CHAPTER VI

SMART DRONE NETWORKS: REVOLUTIONIZING SEARCH AND RESCUE OPERATIONS WITH MACHINE LEARNING AND MODULAR DESIGN

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1. Introduction

Natural disasters such as earthquakes, floods, and wildfires set up significant challenges to search and rescue (SAR) operations. In these critical situations, the ability to locate and provide aid to trapped people is often prevented by environmental obstacles, limited accessibility, and the inefficiency of conventional rescue methods (Yilmaz & Demiröz Yildirim, 2020). This delay can turn out to be a disadvantage in the provision of services where SAR teams take time assessing the affected areas, identifying victims, and delivering care. This primarily leads to delayed responses and increased fatalities (Piatt, 2024) (Administrator, 2024).

Unmanned Aerial Vehicles (UAVs) have become a viable way to improve SAR missions. Drones offer rapid deployment, aerial monitoring, and the ability to navigate hazardous terrains without risking human and rescuers' lives. The efficiency of UAV systems is further increased by integrating artificial intelligence (AI), which makes it possible for automated victim detection, real-time decision-making, and autonomous navigation. SAR teams can greatly increase the success rate of rescue operations by using AI-powered drones to rapidly recognize and detect victims, evaluate their conditions, and deliver necessary supplies.

One of the major challenges in SAR missions is the difficulty in locating victims, especially in areas with debris, collapsed buildings, or flooded regions where visibility is severely limited (*How search and rescue teams pull survivors from rubble* 2021) (Jones et al., 2023). Traditional drone searches are slow and unreliable because they require people to watch hours of video footage; also, human eyes cannot identify victims clearly (Papyan et al., 2024). Even after someone is found, getting them help quickly can be tough because of tricky logistics and unpredictable weather (Pyrro et al., 2021).

This chapter introduces a UAV-based rescue platform (drone carrier) to help in disasters for rescue and relief operations. This smart, automated system is built to respond quickly and effectively. The Primary Carrier-UAV (PC-UAV) will be equipped with a camera, while an onboard AI model, trained to detect human presence in complex disaster-stricken areas, will process the real-time video stream to identify victims and estimate their precise coordinates. The analyzed data will then be transmitted to the ground control station for further action.

The PC-UAV will deploy two small helper drones. Each helper will carry a package with a first aid kit, high-energy food, water, and instructions on what to do in a specific emergency. Each little drone will also have a built-in speaker and microphone, so rescuers can talk directly to people in need, assess their conditions, and give them instructions and guidance. This system uses multiple drones to ensure help goes where it is most needed, giving people caught in a disaster area the best chance of survival. Figure 1 demonstrates the payloads that each small helper drone can carry.

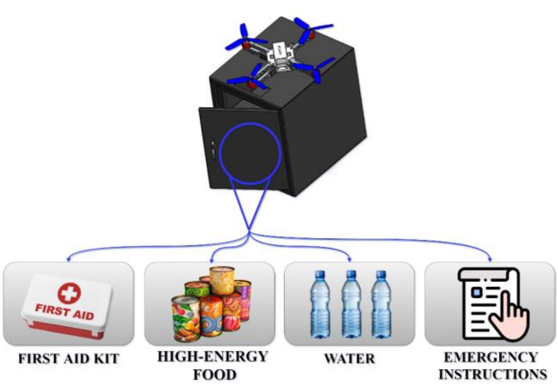

Figure 6. The possible payloads of the small helper drone

This chapter explores several advances that will help the field of autonomous SAR operations:

I. AI-Powered Human Detection

o To increase detection accuracy in difficult and complicated environments, a deep learning model will be implemented and trained to automatically identify and locate victims in real-time, reducing the requirement for human operators with high error merging.

II. Autonomous Multi-Drone Deployment Algorithm Development

o Developing algorithms to manage and control a coordinated system where the PC-UAV strategically sends smaller drones based on detected victim locations, optimizing rescue efforts.

III. Integrated Communication System

o Equipping the small drones with a two-way voice communication system to facilitate real-time interactions between victims and rescue teams to be able to collect data regarding the environment and the victims.

IV. Rapid and Targeted Aid Delivery

o Improving survival rates and reducing rescue delays by ensuring victims receive necessary supplies as fast as possible.

2. Literature Review

Drones or UAVs have been incorporated as integral parts of almost all industries because of their functionalities and modern capabilities. Knowing about their mechanical design, control systems, fly time, and performance optimization will help harness their efficient application in disaster relief, surveillance, and logistics. The mechanical structure of a drone is pivotal in determining its performance and suitability for specific tasks. Key components include the frame, propulsion system, and payload capacity. The frame must offer a balance between strength and weight, often utilizing materials like carbon fiber composites to enhance durability while minimizing mass. The propulsion system, typically comprising brushless motors and propellers, is selected based on the desired thrust and efficiency. To achieve optimal performance, designers must temper the motor and propeller combination carefully, taking into account such variables as thrust-to-weight performance ratio and aerodynamic efficiency. For example, increasing battery capacity would effectively allow flight time to be extended; however, this added weight requires a design loop to take place for balancing all components to fit the required performance (Staff, 2023). The flight control system in a drone consists of sensors, processors, and actuators, which gather the input of the pilot and environmental data and act upon it in real-time. This combination allows the drone to perform intricate maneuvers and remain stable in flight. Advanced control algorithms ingest the data from different sensors, such as accelerometers, gyros, and GPS modules, to modulate motor speeds and control surfaces, thereby ensuring accuracy in navigation and responsiveness (Magdolna, 2024). Flight time is another major factor that is dependent on battery capacity, weight, and aerodynamic configuration. Depending on their design and operational purpose, electric drones usually have flight times measured in 10s of minutes to a bit more than an hour. Prolonging flight time could be an exercise in minimizing weight, maximizing aerodynamic efficiency, or using power sources that pack much energy into a very small weight. However, sizing up battery capacity also increases weight, which is a trade-off designers need to look after. To make longer-endurance flights a reality, technologies like variable-pitch propellers and hybrid power systems are being researched (Mueller et al., 2022). These days, drones have great features, including the ability to take videos, broadcast in real-time to ground control and navigate autonomously. It further enables using drones in applications such as aerial photography, agricultural monitoring, infrastructure inspection, and emergency response to various situations. In the most recent innovations, AI and machine learning (ML) have been heavily integrated, increasing the drones' task-performance capabilities, such as recognizing and detecting objects, building maps of the environments, and planning adaptive courses of flight, hence increasing their usefulness across several industries (Gronemeyer, 2024).

AI indeed has an evolutionary past from which it moved from pure theory into practice-based applications across many industries. Considering the capabilities that unmanned aerial vehicles already offer due to AI consolidation in operation, AI integration has revolutionized capabilities, particularly enhancing and improving search and rescue (SAR) operations. The development of AI started in the middle of the 20th century when attempts were made to create a level of intelligence comparable to that of humans in machines. In the last few decades, AI has emerged as a tool for solving complicated real-life problems through advancements in computing power, data availability, and algorithm development. In this situation, integrating AI technologies allows for

UAVs and drones to execute tasks autonomously without much human involvement and increase operational efficiency. Drones equipped with AI can maneuver through complicated environments, detect and follow objects, as well as execute time-sensitive decisions based on the information gathered from their sensors. The relationship between AI technology and drones will push drone operations toward an autonomous mission application far beyond manual remote control (PAL et al., 2023).

2.1 Advantages of AI in Drones for Search and Rescue Operations

In SAR missions, time is critical, and the ability to quickly locate and assist victims can save lives. Integrating AI with drones presents numerous advantages in this regard:

I. **Autonomous Navigation:** AI allows drones to fly through complex environments without human intervention, guaranteeing that they will be able to reach areas inaccessible or dangerous to rescuers' lives (Skarka & Ashfaq, 2024).

II. **Real-Time Data Processing:** By using AI, drones can process their sensor inputs in real-time to detect the presence of a human by means of heat signatures or motion and efficiently relay that information to rescue teams (Pal et al., 2024).

III. **Advanced and Innovative detection and recognition of objects:** With the aid of ML algorithms, drones can now distinguish between a human and anything else, thus eliminating false positives and concentrating the rescue efforts on the area at most risk (Chen, 2024).

IV. **Coordinated Multi-Drone Operations:** AI technology holds the potential to assist in the coordination of multiple drones into a harmonious fleet, which will speed up the process of covering vast areas in a way that is much more efficient than traditional practice (et al., 2024).

Integrating AI into UAVs has transformed how SAR operations are carried out, driving them to efficiency and effectiveness. It is noted that as AI technology keeps on advancing, its role in aircraft is expected to increase even more in enhancing the capacity of drones under critical missions.

The techniques in image processing and computer vision (CV) have taken the capabilities of UAVs to an entirely new level, particularly enhancing their operational capabilities during SAR operations. These technologies make drones out key instruments in emergency situations by autonomously detecting, identifying, and tracking objects or individuals in very complicated settings. The fusion of computer vision and ML provides further capabilities such that drones become the most versatile people in understanding visual data and taking quick decisions while in the middle of a mission. Adding to this, a huge number of images can now be processed by UAVs to differentiate between various objects and find a point of interest without any human intervention. For example, the Automated Drone Image Analysis Tool (ADIAT) uses algorithms that are programmed to automatically identify digital images captured during search and rescue missions "areas of interest," thereby making the analysis process easier and lightening human operators (*Automated Drone Image Analysis Tool* 2024).

2.2 Applications in Search and Rescue Operations

In SAR operations, the timely and accurate location of missing people is critical. Computer vision-equipped drones have made these missions much easier through several key applications:

I. **Autonomous Person Detection:** Advanced Deep Learning Algorithms were developed to automate aerial person detection (APD). For instance, the Aerial Inspection RetinaNet (AIR) algorithm has shown state-of-the-art performance in the detection of people from aerial footage while improving precision and speed for SAR missions (Pyrro et al., 2021).

II. **Thermal Imaging Integration:** Drones can now detect the heat signatures of humans by merging thermal imaging with computer vision. This is particularly useful in cases of low visibility or very dense terrain. Such a capability has been used quite successfully in searching for missing people in relatively harsh surroundings, as in the case of thermal imaging drones used in the Adirondacks to locate lost pets (Schneider, 2025).

III. **Enhanced Image Analysis:** Computer vision tools are used productively for carrying out analysis on images captured from drones. For instance, open-source applications serve to ease the analysis of UAV images, hence assisting in identifying objects of interest in SAR operations (diesirae200, 2024).

However, technology is still facing various issues that do not allow the use of drones equipped with computer vision for rescue operations. Some of the issues having a general impact on how effective CV and ML models might perform, include the kind of data collected and how relevant it is. Recommendations were made with the aim of optimizing drone imagery acquisition to make it more suitable for CV/ML post-processing, presenting considerations for image resolution, lighting conditions, and environmental factors (Murphy & Manzini, 2023). The next important thing is that in such real-time scenarios, much computation is involved in processing data. Solutions for edge computing and ways to build more efficient algorithms have yet to be investigated. Moreover, adverse weather conditions, dense foliage, and other environmental obstacles can impede the effectiveness of visual sensors. Research into multimodal sensor integration and robust image processing techniques continues to mitigate these challenges. To conclude, image processing and computer vision have greatly augmented the effectiveness and efficiency in the conduct of SAR missions with UAV systems. Research is ongoing to further explore the scope of these technologies and innovations for improving and extending their reliability and autonomy in serious emergencies.

While training the ML model for the project, **DenseNet201** architecture has been selected as a model architecture due to its superior performance in feature extraction and classification tasks, which makes it well-suited for SAR operations. Compared to other architectures, DenseNet201 demonstrates significant advantages. It has been demonstrated that InceptionV3, which is known for its computational efficiency, profits from fusion with DenseNet201 in tasks like breast cancer classification, showing the latter's endurance in obtaining significant features (Ge et al., 2024). Similarly, while ResNet effectively addresses deep network training challenges through residual connections, DenseNet201’s densely connected layers improve feature propagation and parameter efficiency, leading to higher accuracy in image classification tasks (Salim et al., 2023). These strengths make DenseNet201 a more reliable choice for SAR, where precise feature extraction from aerial and satellite imagery is critical for detecting missing persons, obstacles, and important terrain details.

Object detection and recognition play a very important role when it comes to the autonomy and efficiency of UAVs in SAR operations. The various algorithms for object detection have become popular amongst others within the "You Only Look Once" (YOLO) family for real-time processing and accuracy. These algorithms were first proposed in 2015 by Joseph Redmon et al., redefining detection techniques by presenting the issue as a single regression argument, which made the detection faster and more accurate. Over the years, YOLO has changed several iterations over time, each enhancing performance and efficiency:

- **YOLOv1:** Launched in 2015, it utilized a single convolutional neural network (CNN) to predict multiple bounding boxes and class probabilities directly from full images, achieving unprecedented speed.
- **YOLOv2 and YOLOv3:** These iterations improved speed and accuracy by introducing features like multi-scale predictions, batch normalization, and anchor boxes.
- **YOLOv4 and YOLOv5:** Focused on optimizing training strategies and network architecture, features like mosaic data augmentation and cross-stage partial connections were included in these versions.
- **YOLOv6 and YOLOv7:** Model efficiency and real-time performance were improved, and YOLOv7 achieved state-of-the-art scores on several benchmarks.
- **YOLOv8:** The most recent version of 2025, YOLOv8, offers modular plug-and-play optimization that enhances real-time efficiency while maintaining exceptional accuracy, making it perfect for UAV applications in SAR operations (Zhao et al., 2024).

The swift and accurate detection and recognition of objects or people is a primary consideration during any SAR operation. Thus, this marks the best suitability of newer versions of YOLO algorithms, where speed is balanced with precision. For instance, studies have demonstrated the effectiveness of YOLOv8 in maritime rescue scenarios, where real-time detection of individuals in distress is critical (Zhao et al., 2024). The major requirements to fulfil operational needs for SAR are real-time processing, accuracy under any situation, and efficient use of resources. Considering all these criteria, it is safe to say that YOLOv8 is the best choice. Its modularity allows customization of our drone's hardware capabilities, and it has been shown to work in similar applications, establishing its validity. Thus, YOLOv8 implementation would allow our UAV to identify and locate a person in a disaster-riddled area, thereby increasing the chance of successful rescue missions. The continuous advancement of algorithms in the YOLO family has greatly enhanced the capabilities of UAVs in SAR operations. With YOLOv8, the real advantages of a modern object detection system will be realized and put to the great advantage of improving response time and success rate in the most important rescue operations.

In the realm of SAR operations, effective communication between rescuers and victims is extremely important. Traditional communication systems usually have drawbacks such as limited range, damage to infrastructure, and difficulty created by the environment. Such problems may cause a loss of communication entirely during a disaster response. An examination by IGEM for the Queensland 2023-2024 extreme weather season reports glaring deficiencies in disaster response capabilities, including poor coordination and communication among local, state, and federal agencies that have resulted in confusion and inefficacious emergency responses (*It's a disaster: Damning report exposes how system let Qld down* 2025). Additionally, research indicates that existing communications infrastructure is often impaired, destroyed, or overwhelmed during disasters, necessitating the use of substitute communications solutions that may have less sophisticated security characteristics (Alvarez et al., 2016). To address these issues, our project has developed an innovative two-way voice communication system utilizing **NRF24L01** RF modules and **Arduino Nano** microcontrollers, enhancing the capabilities demonstrated in the existing literature.

The NRF24L01 is a low-cost, 2.4 GHz RF transceiver module widely used for wireless communication in various applications. When paired with Arduino microcontrollers, it facilitates reliable data transmission over considerable distances. Previous implementations have primarily focused on basic data exchange between two points, such as remote-control systems for drones and wireless sensor networks. For instance, projects have demonstrated the use of NRF24L01 modules with Arduino Nano boards to create wireless communication links for controlling drones and other remote devices (Indoorgeek & Instructables, 2021). Furthermore, a project has been done by the (GreatScottLab & Instructables, 2020) by using the generic 433MHz RF modules that utilized a functional Walkie-Talkie. Based on these principles of NRF24L01 communication, our system has several significant improvements for specific SAR operations:

- **Small Drones Equipped with Voice Communication**: As seen in Figure 2, each small drone has been installed with a single microcontroller and an NRF24L01 module that would afford two-way voice communication so that rescuers have the possibility of contacting victims directly, enabling them to provide further assurances for them and to solicit their conditions and locales.

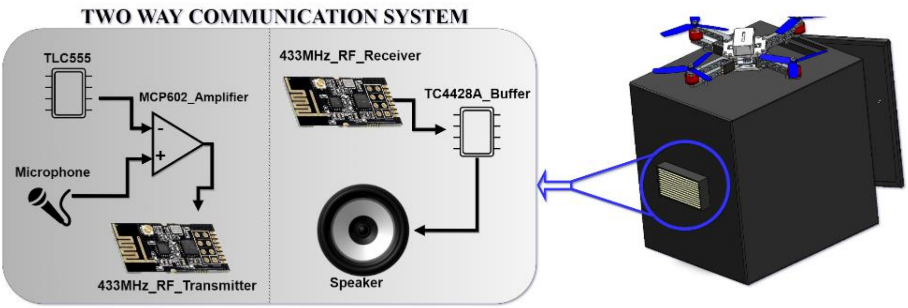

Figure 7. Two-way voice communication system

- **The PC-UAV as a Communication Relay**: The PC-UAV extends communication range over 3 kilometers. It relays small drones' signals to the ground control stations, ensuring constant communication, even in challenging terrains where a direct line of sight may not be possible.
- **Ground Control Station for Real-Time Interaction**: Using the relay system, operators at the ground control station communicate with victims in direct conversation. Such real-time interaction gives a clear view of the situation for immediate assessment and informed decision-making on the rescue mission.

A further important component is the selection of the appropriate flight computer for UAVs' performance and reliability. Their flight computer must execute real-time data processing, enable advanced ML algorithms, and interface with an array of sensors and communications modules. Earlier, our system was based on a USBC Google Coral attached to a Raspberry Pi 4. The configuration was the optimum power and energy-efficient delivery using ML models for object detection and recognition tasks. Raspberry Pi 4 computer, built with a quad-core ARM Cortex-A72 processor, offers a different platform for many applications. When associated with the Google Coral USB Accelerator with Edge TPU designed for high-speed inferencing of the TensorFlow Lite model, it achieved goodness in processing speed. The system is found fit in SAR missions, where drones with the respective hardware configuration are independently capable of detecting and tracking missing humans. A project cited on Hackster.io talks about an autonomous drone utilizing the Coral Edge TPU to effect SAR operations, thus practically demonstrating the benefits of the hardware combination (Bernas, 2022).

3. Methodology

3.1. Building the PC-UAV

Building an efficient and reliable drone for SAR operations involves carefully selecting components to meet specific performance criteria. This section outlines the drone's construction methodology, focusing on motor selection, frame choice, communication systems, and other essential components.

I. Motor Selection

Choosing the appropriate motors is critical to ensure the drone can lift the required payload and achieve the desired flight time. In this chapter, the **Tarot 4108 380KV Brushless Motors** have been selected (*Tarot 4108 380kv 6s brushless motor for RC Drones TL68P07*).

Specifications of Tarot 4108 380KV Motor:

- **KV Rating**: 380 RPM/V
- **Maximum Thrust**: 1620g per motor
- **Weight**: 93g
- **Recommended Propeller Size**: 15-17 inches
- **Operating Voltage**: 6S LiPo (22.2V)

Thrust and Power Calculations (rsr_17, 2022) (MrNams, 2021):

The total weight the drone needs to lift includes the weight of the carrier drone (5 kg) and two small drones (2 kg each), totaling 9 kg. With an octocopter configuration (8 motors).

$$Required\ Thrust\ per\ Motor = \frac{Total\ Weight}{Number\ of\ Motors} \tag{1}$$

$$= \frac{9000g}{8} = 1125\ g$$

According to equation (1), each motor must provide at least 1125g. The Tarot 4108 380KV motor provides a maximum thrust of 1620g, which is sufficient for our requirements.

Flight Time Estimation:

Using a 6S 20000mAh LiPo battery, by using equation (2) the total energy available is:

$$Total\ Energy = Battery\ Voltage \times Battery\ Capacity \tag{2}$$

$$= 22.2V \times 20Ah = 444Wh$$

Assuming an average power consumption of 1200W during hover (as per frame and total weight specifications), the estimated flight time is:

$$Flight\ Time = \frac{Total\ Energy}{Power\ Consumption} \tag{3}$$

$$= \frac{444\ Wh}{1.2\ kW} = 0.370\ hours = 22.2\ minutes$$

According to equation (3), the estimation indicates a flight time of approximately 22 minutes which is below the desired 30 minutes. Factors such as reducing the overall weight, optimizing motor efficiency, or increasing battery capacity will be considered to achieve the target flight time.

II. Frame Selection

The **Tarot X8 TL8X000 PRO 8-Axis Frame** has been chosen for its robustness and suitability for SAR operations (*Tarot x8 heavy lift octocopter frame TL8X000*).

Benefits:

- **High Payload Capacity**: Designed to support up to 10 kg takeoff weight, accommodating the drone's weight and additional payloads.
- **Folding Design**: Features a 5-degree umbrella-type folding arm, facilitating easy transportation and rapid deployment.
- **Retractable Landing Gear**: Equipped with electric retractable landing gear, which provides a stable platform during takeoff and landing and minimizes obstruction to onboard sensors during flight.

These features make the frame ideal for SAR missions, where quick deployment and adaptability are crucial.

III. Two-Way Voice Communication System

Establishing reliable communication with individuals in distress is vital. We have implemented an innovative two-way voice communication system using the **NRF24L01 RF module** paired with **Arduino Nano** microcontrollers.

Implementation:

• **Small Drones**: Each one is equipped with an NRF24L01 module and an Arduino Nano to facilitate voice communication.

• **The PC-UAV**: Acts as a relay station, extending the communication range up to 3 km. Figure 3 demonstrates the concept.

Figure 8. The PC-UAV relay station system

• **Ground Control Station**: Operators can communicate directly with victims, gathering critical information in real-time.

This setup is innovative, and it provides a cost-effective and efficient solution for extended-range communication in SAR operations.

IV. Additional Components

• **GPS Module**: The Ublox NEO-M8N GPS module is used for accurate positioning and navigation.

• **Telemetry System**: Incorporating **3DR telemetry modules** for real-time tracking and data transmission between the PC-UAV and ground control.

• **Flight Controller**: The **Pixhawk 2.4.8** flight controller is selected for its open-source architecture, reliability, and extensive community support, ensuring robust flight performance and flexibility for customization.

• **Propellers**: Equipped with **17-inch propellers**, which are optimized for efficiency and thrust to support the drone's payload.

• **Onboard Processing**: A **Raspberry Pi 4** combined with a **Google Coral USB Accelerator** is used for real-time image processing, enabling advanced computer vision tasks essential for identifying and locating individuals during SAR missions.

Each component has been carefully selected to ensure the drone meets the operational requirements of SAR missions, emphasizing reliability, efficiency, and performance.

3.2. Mechanical Design

Our drone's mechanical design prioritizes rapid deployment and reusability, two critical factors for effective SAR operations. The framework is based on the **Tarot X8 TL8X000 PRO 8-Axis Frame**, which offers significant advantages such as a high payload capacity, robust structural integrity, and modular assembly capabilities. In our design, we have innovated two key elements:

I. Modular Box System for Payloads

Each small drone is equipped with a dedicated box mounted underneath, designed to securely house essential aids such as first aid kits, high-calorie food, and water. Complementing this, the big carrier drone is fitted with a modular box holder. The design employs the frame's floor layers combined with two carbon fiber tubes; each tube supports a bracket that holds a box holder. This configuration enables quick assembly and deployment, allowing the small drones' boxes to be rapidly inserted or removed. This modular approach will not only ensure that payload exchange is simplified but also the efficient reuse of the PC-UAV; after these initial two small drones have been deployed, it returns to ground control for rapid reload and deployment of another pair, thus minimizing the downtime between two successive missions.

II. Quick-Release System for Rapid Assembly

The integration of a quick-release mechanism in the carrier drone's design is a key innovation. By using standardized floor layers and carbon fiber tubes, our design permits the attachment of additional carrier modules above the big drone with minimal effort. An integral part of the system used for first responders after a disaster is that it greatly reduces the time interval between the occurrence of the disaster and the beginning of SAR operation. The reusability of the PC UAV, obtained through this modular quick-release system, further enhances operational flexibility by allowing the quick redeployment of small drones loaded with important supplies.

A better strength-to-weight ratio is one benefit of incorporating carbon fiber into the design, which is crucial for preserving flight efficiency and increasing operational range during rescue operations (Hert et al., 2022). Moreover, the modular quick-release design not only minimizes assembly time but also ensures that the system can be scaled and adapted to various mission requirements without extensive redesign, thus providing a robust and flexible solution in the unpredictable environment of disaster response (Rajoo et al., 2023). Together, these design innovations contribute to a highly adaptable and responsive UAV system, which is capable of rapid deployment and efficient payload management key attributes for improving outcomes in SAR operations. Figure 4 shows the system's overall working flow chart.

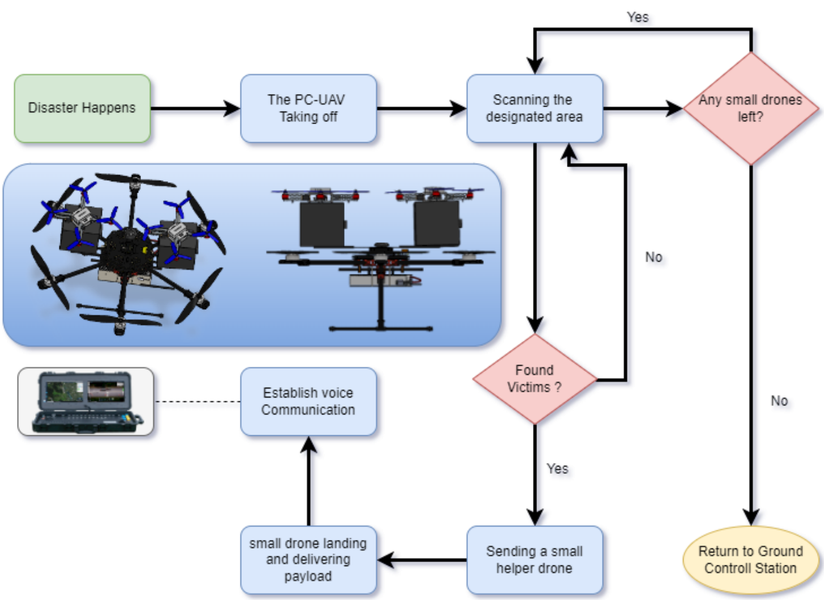

Figure 9. The system's overall working flow chart

3.3. Dataset Collection and Structure

For the development of our ML model, which was aimed at enhancing SAR operations by detecting human beings in complex areas, we used the **Disaster Images Dataset** available on Kaggle. To enable efficient model training and evaluation, this dataset contains a varied collection of photos showing various disaster scenarios that have been methodically arranged (Verma, 2021).

3.3.1. Dataset Overview

The Disaster Images Dataset contains images classified in accordance with the type of disaster, and then an image belonging to a disaster category is stored in a corresponding folder named after the instance of that specific disaster. The dataset also includes images classified as "no damage" for the control group, which is vital in training models to separate affected and unaffected areas concerning the disaster. Such a structure leads to building robust models with the ability to classify with precision among several disaster scenarios.

3.3.2. Data Distribution

The dataset, which includes images of various disasters and non-damage scenarios, is ideal for training our AI model to distinguish between areas affected by and not affected by disasters. The dataset is structured into **12 categories**, each representing a different disaster or non-damage scenario. Below in Table 1, the distribution of images per category is shown:

Table 5. Data distribution table

Disaster Type	Image Count
Drought	201
Earthquake	36
Human Damage	241
Infrastructure Damage	1,418
Landslide	456
Non-Damage Buildings & Streets	4,572
Non-Damage Forest	2,271
Non-Damage Human	120
Non-Damage Sea	2,274
Urban Fire	419
Water Disaster	1,035
Wildfire	514

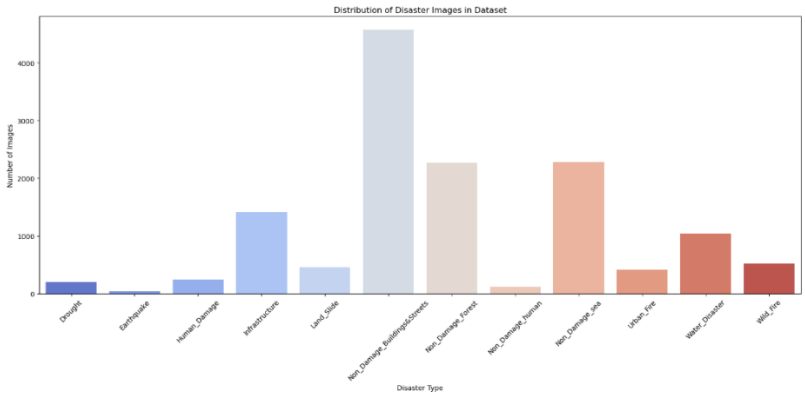

Figure 10. distribution of disaster images in the dataset

From this distribution, as demonstrated in Figure 5, we observe a significantly higher number of image counts in the non-damage categories, especially "Non-Damage Buildings & Streets" (4,572 images) and "Non-Damage Sea" (2,274 images). Some disaster categories, like "Earthquake" (which has only 36 images) and "Drought" (which has 201 images), on the other hand, have fewer images. Some disaster types that are underrepresented may be difficult for the model to identify because of biased training that has resulted from this imbalance. We intend to take this factor into account and use data augmentation techniques (for example, rotation, flipping, contrast adjustment, and synthetic data generation) to help better represent underrepresented disaster types. This would also aid the model in better generalization and enhanced accuracy in real-life SAR operations.

3.3.3. Data Quality and Preprocessing

The dataset comprises images sourced from various platforms, including news portals and social media, resulting in a wide range of image resolutions and qualities. To prepare the data for model training, several preprocessing steps are necessary:

I. **Resizing**: Standardizing image dimensions to ensure uniformity across the dataset; examples are shown in Figure 6.

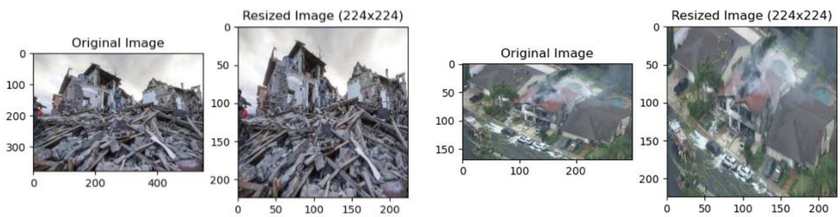

Figure 11. Resizing images to a fixed 224x224 size

II. **Normalization**: After resizing, normalization is done by adjusting pixel values to a consistent scale, typically between 0 and 1, to facilitate efficient model convergence, examples are shown in Figure 7.

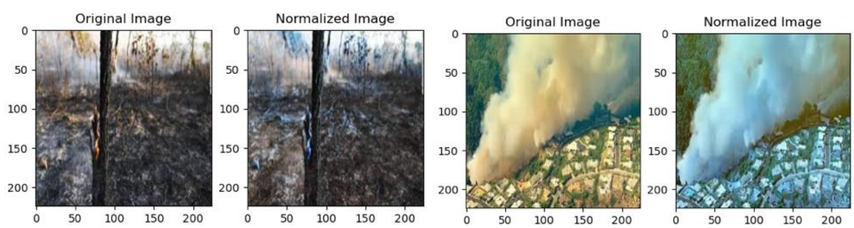

Figure 12. Examples after normalization

III. **Data Augmentation**: As shown in Figure 8, transformations such as rotation, flipping, and cropping have been applied to increase dataset diversity and enhance model generalization capabilities. The transformations included random 90-degree rotations, horizontal and vertical flips, random adjustments to brightness and contrast with (p=0.2), slight shifts, scales, and rotations, and finally, converting the image to a tensor.

IV. Noise Reduction: Noise reduction techniques have been applied to enhance image quality, specifically using Gaussian Blur for denoising. Gaussian Blur smooths the image by averaging pixel values with a Gaussian kernel, reducing high-frequency noise while preserving important structures. A kernel of 5×5 has been applied to the input image in order to effectively minimize random variations and improve clarity. Figure 9 shows an example of Gaussian Blur applied to two images.

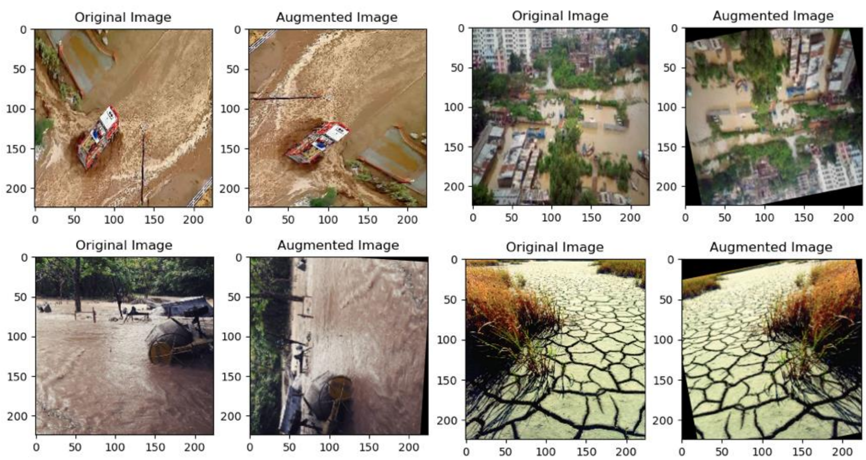

Figure 13. Augmentation examples

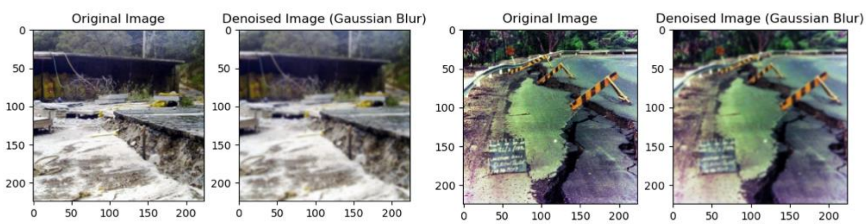

Figure 14. Denoised Images

V. Contrast Enhancement: Our preprocessing session focused on contrast enhancement using CLAHE (Contrast Limited Adaptive Histogram Equalization) to improve image visibility due to its benefits in challenging environments for SAR operations. By converting the image to grayscale and applying CLAHE with a clip limit of 2.0 and an 8×8 tile grid, we enhance local contrast while preventing noise over-amplification. This technique is valuable in SAR applications, where images often suffer from low contrast due to atmospheric interference or sensor limitations. Additionally, edge detection has been performed by converting images to grayscale, which is essential for feature extraction. So, the filtered images will be able to provide clearer details, aiding in target detection, terrain analysis, and overall situational awareness in disaster response operations. Figure 10 shows examples of enhanced contrast images.

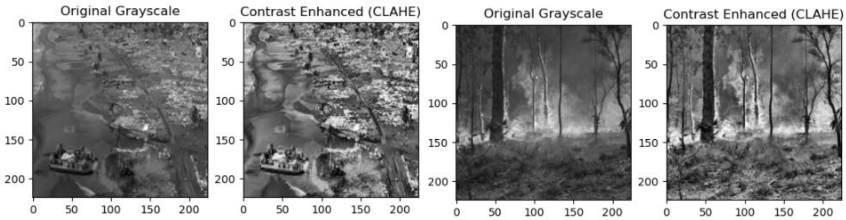

Figure 15. Contrast Enhanced images

These preprocessing steps have been implemented successfully, and they are very essential to maintain data quality and to optimize the performance of the ML model in real-world SAR applications.

3.3.4. Model Architecture

As mentioned earlier in the literature, the **DenseNet201** architecture**,** which is pre-trained on the ImageNet dataset, has been selected. Since it is among the top artificial neural network architectures for image recognition tasks, this approach is used for the model's training. It's a densely connected convolutional network known for its efficiency and performance in image classification tasks. DenseNet201 offers several advantages:

- **Efficient Feature Propagation**: In order to facilitate feature reuse and address the vanishing gradient issue, each layer receives inputs from all preceding layers.
- **Parameter Efficiency**: Dense connections make the model more effective and less likely to overfit by reducing the number of parameters needed.

The final layers for the Classification Layer include a global average pooling layer that reduces the spatial dimensions substantially to make them 1-dimensional for each feature map, thus reducing the chances of overfitting.

Thereafter, it followed a fully connected (dense) layer with 512 neurons and ReLU activation, which allows high-level features to be learned by the network and outputs the probability distribution over classes. It is also important to choose an appropriate optimizer for effective training of the models. After testing other alternatives, we decided to use Adamax which is a variant of Adam optimizer using the infinity norm. The studies show Adamax to be significantly stable and superior regarding different learning rates, making it a perfect match for our image classification task (Kandel et al., 2020). The model was trained using the Adamax optimizer with a learning rate of 0.0001, which combines the benefits of momentum and adaptive learning rates. In addition, we have adopted Categorical Cross-Entropy as the loss function, which is the common choice for multiclass classification problems. The specified function establishes the variance of the predicted probability distribution from the real distribution by the process of optimization. Figure 11 shows the workflow of the proposed system.

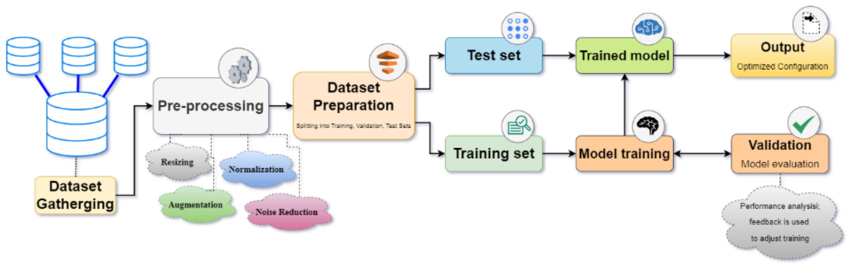

Figure 16. The workflow of the proposed system

3.3.5. Training Setup

For the training of the ML model, a machine with the following specifications was used:

- **Processor (CPU):** 11th Gen Intel(R) Core(TM) i7-1165G7 @ 2.80GHz, with a base clock of 2.80 GHz, which ensures efficient handling of multi-threaded tasks.
- **Memory (RAM):** The system is equipped with 16.0 GB of RAM (15.8 GB usable), supplying enough space to manage large datasets and execute memory-intensive operations while training.
- **Graphics (GPU):** The machine utilizes Intel(R) Iris(R) Xe Graphics.
- **Storage:** The system is equipped with a TOSHIBA-TR200 SSD with a capacity of 1 TB, ensuring fast data read and write operations.

- **Operating System:** Windows 11 Pro (Version 24H2, OS build 26100.3194), offering a stable environment with support for the latest software and tools necessary for deep learning workflows.
- **System Architecture:** The system uses a 64-bit operating system with an x64-based processor, which is ideal for running modern deep learning frameworks.

The given setup provides a very balanced model-training architecture to ensure fast data handling, efficient CPU functioning, and important AI framework support. This environment, equipped with software packages and compatible tools, was optimized for the hardware configuration around model training.

4. Results

As mentioned earlier, the training process was conducted on a system equipped with an Intel Core i7-1165G7 processor, and Intel Iris Xe Graphics. Due to the hardware limitations, the model training time was relatively high compared to systems equipped with dedicated GPUs.

4.1. Training Performance

Training of the model for 30 epochs with a batch size of 16 and an initial learning rate of 0.001 was conducted with a total training time of about five half hours, including forward and backward passes. Loss and accuracy values during training and validation are presented in Table 2.

Table 6. Training and Validation Performance Metrics

Epoch	Training Loss	Validation Loss	Training Accuracy (%)	Validation Accuracy (%)	Time per Epoch (min)
10	1.85	1.92	64.2	58.3	8.4
15	1.42	1.55	72.8	68.1	8.2
20	1.15	1.32	79.4	72.6	8.1
25	0.92	1.08	83.7	76.3	7.9
30	0.78	0.96	87.5	78.9	7.5

Seeing the results, we can infer that accuracy has been continuously improved and loss is reduced across the epochs; validation accuracy has been seen to be lesser than that of training accuracy at all epochs. This indicates some level of overfitting.

4.2. Comparison with Other Systems

In order to assess how good our model really is, we compared it with existing techniques used in search and rescue operations, particularly where human beings are very difficult to detect by using the model in very complex environments or disaster conditions. Table 3 presents a summary of the performance metrics of our proposed model alongside those reported in recent studies.

Our proposed model achieves moderate accuracy, but it lags behind other state-of-the-art approaches, especially CNN-based models, which have better results due to optimized architectures and hardware acceleration. For object detection tasks, the Vision Transformer and ResNet-50 models are well known for their effectiveness. Therefore, even though the proposed methodology performs satisfactorily, there is a need for refinement in accuracy and performance. The proposed future work would optimize the model architecture and the training optimizer for improved SAR performance, possibly through the introduction of ensemble learning methods or experimenting with advanced architectures like those of Vision Transformers.

Table 7. Comparison with Other Systems

Model / Study	Training Accuracy (%)	Validation Accuracy (%)	Training Time (hours)	Test Time per Image (s)
Proposed Model	**87.5**	**78.9**	**5.5**	**0.45**
CNN-Based (Dousai & Lonearic, 2022)	95.11	-	-	-
Vision Transformer (Jing Yuan et al., 2022)	94.7	88.5	6.5	0.42
ResNet-50 (Li et al., 2022)	90.8	83.2	5.8	0.41

4.3. Test Set Performance

For the final evaluation, the trained model was tested on an independent test dataset. The overall test accuracy and test time per image are shown in Table 4.

Table 8. Test Performance Metrics

Metric	**Value**
Test Accuracy (%)	**76.1**
Test Loss	**1.02**
Average Test Time per Image (s)	**0.45**

The final test accuracy is 76.1%, which is lower than the validation accuracy, indicating potential generalization issues. The inference time per image is approximately 0.45 seconds, which is relatively high due to the lack of GPU acceleration.

4.4. Summary of Findings

The eventual training accuracy was 87.5%, and the validation accuracy was 78.9, indicating some overfitting. The training took 5.5 hours, mostly because of the CPU limitations, while the test accuracy was 76.1, which is a clear alienation that the model struggles with generalization. The inference time per image was 0.45 seconds, making real-time deployment on the current hardware challenging. Compared to other models, the proposed system performs moderately well but falls behind CNN-based and Transformer-based architectures, which achieve validation accuracies above 90%. These results emphasize the complexity of training such models, as disaster area datasets are inherently difficult to process and require spatial environments for effective learning. Future improvements are going to focus on enhancing generalization, optimizing the training process, and exploring more advanced architectures to improve performance in search and rescue operations.

Figure 17. showcase the capability of the ML model

4.5. Model Visualization

The images in Figure 12 showcase the capability of our model to detect humans in different disaster scenarios. As mentioned before, it has been tried to train the model to recognize human beings in challenging environments, including earthquake ruins, wildfires, and flood situations. The red bounding boxes highlight the detected humans, along with confidence scores indicating the model's certainty in each detection. These visuals demonstrate the model’s robustness in identifying people across various conditions, such as low lighting, heavy water currents, and obstructed views. The ability to accurately detect individuals in such critical situations is crucial for search and rescue operations, improving response times and increasing survival rates. Our model employs state-of-the-art deep learning techniques to enhance disaster response efficiency, ensuring timely and accurate detection of victims in emergency situations.

5. Conclusion

This chapter introduced an AI-powered UAV-based SAR platform designed to improve disaster response efforts by autonomously detecting and aiding victims. Natural disasters such as earthquakes, floods, and wildfires have become severe threats to the effectiveness of traditional SAR methods in their application, primarily due to environmental obstacles, accessibility issues, and long response times in assessments for such disasters.

These challenges called for a better Advanced UAV system consisting of a Primary Carrier-UAV (PC-UAV) and two smaller assisting drones. The PC-UAV carried an onboard AI model trained for complex environments using real-time video processing to identify victims. In contrast, the helper drones delivered emergency supplies and established a communication link between the victims and rescue teams in both directions.

This methodology focused on the designing and building of a high-performance drone system wherein key mechanical and communication components would allow for efficient SAR operation. Mechanical design has been based on Tarot X8 TL8X000 PRO 8-Axis Frame with a modular payload system and quick-release assembly mechanisms for rapid deployment. The AI model was trained on disaster scenes using the Disaster Images Dataset on Kaggle to ensure exposure to multiple disaster scenarios.

The model was developed and evaluated on an Intel Core i7-1165G7 processor coupled with Intel Iris Xe Graphics with a net training accuracy of 87.5% and a validation accuracy of 78.9%, signifying some degree of overfitting. Having achieved a testing accuracy of 76.1%, with an inference time of 0.45 seconds per image, it did become difficult to deploy in a real-time fashion on current hardware. The results demonstrate the potential and limitations of AI-based SAR systems, suggesting future optimization for model generalization, training efficiency, and real-time processing.

5.1. Future Work

While the proposed AI-powered UAV-based search and rescue system demonstrates promising results, several areas for improvement and expansion remain. Future work will focus on enhancing the system's scalability, efficiency, and overall effectiveness in disaster response. Some improvements include further enhancements to the PC-UAV so it can fly longer and take up to four small UAVs. This feature will improve geographical coverage, minimize time response to emergencies, and allocate resources for rescue missions. Also, improvement in the payload capacity of small UAVs will be made in order to increase the quantity of essential life-saving supplies like medical kits, communication devices, and survival equipment. These improvements will result in the system's ability to provide immediate aid to victims.

Another critical area of advancement is the expansion of the dataset used for training the AI model. Using a more varied set of disasters, environmental conditions, and representations of victims will greatly enhance the generalization and actual victim-detection capability of the model.

Furthermore, using temporal information for detection improvements and decreased false positives could be achieved by converting an image-based detection system to video processing using LSTM networks with YOLO. This combination would construct a valid 4D training paradigm in which spatial and temporal features are learned concurrently.

Future studies may investigate the use of several deep learning models, including new versions of YOLO, Faster R-CNN, and MobileNet, to further increase detection efficiency and accuracy. Furthermore, integrating multiple models to produce an ensemble approach results in a detection method that is reliable as well as effective in a variety of disaster scenarios. Generalizing, improving the training, and investigating more advanced architectures would be other vital areas that require focus to ensure the system's real-time operational efficiency.

Finally, we will conduct a broad survey of hardware optimization techniques and edge computing solutions to enhance the system's real-time capabilities. An inference engine will be executed on stronger embedded hardware, such as NVIDIA Jetson modules, to reduce inference time and, hence, improve the system's responsiveness during SAR missions. Advances will evolve the proposed UAV-based SAR system into a well-rounded, intelligent, and effective solution for disaster response, saving even more lives and enhancing emergency management strategies.

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