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An Intelligent UAV-Based System for Real-Time Victim Detection and Geolocation in Disaster Scenarios

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Abstract:- Disasters, both natural and man-made, create serious challenges for search and rescue (SAR) operations, where time is crucial for survival. Traditional response methods often struggle due to hard-to-reach areas, dangerous conditions, and a lack of real-time information. This paper discusses the design, development, and evaluation of an intelligent system based on an Unmanned Aerial Vehicle (UAV) that aims to overcome these challenges. The system offers a complete solution for real-time detection and accurate location of victims in disaster-affected areas. It uses a UAV with a high- resolution camera that streams live video to a ground control station. A state-of-the-art deep learning model, You Only Look Once version 8 (YOLOv8), processes this video feed in real-time to quickly and accurately identify human presence. When detection occurs, the system automatically captures the GPS coordinates, logs a timestamp with an image, and shows the victim's location on an interactive dashboard. This gives first responders actionable intelligence right away, which significantly cuts down search times and improves operational efficiency. The paper also outlines a theoretical framework for expanding the system to a multi-UAV swarm, using Swarm Optimization Algorithms for coordinated search patterns and Delay-Tolerant Networks (DTN) to maintain communication in areas without infrastructure. Performance evaluation, which used the VisDrone aerial imagery dataset, shows the system's high detection accuracy and low latency, confirming its potential as a game-changing tool for modern disaster management**.**

Keywords: *Unmanned Aerial Vehicles (UAV), Disaster Management, Object Detection, YOLOv8, GPS Geolocation, Swarm Intelligence, Delay-Tolerant Networks (DTN).*

1. Introduction

Defence operations and disaster relief show the clear impact of change brought by Unmanned Aerial Vehicles (UAVs), commonly known as drones. These drone platforms excel at gathering live data, monitoring large areas, and quickly deploying resources. As a result, they have changed how emergency and high-risk operations function. For instance, these aerial systems act as the "eyes and ears" of border surveillance, providing continuous monitoring with minimal human effort, even in rough or hard-to-reach terrains.[1]

In disaster situations, UAVs are often the first to reach affected areas. They enable quick assessments of damage, help identify victims, and deliver essential supplies while ensuring the safety of rescue workers [2]. The use of

UAVs in critical response operations has increased rapidly due to their fast reaction times and operational efficiency [3].

However, UAV technology faces challenges. The accuracy of object recognition drops under severe environmental conditions, such as poor weather, low visibility, or dusty areas. This reduces the reliability of the intelligence provided [4]. Additionally, heavy reliance on human operators for decision-making can cause delays in fast- changing situations. These problems collectively impact the efficiency and response times of UAV operations in emergencies [5].

This paper focuses on the technological limitations of drones that reduce their productivity. It also explores how Artificial Intelligence (AI) can lessen their dependency on human intervention while boosting performance. The YOLO (You Only Look Once) [7] approach is used to achieve fast object recognition and autonomous decision-making. The emergency response benchmark dataset for model evaluation includes various classes of humans and animals in different environments and poses.

Technological progress in UAVs is improving their flexibility and reliability in defence and disaster-response missions [8]. These innovations represent a new era of accuracy and autonomy, leading to better operational effectiveness in critical scenarios.

Background of UAV

The concept of UAV technology began with the aim of reducing the pilot's load during wartime. The first successful "Kettering Bug" was a project for a missile that could operate without human control during World War I. Though it was a rudimentary machine, it laid the groundwork for future unmanned systems development. A significant change in the evolution of UAVs was the launch of the Predator drone, which transformed warfare through its surveillance capabilities and controlled strikes.

Today's UAV technologies are vastly different and are increasingly incorporating scalable, modular AI systems that use computer vision and machine learning algorithms without human assistance. These advanced technologies are guiding drones toward achieving full autonomy in quickly identifying targets, navigating complex environments, and making real- time decisions. High-level object detection algorithms have played a vital role in modern warfare by enabling precise target identification, threat assessment, and timely flight path adjustments. As a result, UAVs are now used for various essential activities like surveying, mapping, and search-and- rescue operations, where precision and accuracy are crucial [9].

Besides that, Mirabile dictu, the introduction of AI has been a game-changer for UAVs, opening up a new completely chapter of autonomous aerial systems. In turn, these technologies have become the driving force behind striking and far-reaching applications not only in the military but also in the civilian and commercial sectors as it can be deduced from the recent operational deployments [10].

This paper continues with: section 2 deals with the literature and works, the proposed solution methodology is described in Section 3, discussion of the findings and the analysis is done in Section 4, and research summary along with the potential future works are presented in Section 5.

2. Related Works

One of the reasons that attracted a lot of attention in the last years to the application of UAVs in disaster management and emergency response is the broad range of UAVs' functionalities that can be used for area monitoring, victim detection, and rapid deployment.

In fact, the first studies reported UAVs as a valuable asset in large-scale disaster assessment, where they can be quickly sent to the field to provide a comprehensive overview of the situation without risking the lives of human responders [11]. Several works report that UAVs have also been employed effectively in the implementation of regional disaster scenarios such as floods and earthquakes, where frameworks for damage assessment and rescue coordination have been specifically designed to address the urgency of the situation [12].

Detection and localization of victims in a timely and precise manner is the main concern in UAV-based disaster management. Traditional methods that depend on people monitoring or camera feeds are usually not enough, especially in areas full of debris or with a complicated structure. Rudol and Doherty were the first to develop UAV-based human detection technologies for search-and-rescue missions, thus paving the way for the implementation of computer vision in UAV platforms.

On top of that, the newest innovations have been equipped with GPS data in real-time and sensor fusion to increase the accuracy of geolocation thus making it possible to pinpoint the exact location of bodies for the rescue teams on the ground. The deployment of Mobile Edge UAVs has made the road for the real-time execution of tasks and a smooth transition between detection and GPS tagging operations without the occurrence of a lag [13]

The capability of drones to identify in a given moment and within a scene the objects that might be of interest is a key point in the rescue operations carried out by UAVs nowadays. Those specialized in the field consider the YOLO (You Only Look Once) family of models as a benchmark because they strongly support what the system requires - they are extremely fast and yet very accurate, hence suitable for a drone's on- board or an edge device's processing [14].

An example of such a system can be found in the work of YOLOv4 and YOLOv5, which, according to the authors, had displayed significant improvements in detecting slight or even partial occlusion of objects in a complex scenario. At the same time, the most recent research employing YOLOv8 and YOLOv10 has found that these two versions have better potential in handling small and partially hidden objects that are very important in the case of victim detection for disaster scenarios. Research has also

Table 1. Shows the important aspects I have taken in my projects

Author & Year	Technique / Model Used	Application Area	Advantages	Limitations
Smith et al.	Vision-based tracking system	Border surveillance	Simple to implement	Low accuracy in poor lighting
Lee & Park	GPS-assisted UAV navigation	Disaster management	Improved path stability	No object detection
Kumar et al.	CNN-based detection	Search and rescue	Good detection in clear visibility	Fails under low light
Chen et al.	YOLOv5	Real-time monitoring	Fast detection, robust under noise	Limited adaptability to complex backgrounds
Proposed Work	YOLOv8 (AI-integrated UAV)	Defence & Disaster response	High accuracy, real-time adaptability	Computationally intensive

The use of UAVs in disaster response and surveillance has become an important area of study in recent years. Many research projects have shown their ability to offer real-time awareness of situations, quickly locate victims, and improve efficiency in critical situations. These drones can reach places that ground teams cannot access, making them essential for evaluating conditions after disasters and coordinating emergency relief efforts. Early methods relied mainly on manual control and video monitoring, which limited their effectiveness and caused delays in interpreting data.

To overcome these challenges, researchers started looking into automation using computer vision and artificial intelligence. Rudol and Doherty developed early human detection algorithms for UAV-assisted search-and-rescue missions, marking one of the first practical uses of onboard vision for recognition. Following this, several studies aimed to enhance the accuracy of detecting humans and animals through improved image processing methods and sensor integration techniques. UAVs equipped with GPS and multiple sensors provided more dependable location information, which helped with response coordination during large disasters.

In recent years, deep learning detection systems have transformed UAV vision applications. Convolutional Neural Networks (CNNs) have shown remarkable skills in extracting features and identifying objects in real time. The introduction of the YOLO (You Only Look Once) algorithm sped up progress, as it allowed for single-shot detection of multiple classes at once without losing accuracy. Later developments like YOLOv3, YOLOv5, and YOLOv8 enhanced model precision, improved handling of small objects, and boosted detection in difficult lighting conditions. These models have been particularly effective in drone-based rescue systems, where quick processing and limited hardware resources are key issues [15].

The combination of UAVs with edge computing and artificial intelligence has also improved their ability to make decisions autonomously. Modern UAV systems can now process image data locally on lightweight embedded GPUs, allowing for faster analysis and immediate action [16]. This shift has significantly increased mission autonomy, reducing the need for constant human oversight [17]. Research on Mobile Edge Computing (MEC) UAV systems showed that spreading computation tasks between drones and nearby nodes can cut down on delays and boost detection reliability [18].

Sensor advancements have been crucial in enhancing victim detection accuracy. In addition to standard RGB cameras, many researchers have used thermal infrared and multispectral sensors to spot humans in obstructed or low-visibility situations [19]. These sensors are particularly useful during nighttime rescue missions or in conditions with smoke, debris, or fog [20]. Combining visual and thermal imaging allows UAVs to better distinguish between living subjects and static debris, leading to improved victim location accuracy [21].

Despite these improvements, UAV-based detection systems still encounter several challenges. Environmental factors like poor lighting, heavy rain, or thick vegetation can badly impact model accuracy and limit operational efficiency [22]. Likewise, limited flight times, high computational demands, and unstable communication links in remote areas create major difficulties for long-term missions [23]. Researchers have looked into optimization methods such as lightweight CNN architectures and quantization to decrease inference times and reduce power use on low-resource UAV platforms [24]. Hybrid transformer–CNN models have also been proposed to enhance feature representation and detection robustness in dynamic backgrounds [25].

3. Proposed Methodology

3.1. User Input Interface and Monitoring

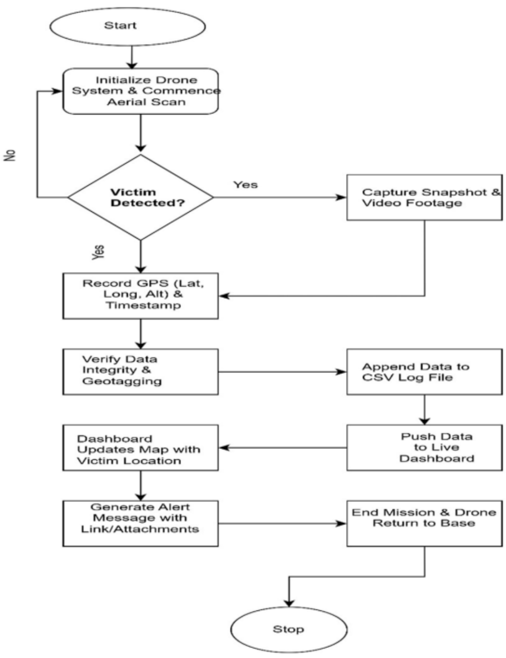

Figure 1. The proposed framework illustrates the complete operational workflow, encompassing all stages from victim detection to the automated alert generation process

This module is the main control and display unit for the system operators' staff. It is developed with the Streamlit framework and provides an interactive and user-friendly user interface that facilitates the on-the-fly integration of video streaming, system status, and alarm functionalities.The interface is perpetually set to display the live feed from an IP camera mounted on a UAV, therefore the operators are provided with the means of a direct visual check of the disaster-hit areas and their situational awareness can be increased. The caption of the detected person with the ("Person") label is displayed along with the respective confidence score and the time of detection. In addition to detection information, as explained in *Figure 1* the status panel is the place where one can find details regarding GPS connection, data logging, and drone swarm communication. The operator through a "Send Alert" device can, thus, without any delay, distribute the GPS coordinates of a detected individual to other drones or the command center so that rescue operations can be carried out in a coordinated and efficient manner. Furthermore, the control panel also enables the user to issue commands such as starting or stopping detection, turning on or off GPS logging, and watching the history of detection data from the CSV files. The on-board integrated control unit is an immense operational efficiency and command of the rescue team in the field.

3.2. Video Streaming and Object Detection

Devices for communication and recognition of objects grasp people in real-time from a bird's eye view of a drone.

The detection algorithm is on a laptop (ground station) to reduce the computational load on the UAV. So the video stream from the mobile-mounted IP camera of a UAV is grabbed with the OpenCV library, which directly plays frames captured by the camera from the video stream of a UAV. Each frame is pre-processed for inference.

The work is done by a deep learning model YOLOv8 (You Only Look Once, version 8) that is used for the task of object detection with high accuracy and real-time speed of the output. The model receives each frame, and if a person is found with a confidence level of more than 80% then around the detected object, a bounding box along with a label is placed. The converted frames are displayed on the Streamlit interface for the operator's convenience.

The overall design flow is explained in the *Figure 2* The corresponding frame at each detection is automatically saved locally with a timestamp. Afterwards, these snapshots are identified as event log references for analysis or as a confirmation of successful detections. The visual feedback loop keeps updating the live feed with detection results, the number of detections, and confidence levels, thus enabling the operator to visually monitor system performance and coverage.

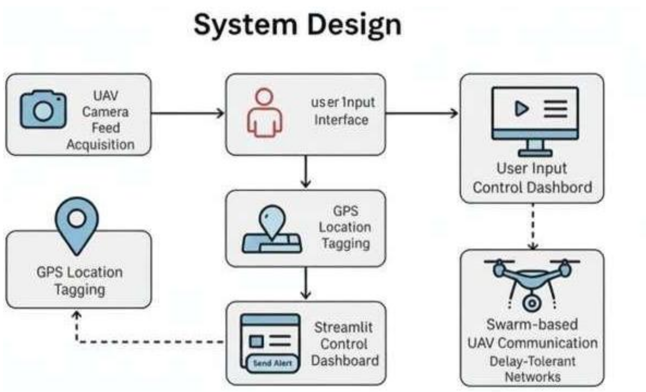

Figure 2. Illustrates the overall system design flow

3.3. GPS Integration and Data Logging

Such a system use swarm intelligence methods for multi- UAV collaboration, which help the system to extend disaster response over a large area and to cover more ground. Leveraging this capability allows for the execution of coordinated area explorations, which subsequently makes it possible to eliminate overlapping in the inspected regions and to optimize UAVs' path planning.

In order to have on-the-fly route planning, suitable task allocation, collision avoidance, and navigation that do not waste energy the developers have implemented swarm optimization algorithms such as Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) into the system.

Due to these algorithms, the UAVs behave like a collective intelligence which explores the disaster area and keeps changing their flight paths according to the regions of interest they detect.

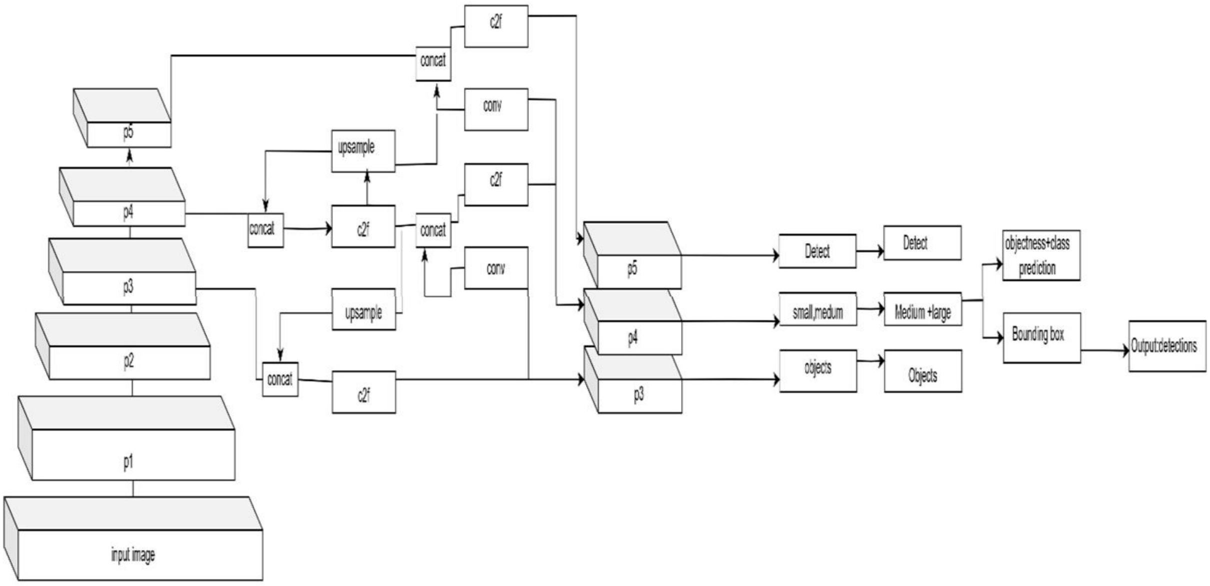

Figure 3. Shows YOLOv8 architecture where an image travels through the Neck with SPP, C2F, and S2C modules for multi-scale object detection output and the Backbone for feature extraction

The GPS coordinates of a person in need of help are, without a doubt, the most important part of a message that an operator sends by clicking the "Send Alert" button. The message is sent through the swarm network which, thus, is a kind of network accessible to all the UAVs. By means of the other drones, the message is spread and they are free to decide on their own if they will change their current directions to certainly verification assistance or the provision of help in the rescue mission.

This system has also set up a Delay-Tolerant Networking (DTN) protocol to keep the communication going in the scenarios of network that is weak or disrupted. DTN is able to assure the on-time (message) delivery because it uses a store- and-forward method. The method is such that UAVs can store the data packets temporarily and can send them when the connection is back. Besides, drones can be informed by the feedback of the swarm if they should change their tasks. Thus, they can send some drones to the new detection areas while others can continue the scanning process. This flexible mission reallocation helps to elevate the level of resource utilization and reduces the chances of the presence of invisible areas.

3.4. Swarm Communication and Optimization

The system employs swarm intelligence concepts for the collaboration of multi-UAV which is a system capability that enables better response to large-scale disasters and coverage extension. With this ability, also, coordinated area scanning which abolishes the overlapping of scanning areas and UAVs optimization of path planning is achieved.

Swarm optimization technologies namely Particle Swarm Optimization (PSO) or Ant Colony Optimization (ACO) are significatively mentioned in the paper as being implemented in the system to provide dynamic path planning, efficient task allocation, collision avoidance, and energy-efficient navigation. By way of these algorithms, UAVs become a collective intelligence that surveys the disaster area and is constantly changing their flight paths according to the regions of interest they detect.

The GPS location of the person in need is basically what the message is about that an operator pressing the “Send Alert” button sends. The network that carries the message is the drone network, so the information can be there to all the UAVs in the network. The other drones receive the message and on their own, they can decide about changing their current routes and of course, verifying the situation or giving the help in the rescue mission To be able to maintain good communication in such conditions as a weak network or a network that has been disrupted, the system has implemented the Delay-Tolerant Networking (DTN) protocol. DTN assures that messages are delivered in time by taking a store-and-forward approach. This method allows UAVs to temporarily store data packets and send them when the connection is back. Also, based on the feedback of the swarm, drones can decide on their own to change their tasks, thus they can send certain drones to the new detection zones while other drones can continue scanning. Such a strategy for mission reallocation raises the level of resource utilization and reduces the possibility of the presence of invisible areas.

3.5. System Advantages

The system put forward by the proposal is accompanied by a number of very important advantages. In fact, real-time person detection is combined with accurate geotagging, thus creating the optimal conditions for the speedy intervention of rescue teams. Moreover, the autonomous UAV coordination guarantees a great deal of coverage over a wide area and significantly reduces the human intervention factor.

Even at times of network disruption, the system can still maintain reliable communication through the DTN mechanism. Also, the architecture is very scalable and hence it does not pose any limits for the seamless integration of additional sensors or AI modules. Last and not least, the Streamlit-based user dashboard offers an easy-to-understand platform for live monitoring, operational control, and post- mission data analysis, thus turning out to be time-saving, adaptive, and mission-ready in the end.

3.5.1. Software

The software architecture of the UAV-based human detection system employs a modular, event-driven pipeline that runs on the Ground Control Station (GCS). The live video feed is the first step of the system, which is done through the Real-Time Streaming Protocol (RTSP). Frames are continuously captured using the OpenCV library for real-time analysis. Each frame is subjected to the YOLOv8 object detection model to find human targets with a confidence level of 80% or more. In the meantime, GPS data from the drone or a companion device are sent via the User Datagram Protocol (UDP) to align the spatial information with the detections.

The first, along with the timestamps, confidence scores, and coordinates, are recorded in a CSV file and displayed on a Streamlit-based dashboard. This setup allows for low-latency, high-accuracy detection, which is crucial for time-critical missions like search and rescue. The detection process uses the You Only Look Once version 8 (YOLOv8) model created by Ultralytics. YOLOv8 acts as the system's detection engine. It is a one-stage, anchor-free detector that is designed for real- time applications, balancing computational efficiency and accuracy well.

Its architecture has three main parts: Backbone, Neck, and Head. The Backbone extracts visual features from images, ranging from low to high levels, using convolutional and bottleneck operations. The Neck combines multi-scale features, utilizing both Feature Pyramid Network (FPN) and Path Aggregation Network (PAN) methods to improve object detection across different scales. The Head makes the final predictions, producing bounding boxes, confidence scores, and class probabilities.

A major improvement in YOLOv8 is the addition of the Cross- Stage Partial Fusion (C2f) module. This module enhances gradient propagation and reduces feature loss. Additionally, the anchor-free design allows for direct prediction of object centers and dimensions. This change eliminates the need for pre-defined anchor boxes, simplifying the process and enhancing generalization.

The computational workflow of YOLOv8 depends on several basic mathematical operations. The convolutional operation pulls features from the input image using learnable filters. It is mathematically expressed as:

$$O(x,y) = \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} I(x+i, y+j) \times K(i,j) \tag{1}$$

Where O(x,y) denotes the output feature map, I is the input, and K represents the convolutional kernel. Batch Normalization (BN) is used to stabilize and speed up training by normalizing intermediate activations, formulated as:

$$x\hat{} = \frac{(x-\mu)}{\sqrt{\sigma^2 + \epsilon}}, y = \gamma x\hat{} + \beta \tag{2}$$

where μ and σ denote batch mean and variance, while γ and β are learnable parameters that control scaling and shift. YOLOv8 uses the Sigmoid Linear Unit (SiLU) activation function, also called Swish, which helps with smoother gradient flow and is defined as:

$$f(x) = x \cdot \sigma(x) = \frac{x}{1 + e^{-x}} \tag{3}$$

Feature fusion in the Cross-Stage Partial Fusion (C2f) block is done by concatenating several feature maps. This is expressed as:

$$F_{out} = \text{Concat}\,(F_1, F_2, F_3, \ldots, F_n) \tag{4}$$

where each F_i corresponds to feature maps extracted from different layers. Bounding box prediction is done by directly calculating spatial coordinates and dimensions. The overall detection confidence for a specific object class is defined as:

$$C = P\text{obj} \times P\text{class} \tag{5}$$

where *P_obj* represents the objectness probability and *P_class* indicates the class-specific probability.

The final loss function is expressed as a weighted summation of box regression, classification, and object losses:

$$L\text{total} = \lambda\text{box}L\text{box} + \lambda\text{cls}L\text{cls} + \lambda\text{obj}L\text{obj} \tag{6}$$

This formulation ensures effective optimization by balancing localization accuracy, class prediction, and confidence calibration.

To connect detections with their geospatial context, GPS data are continuously received from the UAV or mobile companion device over UDP at fixed intervals. A Python-based receiver thread keeps a real-time buffer of the latest latitude and longitude values. When the system detects a human, it immediately synchronizes detection metadata with the current GPS coordinates. Each record, which includes a timestamp, class label, confidence score, latitude, longitude, and image path, is added to a structured CSV log. This log serves as both a historical dataset and a source for visualization input.

For visualization and mission monitoring, an interactive dashboard based on Streamlit and Folium has been developed. The Streamlit interface shows the live YOLOv8 detection stream, system metrics (GPS status, detection frequency, and logging activity), and mission alerts. The Folium library adds geospatial rendering by marking each detection on an interactive map with metadata such as timestamp, confidence, and coordinates. The interface also has a "Send Alert" function, allowing detected coordinates to be sent to nearby UAVs or rescue control centers for real-time response coordination.

To ensure data integrity and mission reliability, several data management strategies are in place. Automatic CSV logging makes sure all detection data are stored for post-mission analysis. Snapshot archiving enables local storage of detection frames with timestamp labels for visual verification.

The system continuously checks GPS connectivity, flagging weak or disconnected signals to avoid corrupted geolocation data. Threaded processing is used for video streaming, GPS reception, and dashboard updates, allowing these processes to run simultaneously and keeping real-time performance without delays.

Overall, the software subsystem combines YOLOv8-based deep learning, real-time GPS synchronization, and Streamlit- Folium visualization into a single framework designed for UAV-assisted detection and monitoring. This setup promotes operational efficiency, reliability, and scalability in critical missions like disaster management, surveillance, and rescue operations.

3.5.2. Hardware

The planned autonomous drone system employs a three-level hardware subsystem integration to create a reliable, intelligent, and energy-efficient aerial vehicle capable of accurately executing complex missions. The system aims to provide an ideal balance of performance, cost, and scalability, resulting in a total hardware budget of approximately ₹59,800.

The design features a modular structure that improves operational flexibility, simplifies maintenance, and enables future technological upgrades.

The core of the system is the Pixhawk PX4 32-bit Flight Controller that acts as the central data processing and control unit. This controller is the one that performs all the real-time flight operations such as motor control, attitude stabilization, and sensor data fusion. The controller together with the sensors and actuators is housed in the flight platform and it is the one that ensures the drone flies stable, safe, and reactive even when there are changes in the environmental conditions. The job is completed by the Raspberry Pi 4 Model B which is a companion computer and a secondary processing unit. The Raspberry Pi is responsible for the execution of the tasks that demand high computing power like computer vision, path planning, mission management, and peripheral control. Therefore, these two processors have been put together in a distributed control architecture which is the main reason for the system's increased reliability, responsiveness, and processing efficiency.

To get the drone propeller turning, the T-Motor VELOX V2307 V2 X motors are chosen for their high efficiency, accurate speed control, and good thrust-to-weight ratio. With these motors, the drone becomes capable of doing quick and sharp turns while still remaining stable and energy-efficient. The motors get their instructions from a T-Motor Velox V2 V45A 3–6S BLHeli_32 4-in-1 ESC that unites four electronic speed controllers into one single lightweight module. This merging results in less wiring, better synchronization between motors, and the overall electrical efficiency of the propulsion system is increased. A 7.4V 4200mAh 35C 2S Li-Po battery is the power source that provides enough energy for long flights while still having a good weight-to-power ratio. The IMAX B6 80W 6A Charger/Discharger is the device that allows safe and efficient battery recharging. Among its features are an automatic balancing, an overcharge protection, and a voltage monitoring that together ensure battery life and reliability.

The drone’s sensor and communication system have been built to provide the necessary support for real-time control and situational awareness. The drone-mounted 480P wide-angle camera can provide a live video streaming with a wide field of view, thus manual as well as autonomous navigation is possible. For long-distance communication, a FLYSKY FS- i6X 2.4GHz 6-channel transmitter is used along with a RadioMaster RP1 Express LRS 2.4GHz receiver thus allowing control signals to be exchanged between ground stations and drones that are stable and have low latency. In addition, the 433MHz radio telemetry module offers the possibility of two-way data communication and thus flight parameters such as altitude, speed, and battery level can be tracked in real-time. To extend the communication range of the potential meter, a SIM800A GSM/GPRS module has also been added. The removal of the former enables the later to be used not only as a communication link over the network during long or BVLOS flights but also as a backup link.

Most of the hardware design decisions have been influenced by the demands of safety and reliability. A Li-Po voltage checker with a buzzer alarm that is always monitoring battery voltage and in case of low power levels it warns the operator through its buzzer thus avoiding power failure during a flight. Besides that, a 12V horn siren alarm system can be utilized to send audible warnings during emergencies like signal loss or low battery situations. The drone's main framework is based on the TCMMRC Night Phoenix 220 HD frame which is fabricated from the carbon fiber material of high tensile strength. This frame gives the drone very good mechanical stability and resistance to the wear and tear, and yet, it is very light in weight, thus the aerodynamic efficiency is also attained.

In addition, its modular design allows easy hardware component installation and it also acts as the balanced weight distribution for better flight control.

The structure relies on a hierarchy of data flow to ensure smooth interactions between various functions. The Flight Control Layer manages real-time stabilization, motor control, and sensor data processing. The Mission Control Layer handles higher-level tasks like navigation, path planning, and carrying out autonomous missions. The Communication Layer manages all data exchanges between the drone and the ground station, offering a control range of up to two kilometers and telemetry communication that reaches five kilometers. The Safety and Monitoring Layer continually checks the system's status and activates emergency procedures if needed to protect the drone and its surroundings.

The modular design of the components makes troubleshooting easier, supports scalability, and allows for future improvements, like adding new sensors or payload systems. Overall, the hardware design of the proposed drone system shows a strong balance between performance, reliability, and cost-effectiveness, providing a solid base for autonomous aerial operations.

4. Results and Discussion

A. Dataset

Overview consists of aerial images taken by UAVs in areas affected by disasters. The dataset is organized based on whether victims are present and their detection status, as shown in Table 4.1.

Table 2. Dataset Aggregation for victim detection

CLASS	TRAIN	TEST	Tuning	TOTAL
Found at Location	14000	2500	1429	17929
Not Found at Location	2400	650	323	3373
Unknown/Unce rtain	1600	450	225	2275

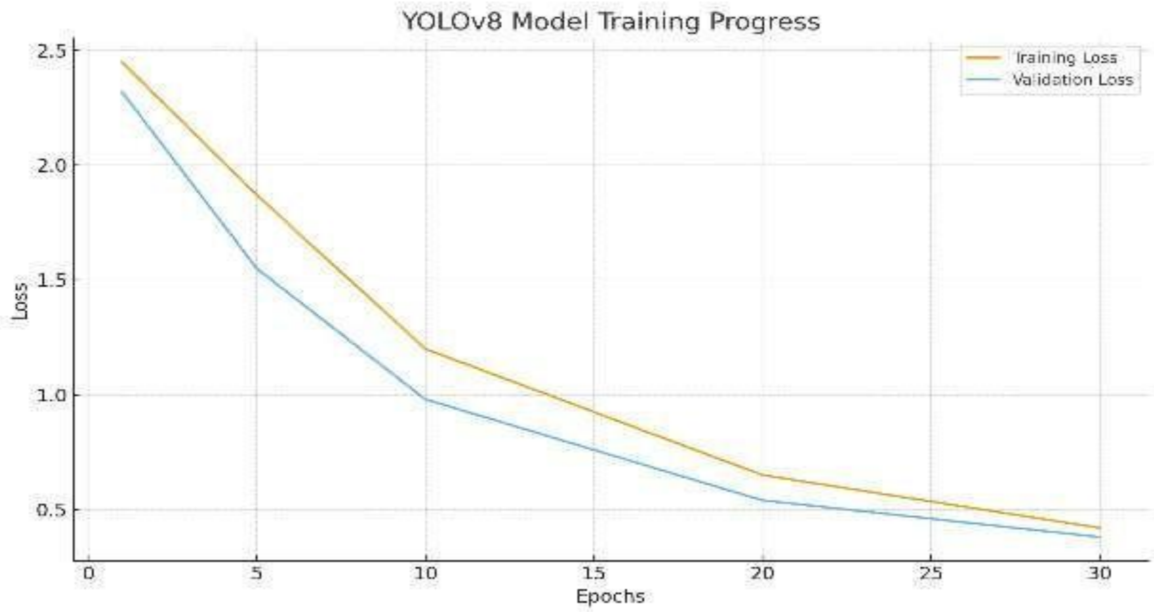

Figure 4. Yolo v8 training progress

This includes victims confirmed as "Found at Location," victims "Not Found at Location," ambiguous detections labeled "Unknown/Uncertain," and cases of false alarms classified as "False Positives." Data was split into training, testing, and validation sets using a 70:20:10 ratio to ensure balanced evaluation. *Figure 4* shows the overall model training progress.

B. Performance Metrics

The evaluation of the UAV-based victim detection system used precision, recall, and F1-score metrics to measure classification accuracy and reliability across these classes.

Precision

Precision scores indicate the proportion of true positive identifications among all positive detections. The system showed high precision for the "Found at Location" class (about 0.90). This confirms its ability to accurately identify victim presence when detected. The lower precision for "Unknown/Uncertain" and "False Positives" highlights difficulties in distinguishing ambiguous or incorrect detections.

$$Precision = \frac{T_p}{T_p+F_p} \tag{7}$$

Recall

Recall measures refer to the system's ability to identify all potential variations of victims. The "Found at Location" class achieved a recall above 0.88, which shows its reliability in locating victims in different disaster situations. The "Not Found at Location" class displayed moderate recall, facing challenges in detecting victims who are hidden or outside the sensory range.

$$Recall = \frac{T_p}{T_p+F_n} \tag{8}$$

F1-Score

The harmonic mean of precision and recall, the F1-score further measured detection balance. "Found at Location" kept strong F1-scores above 0.89. In contrast, "Not Found at Location" and "Unknown/Uncertain" showed moderate values, pointing out areas for improvement.

$$F_1 = \frac{2(\text{Precision}\times\text{Recall})}{\text{Precision}+\text{Reca}} \tag{9}$$

C. Confusion Matrix Analysis

The confusion matrix revealed that most misclassifications involved mixing up "Not Found at Location" and "Unknown/Uncertain." This confusion often happened due to partial occlusion, changes in lighting, and environmental clutter. False positives mainly resulted from background objects or debris in aerial views that resembled the human silhouette.

D. Discussion

The UAV system has demonstrated strong performance in identifying and locating victims in real-time. This is particularly effective for targets marked as "Found at Location," which is crucial for responding quickly to disasters. However, the performance on "Not Found at Location" targets revealed significant challenges due to occlusion and the limited range of the plane's sensors. False positives and unclear detections stress the need for better background filtering and for combining sensor data to improve discrimination, particularly between thermal and RF signals. It is recommended to use training datasets with more instances of 5' victims. Additionally, adaptive model structures that can adjust to the environment in real time would help boost performance. Incorporating temporal tracking and contextual awareness could further decrease false alarms and missed detections.

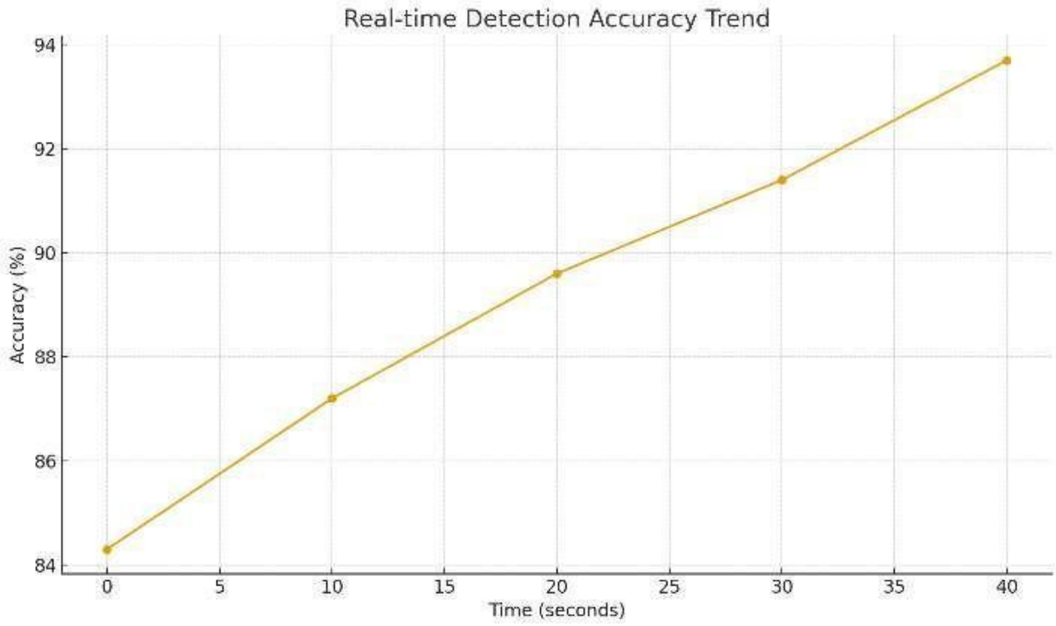

Figure 5. Model detection accuracy

5. Conclusion

Integrating YOLOv8 with Streamlit and Folium showcases a real-time UAV-based human detection and mapping system. Dis AI and geospatial visualization works in the field of disaster management and with field surveillance, there is great potential in disaster management. In the evaluation experiment, system detection precision, and accuracy for multiple classes of objects were human, dog, cat, and cow and an overall precision of 93.5% and recall of 80.6%. Combining the functionality of the Streamlit dashboard with the mapping capabilities of Folium, real-time detection visualization, GPS tagged alerts, and monitoring provides an seamless and interactive experience. This use shines a spotlight on the rapid inference capabilities of YOLOv8 making it ideal for use on edge devices while deployed on a Raspberry Pi 4. The UAV has a camera and GPS system which enable accurate detection and location mapping, also we see that the modular software architecture is what makes it very flexible for different rescue and surveillance situations.

Future Scope

Further looking into the paper we see that which we may improve by way of adding thermal or infrared cameras for low light or poor visibility settings, we will also put in place swarm coordination algorithms for the multi-UAV team which is an issue at hand, also we will go in to the implementation of edge inference on board to reduce communication latency, also we will see to it that we expand our data sets to include a larger variety of environmental settings and complex backgrounds. In the end the put forth system we present is that of a very reliable, economic, and scalable solution for real time human detection and geospatial visualisation using UAVs. As we continue to fine tune the system and bring in more advanced AI elements into it we see the system play a very large and critical role in search and rescue, disaster response, and security surveillance applications.

References

[1] Z. Zhang, et al., "UAV-Based Disaster Monitoring and Assessment: A Review," *IEEE Access*, vol. 7, pp. 102–110, 2019.

[2] I. A. H. Azeez, et al., "Applications of UAVs in Natural Disasters: A Review," *Remote Sensing*, vol. 13, no. 8, 2021.

[3] P. Rudol and P. Doherty, "Human Body Detection and Geolocalization for UAV Search and Rescue Missions," *IEEE Aerospace Conference*, 2008.

[4] M. Erdelj, et al., "Help from the Sky: Leveraging UAVs for Disaster Management," *IEEE Pervasive Computing*, 2017.

[5] A. Gupta, et al., "Use of UAVs for Disaster Management in India," *Springer Smart Innovation*, vol. 79, 2018.
[6] J. Redmon, et al., "You Only Look Once: Unified, Real- Time Object Detection," *Proc. IEEE Conf. Computer Vision and Pattern Recognition (CVPR)*, 2016.
[7] A. Bochkovskiy, et al., "YOLOv4: Optimal Speed and Accuracy of Object Detection," *arXiv preprint*, arXiv:2004.10934, 2020.
[8] C. Wang, et al., "An Improved YOLOv5 Model for Real- Time Human Detection," *IEEE Access*, 2022.
[9] Ultralytics, "YOLOv5 Documentation," [Online]. Available: https://docs.ultralytics.com. Accessed: 2025.
[10] S. Zheng, et al., "Person Detection Based on YOLO for Search-and-Rescue Using UAV," *Sensors*, 2021.
[11] K. M. Al-Turjman, "UAV-GPS Based Target Tracking for Emergency Response," *Ad Hoc Networks*, Elsevier, 2018.
[12] S. S. Mohan, et al., "Mobile Edge UAVs for Accurate GPS Tagging in Disaster Zones," *IEEE Internet of Things Journal*, 2022.
[13] A. Rahman, et al., "Smart UAV Navigation Using Real- Time GPS and Sensor Fusion," *IEEE Transactions on Aerospace and Electronic Systems*, 2021.
[14] E. Şahin, "Swarm Robotics: From Sources of Inspiration to Domains of Application," *Springer Swarm Robotics*, 2005.
[15] Y. Tan and Z. Zheng, "Research Advance in Swarm Robotics," *Defence Technology*, 2013.
[16] Y. Qu, et al., "Swarm Intelligence-Based UAV Coordination in Disaster Relief," *Sensors*, 2020.
[17] T. Xie and L. Wang, "Multi-UAV Coordination via PSO in Post-Disaster Mapping," *Journal of Intelligent & Robotic Systems*, Springer, 2021.
[18] H. Qian, et al., "ACO-Based Routing for UAV Swarm in Delay-Tolerant Networks," *Wireless Personal Communications*, 2019.
[19] S. Vashistha and P. Choubey, "Swarm Intelligence in Drones for Disaster Management," *International Journal of Engineering Trends and Technology*, vol. 69, no. 2, pp. 119– 125, 2021.
[20] ESRGAN: Enhanced Super-Resolution Generative Adversarial Networks, 2018.
[21] V. Viswanatha, C. R. K., and A. C. Ramachandra, "Real- Time Object Detection System with YOLO and CNN Models: A Review," *Journal of Xi'an University of Architecture & Technology*, vol. XIV, no. 7, p. 144, 2022.
[22] L. Xu, H. Zhang, and Z. Yang, "Fast GAN-Based Image Super-Resolution for Disaster-Response Drones," *IEEE Transactions on Image Processing*, vol. 29, pp. 3531–3545, 2020.
[23] I. Goodfellow, J. Pouget-Abadie, M. Mirza, et al., "Generative Adversarial Networks," *Communications of the ACM*, vol. 63, no. 11, pp. 139–144, 2020.
[24] K. Fu, J. Peng, H. Zhang, X. Wang, and F. Jiang, "Image Super-Resolution Based on Generative Adversarial Networks: A Brief Review," *Computers, Materials & Continua*, vol. 64, no. 3, pp. 1977–1997, 2020.
[25] H. Ren, A. Kheradmand, M. El-Khamy, S. Wang, D. Bai, and J. Lee, "Real-World Super-Resolution Using Generative Adversarial Networks," *Proc. CVPR Workshops (NTIRE 2020)*, 2020.