive power savings with different constraints; it is highly dependent on UAV propulsion efficiency and macro base station offloading. All layers of cloud-fog architecture are integrated in the study to demonstrate practical offloading decisions for UAV operations. This work enhances UAV deployment in smart cities by increasing energy efficiency and enabling optimal resource management in distributed systems for applications such as surveillance, wireless communication and rescue missions.

## III. METHODOLOGY

This approach integrates advanced technologies to enhance disaster response operations. It follows a systematic process encompassing real-time deployment, data preparation, edge device configuration, and model training. Key steps include curating diverse datasets, training the YOLOv8 model, configuring edge devices, and utilizing 5G networks for low-latency communication. The system processes live video feeds to detect survivors, annotates results in real time, and transmits data to rescue teams. This structured methodology ensures that search-and-rescue operations remain precise, efficient, and highly reliable.

### *A. Dataset Collection and Preparation*

Data The data set was collected and prepared from several sources, 1. IEEE data port, 2. COCO data set (only the class "Person") and 3. A custom dataset, which was specially designed for this work. Overall, the size of the dataset was 9,650 images, with training images being 9,176, validation images being 456, and test images being 18. For further enhancement of the model, dataset augmentation techniques such as random cropping, flipping, and color adjustment were used. Each image was stored in both color and black-and-white forms to maximize detection efficiency on edge devices. All images were sized to have a resolution of 640x640 pixels for uniformity and compatibility with the YOLOv8 model and to have an efficient performance with Raspberry pi 5. This preprocessing step allowed for consistent input dimensions during training and inference.

### *B. Edge Device Preparation*

The edge device used in the drone was the Raspberry Pi 5 Model B 8GB RAM integrated with the Hailo AI kit. The hardware configuration was sufficient in terms of computational power that was required to perform real time inference while it was portable and cost effective. A python environment was set up in the edge device to install the required libraries and the packages to run the proposed system. The webcam used was a 720p HD camera to capture the live video feed and send it for inferencing in real time. The Hardware and software configurations were designed and optimized to only minimize latency of inferencing and maximize the performance of the device during search and rescue operations. Furthermore, once the edge device is set up, the flight controller PIXHAWK is then connected to the edge device via a USB B cable using a UDP (User Datagram Protocol). This enabled the communication of the drone from the edge device. The edge device must always be kept in a closed case and be mounted with a cooling fan, for an efficient operation. This setup allowed a hassle-free deployment of the YOLO v8 model on the edge device, ensuring that computationally intensive tasks, such as object detection and annotation, were handled efficiently in disaster-stricken environments.

### *C. Machine Learning Model*

The YOLOv8 model was chosen for this work because it has state-of-the-art object detection capabilities, has very high inferencing speeds, and relatively low computational process, making it a perfect model for deployment on edge devices. In YOLOV8 the YOLOV8n model is used for deployment. The YOLOV8 model provides better accuracy, optimized architecture and takes up low computational process. The fact that the model can infer the live feed and detect the survivors in a timely and accurate manner makes it the ideal model for deployment. The live inference frame rate of survivor's spans from 18 - 24 FPS (frames per second). Additionally, the YOLOV8 model can be easily deployed in any type of edge device without any obstruction. The model allows the system to operate efficiently in low resource environments and have the necessary accuracy to recognize stranded individuals. It plays a vital role in making quick and accurate responses in search and rescue operations.

For Real time validation, the trained YOLOV8 model is deployed on live video feed to detect survivors. The model processes the frames from the camera and applies preprocessing such as resizing and then it predicts bounding boxes, class labels and confidence scores. Each detected object is assigned a confidence scored indicating the model's certainty, any score above 0.5 are considered valid. The intersection over Union (IoU) metric is used to measure the overlap between predicted and the actual bounding boxes. The key metrics measured include Precision, Recall and mAP (Mean Average Precision).

The AI system can be improved by training and deploying the system with higher order YOLO model like YOLOV8m; YOLOV8l and YOLOV8x. Addition of new and more datasets consisting of survivors from diverse environment condition will enhance the accuracy overall improve the performance of the system. When the system is equipped with better AI system, the decision-making process gets simpler for the search and rescue team, since they will be updated with most accurate data for the rescue operation.

### *D. Export Model*

Upon training completion, the model was exported in ONNX format, giving better portability. It then was converted into Hailo's HEF format to be deployed on the Raspberry Pi by using the Hailo AI kit. This conversion ensured optimized inference in the final deployment process. The trained model performed excellently, achieving good performance in the detection of survivors by processing live video feeds in real-time. Using high-performance hardware and efficient training processes, the system was ready for deployment on the edge device with reliability in a disaster response scenario.

### *E. Integration with the 5G Network*

To achieve real-time communication, the CPE (Customer Premise Equipment) is used, the edge device is connected to the CPE which has a SIM card which is connected to 5G network, with wireless connectivity between the CPE and the Raspberry Pi, it is made that the edge device is connected to the 5G network. The CPE port forwards the Raspberry pi to the 5g network for data transfer across the network. The implementation of 5G Communication provided Ultra-Reliable Low Latency Communications (URLLC) and Enhanced Mobile Broadband (eMBB), which are highly essential for

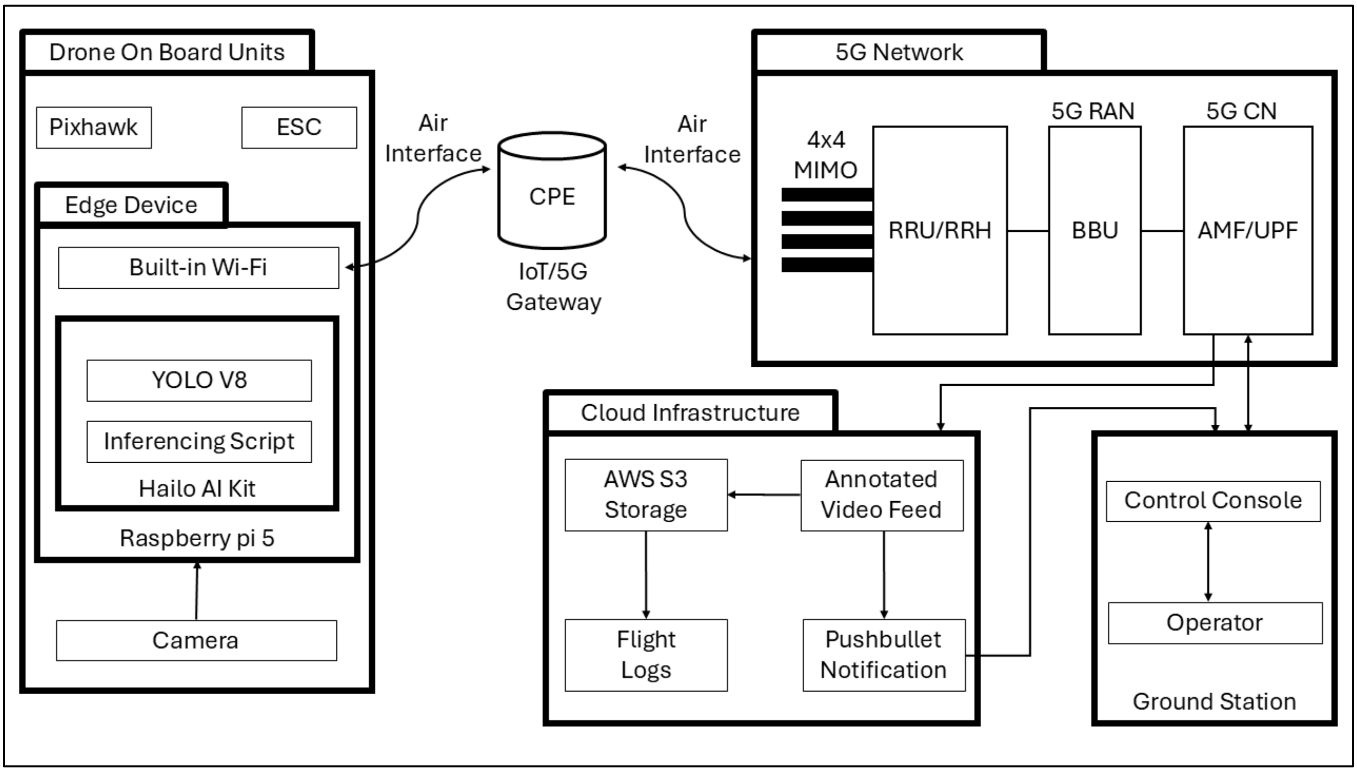


***Fig. 1 Architecture Diagram***

transmitting annotated video feeds and telemetry data in real-time. The 5G network setup ensured uninterrupted communication between the edge device and the ground station, providing a seamless coordination in disaster relief efforts.

The Architecture diagram shown in Figure 1 depicts the entire working system of the proposed solution. The system has five main parts: (1) Edge device AI processing, (2) Customer Premises equipment (CPE), (3) Cloud infrastructure, (4) 5G Network, (5) Ground Station. The design is optimized for real-time object detection (in this scenario, survivors during and after disaster) and analysis of the data. The UAV has an AI processing module based on Raspberry Pi 5 coupled with Hailo AI Kit for survivor detection.

To implement real-time object detection, the AI module runs a YOLO V8-based inferencing script on video feed processed from the onboard camera. The unit processes data from a Pixhawk flight controller to conduct autonomous flight and mission execution. The onboard Wi-Fi module provides connectivity to the 5G network. While the UAV is connected to the CPE and then the CPE is connected to the 5G network through air interface, the whole 5G infrastructure comprises a Remote Radio Unit/Remote Radio Head (RRU/RRH), Baseband Unit (BBU) located in the RAN and an AMF-UPF in CN. This enables low-latency data transfer and high-speed connectivity for real-time analytics and remote control.

The support for annotated video feed is provided with streaming to AWS S3 bucket for cloud storage, and the flight logs will be stocked for post-mission analysis. The annotated video feed is stored in S3 bucket and in local storage in Raspberry pi 5. It uses Push bullet notification services to inform operators on critical events and detections. The operators would interact with the control console that provides seamless monitoring and decision-making.

## IV. RESULT AND DISCUSSION

In this section, we will be looking at the real time results of the proposed system in detail. This will include comparisons with other works and the results generated by the AI system.

The system was tested and proved to be very efficient and accurate, with real-time detection and reporting of survivors in simulated disaster scenarios. At a frame rate of 18-20 FPS, the YOLOv8 model worked well on live video feeds and produced annotated outputs with minimal delay. The model performed well on detecting stranded people, even under adverse conditions such as low visibility and cluttered environments. The use of black-and-white image versions enhanced the reliability of detection on edge devices, optimizing resource utilization without loss of accuracy.

The integration of the 5G network ensured further aided to the system. The 5G network facilitated a seamless network connectivity between the drone, CPE and the ground station. The highspeed connectivity between the devices ensured the transfer of live video with the annotated survivors from the edge device to the ground station without any lags or stuttering. Since the entire network was interconnected with each other (in a local network), the transfer of files and streaming of the video to the ground station was done without internet. The flight logs were successfully stored in the edge device locally and have been stored in the AWS S3 bucket periodically

TABLE I. Comparison of Edge Technologies and Networks with other works

| **Paper Title** | **Edge Devices and Technologies Used** | **Network Used for Communication** |
|---|---|---|
| **Optimal Measurement of Drone Swarm in RSS-Based Passive Localization** | RSS-based sensors, Wireless communication modules, FIM sensors | Wi-Fi ad hoc networks, UAV-to-Ground communication |
| **3DSAR+ A Single-Drone 3D Cellular Search and Rescue Solution Leveraging 5G-NR** | AI processors, Distance & angle estimation sensors, SRS localization | 5G-NR mobile base stations, Cellular network |
| **The Role of Drones in Disaster Response** | Infrared & thermal sensors, LoRa-based modules | Mesh networks, LoRaWAN for long-range transmission |
| **This work** | Raspberry Pi 5+ Hailo AI kit, YOLOv8 model, Pixhawk Flight Controller | 5G Network using CPE |

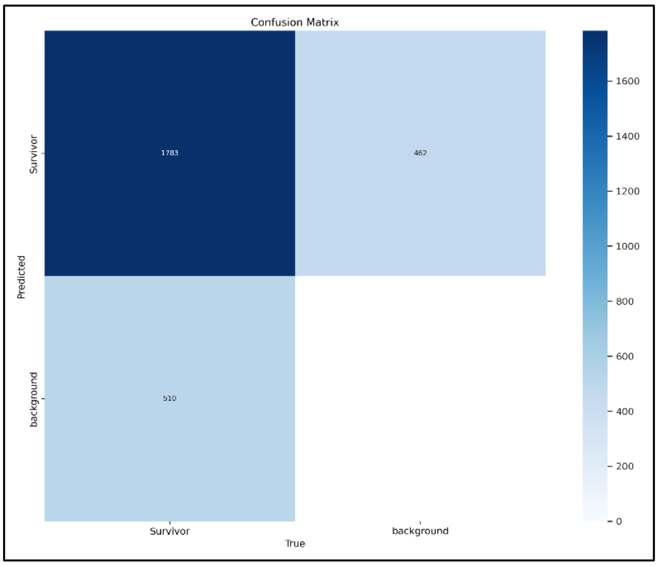


*Fig. 2 Confusion Matrix*

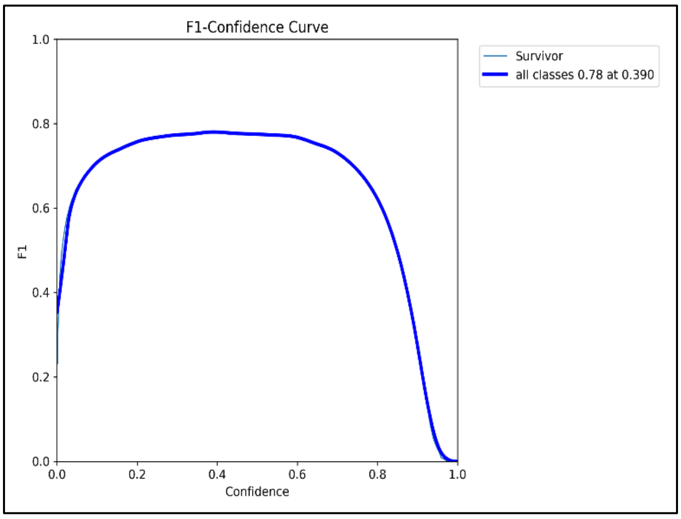


*Fig. 4 F1-Confidence curve*

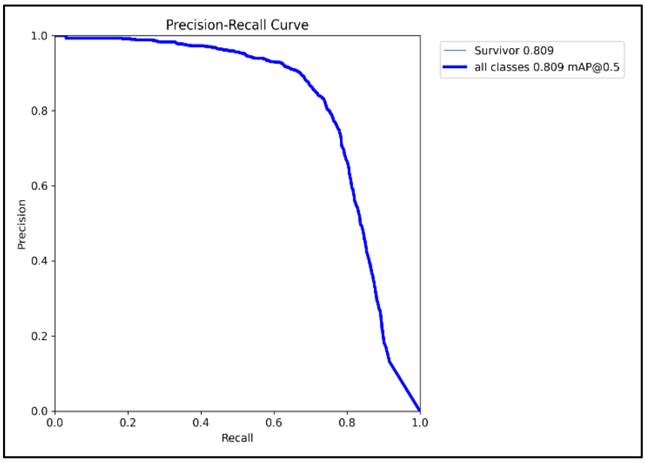


*Fig. 3 Precision-Recall Curve*

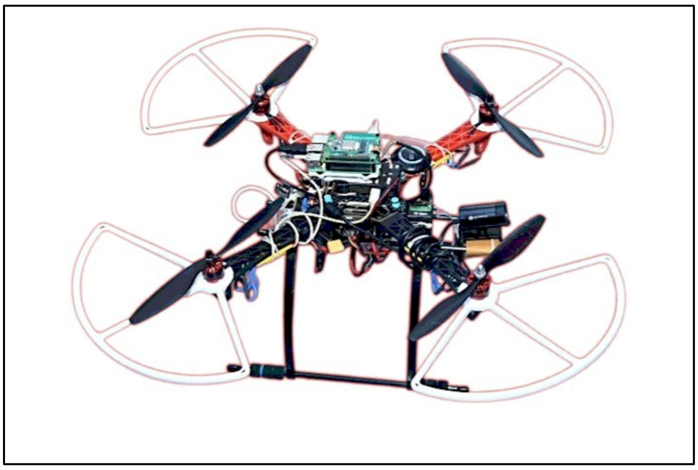

*Fig. 5 Drone*

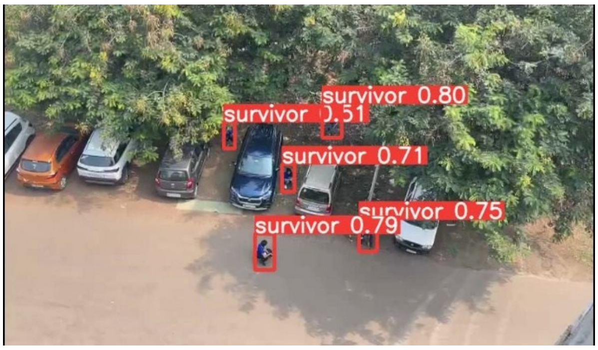


***Fig 6 Live Inference***

Table I shows the comparison analysis between edge devices & technologies used and the type communication networks in other works. It showcases the key hardware components, including the type of AI processors, sensors, and controllers, along with the network infrastructure used for real-time data transmission and decision-making. Different methods, such as RSS-based localization, 3D search and rescue using 5G, and LoRa-based communications, are used in other works. This work introduces a novel approach using Raspberry Pi 5 with a Hailo AI kit, integrating the YOLOv8 model and a Pixhawk Flight Controller, while utilizing a 5G network via CPE for efficient communication and the video transmission in this work can be done without the use of Internet over long distances.

The confusion matrix in Figure 2 brings out the performance of the model in identifying survivors. It may serve as an indicator of how accurately the system differentiates the classified survivors, signs of positives, negatives, and true performance in comparison to the expectations. In the generated confusion matrix, it is shown that the true positive (upper left) value is much higher than true negative value (lower left) and the false positive value (upper right). This depicts the model is trained to its finest and exerting an accurate and efficient performance.

Figure 3 depicts the trade-offs between precision and recall at various confidence levels. The curve persistent reconnaissance captures accompanied with recall diminishment were noted as the confidence level rose. These changes reflect the model's focus on affirming detection when false positive instances are minimal. The curve confirms the strength of the model with respect to the parameters which provide value precision 82.85 % and recall 73.00 % during the model testing.

Figure 4 is the F1-Confidence curve for the YOLOv8 model exhibits the F1 score versus confidence threshold curves. The highest point on the curve corresponds to the most balanced F1 score, indicating the confidence threshold that yields the optimal result. The highest F1 measure recorded was 0.77, indicating the effectiveness of the model during testing as well as the true positive captured and false positive acceptance.

Figure 5 shows us the drone, which is equipped with the necessary components required for Survivor detection during disaster prone times.

Figure 6 shows the onboard inference done with the Raspberry Pi 5 integrated with the Hailo AI kit, while the drone was in flight at an altitude of 10 meters above ground level. The results showed the model's capability to detect survivors. Even when the individuals seek refuge under a tree during disasters or after.

The URLLC (Ultra Reliable Low Latency Communication) and eMBB (Enhanced Mobile Broadband) ensures real time control, near-instant updates and seamless video streaming respectively. The 5G network communication allowed rescue teams to monitor operations and respond swiftly to real-time detections. The regular uploads of flight logs and annotated data to AWS S3 bucket showcases centralized data management and post-mission analysis. The test showed that the edge device Raspberry pi 5 performed highly effectively for edge computing tasks, it also showed low power consumption, and efficient resource management.

Python is used to create an inferencing pipeline which ensures smooth functioning like handling real time detection, flight data logging and cloud data pushing. The ability of the system to integrate different functions on a small device ensures that scalability can be done in various disaster scenarios. Preparing the dataset and training the AI model are also crucial for attaining high accuracy and robustness. The augmented dataset, Black & White and resized images also aided the accurate detections done in edge device.

With over 400 epoch of training the YOLOV8 model, the performance metrics reveal that the YOLOV8 model system is excellent with respect to precision, recall and overall accuracy of detection. The inferred or annotated video streams were consistently spotting survivors with less false positives and negatives, enabling the search and rescue teams for quick response. Incorporation of the flight's telemetry data like (battery level, altitude, pitch, yaw, speed, GPS Co-ordinates) into the inference pipeline also added more value in planning the operation. These data points were highly crucial in the mission's continuity and safety in operations with the drone.

In overview, the system showcased high reliability, accuracy and efficiency in the operation during disaster response scenarios. The integration of drones, AI, edge computing, cloud technology and 5G communications into this work has overcome some of the major hassles and challenges faced in traditional search and rescue operations. The real-time detections, combined with URLLC and centralized control and data storage, make this system a potential revolution in disaster management practices.

## V. CONCLUSION

This work showcases the integral roles of AI, edge computing, and 5G in search and rescue operations (disaster response). The deployed YOLOv8n model was trained on both color and monochrome images, which enhances the model's performance in complex environments. A Raspberry Pi 5 Model B with a Hailo AI Kit is used for edge computing, enabling cost-effective, low-latency real-time inferencing of the live feed from the camera, while the 5G network's URLLC and eMBB support high-resolution streaming and low-latency communication. The AWS S3 bucket provides cloud storage for data review and serves as a storage bucket for detections. The system was successfully tested in simulated disaster conditions; the results were valid and impressive. In conclusion, using drones equipped with AI and low-latency communication for real-time survivor detection, this study advances intelligent disaster response, enhancing efficiency and scalability to save lives.

## REFERENCES

[1] M. M. Z. Shaheen, H. H. Amer and N. A. Ali, "Robust Air-to-Air Channel Model for Swarms of Drones in Search and Rescue Missions," in IEEE Access, vol. 11, pp. 68890-68896, 2023, doi: 10.1109/ACCESS.2023.3292517.

[2] F. Dell'Agnola et al., "Machine-Learning Based Monitoring of Cognitive Workload in Rescue Missions With Drones," in IEEE Journal of Biomedical and Health Informatics, vol. 26, no. 9, pp. 4751-4762, Sept. 2022, doi: 10.1109/JBHI.2022.3186625.

[3] W. Yang, S. Wang, X. Yin, X. Wang and J. Hu, "A Review on Security Issues and Solutions of the Internet of Drones," in IEEE Open Journal of the Computer Society, vol. 3, pp. 96-110, 2022, doi: 10.1109/OJCS.2022.3183003.

[4] D. Hanover et al., "Autonomous Drone Racing: A Survey," in IEEE Transactions on Robotics, vol. 40, pp. 3044-3067, 2024, doi: 10.1109/TRO.2024.3400838.

[5] J. Taipalmaa, J. Raitoharju, J. P. Queralta, T. Westerlund and M. Gabbouj, "On Automatic Person-in-Water Detection for Marine Search and Rescue Operations," in IEEE Access, vol. 12, pp. 52428-52438, 2024, doi: 10.1109/ACCESS.2024.3386640.

[6] A. Blaga, F. Campolo, M. Rea and X. Costa-Pérez, "3DSAR+: A Single-Drone 3D Cellular Search and Rescue Solution Leveraging 5G-NR," in IEEE Open Journal of the Communications Society, vol. 5, pp. 4808-4822, 2024, doi: 10.1109/OJCOMS.2024.3437681.

[7] D. Rahbari, M. M. Alam, Y. Le Moullec and M. Jenihhin, "Applying RIS-Based Communication for Collaborative Computing in a Swarm of Drones," in IEEE Access, vol. 11, pp. 70093-70109, 2023, doi: 10.1109/ACCESS.2023.3293737.

[8] J. Cantizani-Estepa et al., "Bluetooth Low Energy for Close Detection in Search and Rescue Missions With Robotic Platforms: An Experimental Evaluation," in IEEE Access, vol. 10, pp. 106169-106179, 2022, doi: 10.1109/ACCESS.2022.3204272.

[9] A. Albanese, V. Sciancalepore and X. Costa-Pérez, "SARDO: An Automated Search-and-Rescue Drone-Based Solution for Victims Localization," in IEEE Transactions on Mobile Computing, vol. 21, no. 9, pp. 3312-3325, 1 Sept. 2022, doi: 10.1109/TMC.2021.3051273.

[10] T. Calamoneri, F. Corò and S. Mancini, "A Realistic Model to Support Rescue Operations After an Earthquake via UAVs," in IEEE Access, vol. 10, pp. 6109-6125, 2022, doi: 10.1109/ACCESS.2022.3141216.

[11] N. M. K. Dousai and S. Lončarić, "Detecting Humans in Search and Rescue Operations Based on Ensemble Learning," in IEEE Access, vol. 10, pp. 26481-26492, 2022, doi: 10.1109/ACCESS.2022.3156903.

[12] W. Li and J. Guo, "UAV Network Channel Allocation Method Based on Bipartite Graph Popular Matching Algorithm," in IEEE Access, vol. 12, pp. 10069-10086, 2024, doi: 10.1109/ACCESS.2023.3344462.

[13] S. -Y. Huang and R. -B. Wu, "Positioning for Search and Rescue in GPS-Denied Area by Distributed WiFi RSS-Based DoA Modules," in IEEE Access, vol. 10, pp. 76105-76113, 2022, doi: 10.1109/ACCESS.2022.3183094.

[14] M. Girolami, F. Mavilia, A. Berton, G. Marrocco and G. Maria Bianco, "An Experimental Dataset for Search and Rescue Operations in Avalanche Scenarios Based on LoRa Technology," in IEEE Access, vol. 12, pp. 171015-171035, 2024, doi: 10.1109/ACCESS.2024.3497654.

[15] M. Ghamari, P. Rangel, M. Mehrubeoglu, G. S. Tewolde and R. S. Sherratt, "Unmanned Aerial Vehicle Communications for Civil Applications: A Review," in IEEE Access, vol. 10, pp. 102492-102531, 2022, doi: 10.1109/ACCESS.2022.3208571.

[16] X. Cheng, F. Shu, Y. Li, Z. Zhuang, D. Wu and J. Wang, "Optimal Measurement of Drone Swarm in RSS-Based Passive Localization With Region Constraints," in IEEE Open Journal of Vehicular Technology, vol. 4, pp. 1-11, 2023, doi: 10.1109/OJVT.2022.3213866.

[17] R. G. Thalagala et al., "Interchangeable Visual Inertial LiDAR Odometry and Mapping Payload Unit for Aerial Vehicles," in IEEE Access, vol. 12, pp. 148904-148915, 2024, doi: 10.1109/ACCESS.2024.3471179.

[18] P. Ling, Y. Zhang and S. Ma, "Maritime Small Object Detection Algorithm in Drone Aerial Images Based on Improved YOLOv8," in IEEE Access, vol. 12, pp. 176527-176538, 2024, doi: 10.1109/ACCESS.2024.3490610.

[19] K. Teixeira, G. Miguel, H. S. Silva and F. Madeiro, "A Survey on Applications of Unmanned Aerial Vehicles Using Machine Learning," in IEEE Access, vol. 11, pp. 117582-117621, 2023, doi: 10.1109/ACCESS.2023.3326101.

[20] H. A. Alharbi, B. A. Yosuf, M. Aldossary, J. Almutairi and J. M. H. Elmirghani, "Energy Efficient UAV-Based Service Offloading Over Cloud-Fog Architectures," in IEEE Access, vol. 10, pp. 89598-89613, 2022, doi: 10.1109/ACCESS.2022.3201112.