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A Review of Smart Drone Technologies for Security Surveillance and Search and Rescue

Noof Ali Khashusha[a*], Mustafa Jawad Radif[b], Zainab Khyioon Abdalrdha[c]

[a, b] *College of Computer Sciences and Information Technology, University of A*l-Qadisiyah, Al-Qadisiyah, Iraq,

[a]master.student2410@qu.edu.iq, [b] mustafa.radif@qu.edu.iq

[c] *Mustansiriyah University, College of Basic Education, Department of Computer Science, Baghdad- Iraq , zainabkhyioon83@uomustansiriyah.edu.iq*

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ABSTRACT

Drones are increasingly being used in search and rescue operations due to their ease of use, wide coverage, and cost. Therefore, this research has faced challenges, including identifying human figures in aerial photographs, as these figures may be small and unclear, and are also affected by several factors, such as darkness or bad weather conditions, such as fog and dust, or because of debris resulting from disasters. One of the most important areas of research currently in vogue is the integration of drones with cloud computing systems and attackable devices. This integration leads to increased efficiency in emergency response. Furthermore, small, lightweight, and power-efficient embedded devices such as the Jetson Nano are powered by advanced portable AI systems that offer real-time analysis with the necessary precision and speed. This is an encouraging development in the field of application. In the field of computer vision, advancements have been made in detection models, such as the introduction of context enrichment modules to enhance the accuracy of small target detection. Efforts have also been made to create new databases, such as thermal imaging of partially occluded individuals, which contributes to filling a clear gap in available resources. In the field of multi-sensing, thermal and optical imaging are combined using transformer techniques to overcome the limitations of traditional convolutional networks, and acoustic sensing is used to identify human cries and characteristic signals in disaster environments. The novelty of these studies lies in the construction of new databases that support challenging rescue scenarios, the optimization of lightweight models to suit capacity-limited devices, and the potential for integrating drones with multiple sensing and communication channels (optical, thermal, acoustic, and wearable devices). These contributions also form the basis for developing practical frameworks that support future surveillance and search and rescue missions.

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1. Introduction

This section describes many parts, such as the problem background, limitations of traditional solutions and their causes, the proposed solution, and the scope and objective of the review.

*Corresponding author Noof Ali Khashusha

Email addresses: master.student2410@qu.edu.iq

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1.1 Problem Background

Recent years have witnessed a significant increase in the use of drones in search and rescue missions, as well as security operations, due to their efficiency in comprehensive aerial photography and the ability to access open and complex areas[1] . Despite these advantages, the task of detecting missing persons in drone images remains difficult due to the small size of the target in aerial images, the multiple shooting angles, and the height of the aircraft [2], [3]. Furthermore, some studies have addressed the fact that variations in lighting conditions and occlusion are an obstacle to the accuracy of traditional models.[4].

1.2 Limitations of traditional solutions and their causes

Manual inspection of aerial images is time-consuming and does not achieve real-time results [5], [6]. Classic methods based on manual features, such as SVM or HOG, are ineffective for crowded scenes and small targets. [6], [7], [8]. Because they are not designed to handle differences in elevation and spatial resolution, models based on convolutional neural networks (CNNs) have limited results.[9], [10].

1.3 Proposed Solution

The integration of AI algorithms with autonomous aerial vehicles like drones to detect missing individuals in intricate surroundings is necessary. Drones, along with smart watches and bracelets, can augment the life-saving mechanism of the drones by sending out SOS signals and linking the wearer to monitoring systems, thus forming a hybrid network of drones and real-time data analysis of computer vision. [10], [11].

1.4 Research gap

Most previous studies addressed a specific problem or case, such as detecting people using drones using visual images, or detecting people using drones using thermal images. One of the studies may include the role of wearable devices in supporting search and rescue operations, but there is a very clear gap, which is the absence of building an integrated system that combines these cases, such as integrating detection using visual and thermal images together, in addition to wearable device data, to be processed between the edge and the cloud, and then tested in a realistic environment under different environmental conditions.

1.5 Scope and Objective of the Review

This review aims to analyze the latest research from 2020 to 2025 related to smart drone systems for search and rescue operations. This review focuses on:

- Artificial intelligence techniques for detecting missing persons
- Integration or linkage between drones and wearable devices
- Future trends in developing hybrid models that combine visual and thermal data

The scope involves an evaluation of the current models' strengths and weaknesses, focusing on the gaps in the literature.

2. Unmanned Aerial Vehicles (UAVs)

One of the most important technologies of this era is the unmanned aerial vehicle, which is of great importance in search and rescue operations. It is also distinguished by its high ability to collect multimedia data in real time, in addition to its ability to reach locations of great danger, and also difficult for rescue teams to reach.

- **Quadcopters (Multirotor UAVs):** This type is the most widely used in search and rescue research. It has advantages, including ease of vertical take-off and landing, and also the ability to fly in narrow and rugged areas[12] .

- **Fixed-Wing UAVs:** Fixed-wing aircraft capable of covering large areas quickly. They require a runway or launch/landing mechanism. They are useful for searching large areas such as deserts[13].
- **Hybrid UAVs (VTOL Fixed-Wing):** Hybrid drones combine the skills of multi-rotor vertical take-off and landing aircraft and fixed-wing aircraft, and they are characterized by speed and longer range.[14].
- **Nano / Small Drones:** To search closed and narrow spaces, such as buildings after disasters, small-sized aircraft are used[15].
- **Multi-UAV Systems (Drone Swarms):** A group of drones working in coordination (data is shared via cloud) to cover a wide area very quickly[16]**.**

3. Related Work

3.1 Missing Persons Detection Systems Using Unmanned Aerial Vehicles (UAVs)

Detection of missing persons using unmanned aerial vehicles (UAVs) is one of the most interesting applications in recent years, as these systems can cover large areas and can reach areas that are difficult for human rescue teams to reach[16]Introduced the CloudTrack system, which relies on open-vocabulary tracking using verbal descriptions of missing persons, such as clothing color, instead of relying solely on pre-trained data. This system is distinguished by integrating vision-language models with cloud processing capabilities to overcome the hardware limitations on board the UAV. To tackle the problem of small-object detection in intricate aerial scenes, [17]Subsequently created an integrated framework based on enhancements to the YOLOv5 and YOLOv8 algorithms. By pre-training on VisDrone and then refining on the Heridal dataset, which was created especially for SAR operations, the researchers used a transfer learning technique. YOLOv5s-PBFPN-Deconvolution, the improved model, obtained a mAP@50

of 0.802 and was able to run on a Jetson Nano at a rate of 1–2 frames per second, confirming its real-time applicability to support civil protection authorities. In terms of computer vision, the study by [18]. By relying on several algorithms such as CNN, YOLOv4, and Faster R-CNN, and also improving the system for detecting aerial images captured by drone streams, this process showed high-accuracy results in different environments, which provides a promising approach for search and rescue operations. From a practical perspective, the study by [4]presented a real-world field experiment in a rugged wilderness environment, where the YOLOv8 model was combined with the HEDAC (Heat Equation-Driven Area Coverage) algorithm to intelligently guide drones in covering the area and increasing the likelihood of locating missing persons. The experiment involved more than 78 volunteers and demonstrated that combining intelligent control with computer vision can significantly improve the effectiveness of search operations. In addition, a newly released dataset (POP Dataset, 2025) contains thermal images of partially occluded individuals behind trees or in complex environments. This dataset has proven effective in training detection models such as YOLOv5 and YOLOv8 to improve performance even with occlusion levels of up to 70%. This represents a significant advancement for realistic scenarios where a person may not be fully visible. [19].

3.2 Smart Wearable.

Smart wearable devices have recently gained attention as valuable complements to UAV-based search-and-rescue (SAR) systems.

Proposed a collaborative architecture where drones interact with wearable IoT devices carried by first responders. Their study emphasized network performance parameters such as delay, throughput, and load, demonstrating that wearable sensors (e.g., smart watches and biometric devices) can provide real-time information about responders' location, health status, and motion, thereby improving coordination and situational awareness during disaster missions. [20].

On the other hand, TagTeam, a wearable-assisted guidance paradigm for implicit human–drone teaming, was presented by Jayarajah et al. in 2022. Their prototype achieved high synchronization between human movements and drone responses by enabling drones to infer human attention and intent through the use of gadgets like motion sensors, earables, and smart glasses (HoloLens 2). In SAR operations, this implicit guidance mechanism improves cooperative visual scanning and lowers communication overhead [21].

3.3 Onboard Artificial Intelligence Models

One of the most important trends in drone research is running AI algorithms directly onboard the drone, without relying entirely on cloud servers. This trend aims to reduce response time, promoting the drone's operational autonomy, and achieve processing power in settings without constant network connectivity.

In order to run computer vision algorithms directly on the UAV, Bhavishya et al. (2021) presented a system based on the NVIDIA Jetson Xavier NX. This improved UAV autonomy during search and rescue operations by proving that real-time processing is feasible without totally depending on cloud servers. [22].

A model that uses aerial image sequences rather than individual static images was created by Kundid Vasić & Papić (2022). They increased the accuracy of human detection in SAR scenarios and decreased false positives by using the displacement vector [23]. Hoang (2023) combined an Internet of Things-based surveillance system with artificial intelligence techniques (YOLOv8 and Cascade Classifier). The model was created to identify fires, dangerous objects, and people. A hybrid approach between onboard AI and external IoT communication was demonstrated by the direct onboard execution of certain control and navigation functions, such as the PID controller. [24]. In order to improve small-object detection in intricate aerial images, Alhawsawi et al. (2024) suggested an improved YOLOv8 architecture by including a Context Enrichment Module (CEM). The model is appropriate for real-time SAR applications because it was created for effective deployment on Edge/Onboard devices. [25]. Using UAVs fitted with YOLOv8 integrated into the HEDAC motion control algorithm, Dumenčić et al. (2025) carried out practical field tests in challenging conditions. The study demonstrated the dependability of onboard AI models under realistic SAR conditions by validating that onboard detection results can directly influence UAV flight decisions in real time. [4].

3.4 The deployment of edge computing architectures and lightweight AI models across multi-UAV systems was the main focus of Peña Queralta et al. (2025, AutoSOS Project). Distributing onboard processing between UAVs and rescue boats was intended to improve maritime search and rescue operations dependability and response times [26].

3.5 Integrated System Architecture – UAV–Cloud Communication

Building integrated system architectures for search and rescue (SAR) operations that integrate cloud computing and unmanned aerial vehicles (UAVs) has received more attention in recent years. This integration allows for faster and more secure transfer of information between drones, ground control stations, and field teams. This integration also provides real-time analysis of the data, which can then be combined and disseminated, making decision-making faster. [27]. In this context, Alsamhi et al. (2021) proposed such a system through edge intelligence for the integration of multiple UAVs and wearable devices. The environmental and biometric data sensed through the UAVs are transmitted first to edge nodes and then to the cloud. The data is processed and then sent to SAR teams in the form of alarms or intelligent insights. This enables the right situational awareness and coordination by creating a single lane for the flow of data: UAV → Edge Node → Cloud → Rescue Team.[20]. Hoang (2023) also emphasized integration through the Internet of Things (IoT) and artificial intelligence (e.g., YOLOv8 and Cascade Classifier) for real-time observation. The UAVs are equipped with pyroelectric and flame detectors for data sensing and conduct some processing onboard in this context. The results are then sent to the local workstation connected through Wi-Fi (ESP32 microcontroller) to the cloud. This architecture ensures the ability of the system to detect and respond to threats relatively more swiftly by facilitating the sharing of alarms and monitoring data in real-time with security personnel or rescue teams. [24]. Song et al. (2025) developed the POP Dataset, a thermal infrared dataset for the detection of people who are partly occluded extensively, from the dataset angle. Sophisticated models such as YOLO and DINO are trained using thermal photos captured by UAVs and uploaded onto cloud storage. The models are then installed onto unmanned aerial vehicles (UAVs) for deployment in SAR complex environments after being taught. This demonstrates how the cloud acts as the single central hub for warehousing the data and central model training and deployment of intelligent algorithms onto UAVs at scale. [19]. One such hybrid complex solution includes the AutoSOS Project (Peña Queralta et al., 2025). UAVs in the ongoing maritime SAR system employ onboard lightweight AI models for conducting preliminary detection. The results are then transmitted via multi-hop communication to a rescue vessel acting as a mobile cloud node, where deeper verification and analysis occur before the information is sent to the rescue team. Table 1 compares the various studies involved in this research in terms of the objective, technology used, and dataset, as well as the best method, the proposed method, and the best results. Table 1 summarizes the studies used and compares the major issues from the literature review.

Table 1 Compares Key Literature Review Concerns.

Ref	Aim	Technology Used	Dataset	Best Way	Strengths	Weaknesses	Best performance
[18]	The major goal is to create an automated system that uses UAVs and computer vision to find missing people in SAR missions..	CNNs were used for person detection with Faster R-CNN, YOLO, and SSD, using image preprocessing and evaluated via Precision, Recall, F1-score, and mAP.	Stanford Drone Dataset &VEDAI Dataset	YOLOv4: Real-Time Search and Rescue • Balances speed and accuracy.	YOLOv4: Fastest, High-Real-Time Accuracy • Faster R-CNN for precision • SSD balances speed and accuracy.	YOLOv4 vs R-CNN: • Fast but inaccurate on small targets. • Faster R-CNN is exact but sluggish. • SSD is middling. • Dataset diversity impacts performance.	SSD Performance • Moderate. • Faster R-CNN for precision. • YOLOv4 for speed and accuracy.
[25]	The goal of this research is to use drone-captured images to improve the accuracy of people counting in complex scenes with noise and small targets.	YOLOv8 & context Enrichment Module, SPPF(Spatial Pyramid Pooling)	VisDrone-CC2020 dataset	YOLOv8 & context Enrichment Module	"Excellence in Small Targets and Complex Backgrounds" • Counts, identifies, performs well. • Differentiates individuals from complex backgrounds.	Error in detecting small targets, increased computational complexity and model size, and longer inference time.	best performance mAP@50=82.10 mAP@70=76.23 MAE=25.42 MSE=34.73
[4]	Testing a system for using drones to look for and find missing people in a real-world natural setting	Heat equation driven area coverage(HEDAC) & Model Predictive Control (MPC) Computer vision is used to detect people, train the model, and then retrain it using collected raw data.	Collect these models together. (HEDAC + MPC + YOLOv8)	A new dataset has been created and made available.	Motion Control and Detection Methods • Collect methods. • Test frames in real time. • Generate public dataset.	Camera and environmental changes significantly affect performance. Difficulty detecting very small targets. No real-time processing.	The retrained model achieved higher accuracy compared to the regular YOLOv8.

Ref	Aim	Technology Used	Dataset	Best Way	Strengths	Weaknesses	Best performance
[22]	The project aims to develop an **NVIDIA Jetson Xavier NX-powered drone device** to analyze real-time video for identifying power grid hazards and assisting maintenance teams.	The technology uses **Edge Computing** on the drone to analyze data locally and instantly. **AI models** are trained on the cloud and then deployed and run on the device.	The researchers used images and videos from **DJI drones** for training and experiments.	Running artificial intelligence directly on the drone using Jetson Xavier NX with TensorRT to achieve high speed and accuracy	The project's strengths are its **real-time onboard processing** and **high accuracy** with **TensorRT**, all made flexible by using **DJI drones.**	The project is limited by the drone's **onboard power and processing**, requires updates from the cloud, and is not versatile for other uses.	The **Jetson Xavier NX with TensorRT** is the best technology for its balance of power and efficiency, while the **DJI Matrice 300** is the best drone for the task.
[28]	The objective is to create an **AI drone system** that can **detect and track humans** in real-time for surveillance, security, and rescue missions.	The system uses **YOLO** and **Deep SORT** with **CNNs** to detect and track people in real time from a drone, using **OpenCV** and **TensorFlow/Keras** for processing.	The system was trained on **PASCAL VOC**, **COCO**, and **MOT** datasets, along with drone-collected data.	The best method combines **YOLOv4/v5** and **Deep SORT** for a balance of **speed and accuracy**.	The system is strong due to its **real-time operation**, high **accuracy**, and ability to run on **low-resource devices.**	The system is weak in **poor lighting**, requires **high computing power**, and can have **false positives**, especially in complex environments.	The system's **YOLO + Deep SORT** model achieved the best performance with **90% mAP** and **86% tracking accuracy.**
[24]	The research aims to develop a **drone-based system** using **computer vision** to detect people in **search and rescue** missions.	The study used **deep learning** with **YOLOv4** and **Faster R-CNN** for object detection, enhancing performance through **transfer learning** and **data augmentation.**	The study used the **Stanford Drone Dataset**, **VEDAI Dataset**, and a **custom drone dataset.**	The best approach is using **YOLOv4**, which balances speed and accuracy, making it ideal for real-time field applications.	The project's strengths are its **immediate response capability**, use of **diverse data**, and a balance of **speed and accuracy**.	The system is affected by **poor weather**, **high resource consumption**, and a need for powerful hardware.	YOLOv4 offered the best real-time performance, while Faster R-CNN was slower, despite being slightly more accurate.

Ref	Aim	Technology Used	Dataset	Best Way	Strengths	Weaknesses	Best performance
[17]	The goal is to use **multimodal fusion** of visual and thermal drone images to develop a new framework for **accurate object detection** in challenging conditions.	The system uses **CNNs** to combine visual and thermal data with **Attention Mechanisms** for accurate detection of objects at different angles.	The model was trained on the **Drone Vehicle dataset**, which has **visual and thermal drone images**.	The best method is a model that uses multimodal fusion with Attention and a CNN backbone to balance **efficiency** and **accuracy**.	The system is more **accurate** by combining visual and thermal images, performing better in **poor weather** and having a **lower error rate**.	The framework is weak due to its **reliance on aligned data**, the need for a powerful **GPU**, and poor performance in **cluttered scenes**.	Drone Vehicle Model Performance • Outperformed Faster R-CNN and YOLOv3/YOLOv5 with higher mAP.
[27]	The **VIP-Det** framework uses a **Vision Transformer** to combine visual and thermal drone data, improving object detection in bad conditions.	The system uses a **Vision Transformer (ViT)** to combine visual and thermal data, with **Prompt-Based Fusion** for better object detection.	The model was trained on the **Drone Vehicle dataset**, which has **visual and thermal drone images**.	The best method uses **VIP-Det**, which combines **Vision Transformer** with **Prompt-Based Fusion** for efficient data integration.	The strengths are **fewer parameters**, efficient **data fusion**, strong performance in **difficult environments**, and a significant improvement in **mAP**.	The framework has a **slight performance edge**, needs a powerful **GPU** for training, and relies on **pre-aligned data**.	**VIP-Det** achieved the best performance with an **mAP of 75.5%** on the DroneVehicle dataset, outperforming other methods like C2Former and TSFADet.
[29]	The research aims to enhance **search and rescue (SAR)** missions by using a **thermal camera-equipped drone** and **AI** to locate missing persons, even in difficult environments.	The system uses **YOLOv5** to detect objects in thermal video and the **Kalman Filter** to track them, improving accuracy with **Bounding Box Gating** and **Track Association.**	The system was trained on a **custom thermal dataset** and tested on three thermal videos from a **DJI Inspire 2 drone.**	The best method combines **YOLOv5x** and the **Kalman Filter** with **Bounding Box Gating** and **Track Association** to achieve the highest performance.	The system is strong because of its **high accuracy**, performance in **difficult conditions**, and **low data consumption**.	The system's weaknesses are a **limited dataset** and **track breakage** due to the drone's speed and environmental factors.	**YOLOv5x** performed well, with a **Recall** of **0.862** to **0.992** and perfect **Precision (1.0)**. It also achieved high scores for both **Total Track Life** and **Track Purity**.

Ref	Aim	Technology Used	Dataset	Best Way	Strengths	Weaknesses	Best performance
[33]	Utilizing Drone Processing for Military Vehicle Detection • Quick, secure, offline vehicle classification.	Raspberry Pi 4 Military Vehicle Detection System • Utilizes YOLOv5 and EfficientNet-b0. • Uses DeblurGAN v2 for blur removal.	System trained on 6,999 military vehicle images from Kaggle and ImageNet.	YOLOv5 Upgrade: Optimizes Accuracy and Speed • Utilizes EfficientNet-b0 and DeblurGANv2.	The system offers **low latency**, **high accuracy (88%)**, and **data security.** It also runs on **low-cost devices**.	Project Weakness: Raspberry Pi's Power Limitations • Poor performance with small objects • Small dataset.	The enhanced **YOLOv5** model was the best, achieving **88% accuracy.**
[35]	The project aims to develop a real-time drone detection system that can distinguish drones from birds to improve security in sensitive areas.	The researchers used **YOLOv5** and **CNN** for real-time detection, with a **GPS tracker** and **Telegram API** for location and alerts.	A custom dataset was created using **12,700 drone images** and **5,300 bird images**.	The best approach is to use **YOLOv5 with an A9G GPS Tracker** on the system, as it achieves the best balance of speed, accuracy, and practicality.	The system is highly **accurate** (96.2% precision, 95% mAP) and **fast** with YOLOv5. It's a practical, **low-cost** solution that sends instant alerts via Telegram.	The system is limited by its **inability to work at night** and **fixed camera coverage**, and it has **poor tracking** in areas with weak cellular signals.	Based on the metrics (95.5% accuracy, 96.2% precision, 95% mAP), the **YOLOv5 + GPS tracking system** performed the best.
[36]	The research aims to replace traditional surveillance with a **smart drone system** that can **dynamically monitor and track people in real time**.	The study uses the **TIMT algorithm** with **Dlib** and **OpenPose** to **track and recognize faces and body poses**, while **Equidistant Tracking** maintains a fixed distance.	The study used a custom dataset from local experiments, with 40 tests of humans in different conditions, instead of using public databases.	The best method is to combine **Dlib** and **OpenPose** within the **TIMT Algorithm** for high-accuracy, fast-response face and pose detection.	The system is a smart, mobile alternative to fixed cameras, offering **high accuracy** and a **fast response time** even with changes in lighting.	The system's weaknesses include **low accuracy at wide angles** and **long distances**, and its performance is affected by **transmission delays** and **low light**.	The system showed high accuracy in both **face detection** and **pose recognition**, with a **fast response time.**

Ref	Aim	Technology Used	Dataset	Best Way	Strengths	Weaknesses	Best performance
[38]	The main goal is to create a **low-cost drone** with **AI** and **computer vision** for **near-real-time search and rescue.**	The system uses **YOLOv4-tiny** and **OpenCV** on a **Raspberry Pi 4** for on-board object detection.	The model was trained using the **COCO Dataset** and **local field images**.	Fine-tuning YOLOv4-tiny for Local Pics" • Balances accuracy, speed, low costs.	The project's strengths are its **low cost**, **near-real-time detection** for quick response, and **scalability**.	The system is limited by **low accuracy**, poor performance in **bad lighting**, and **weak processing** from the Raspberry Pi.	Fine-tuning YOLOv4-tiny for Speed, Accuracy, Low Cost

NOMENCLATURE

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4. Research Gap Identification

1. Multi-Drone Edge Intelligence and SAR Smart Wearable

The research here focuses on improving the network performance between the drone and wearable devices, but the research did not address how to integrate advanced computer vision algorithms, such as YOLO, CNNs, to actually detect people.[20].

2. Enhanced YOLOv8 Crowd Counting

The model is developed to detect crowds in aerial images, but this research does not cover direct use in search and rescue missions when people are scattered or obscured, nor does it include dealing with difficult environmental conditions, nor does it include field testing on an actual drone, because the focus was experimental on VisDrone data only.[25].

3. POP Infrared Dataset

This research presented the first thermal dataset of partially invisible people. This research did not present a complete rescue framework, and experiments were limited to general detection networks (YOLO, RTMDet) without custom algorithm modification, and also did not include the operational level.[19].

4. Experimental Validation of UAV SAR in Wilderness

The experiment is excellent in a field environment, but it did not address the overall autonomy of the drone (it relied on the YOLOv8 + HEDAC model for research), nor did it discuss the fact that there are diverse climatic conditions, such as snow and forests, nor did it address the integration of wearable devices or communication channels. [4].

5. Auto SOS Multi-UAV Maritime SAR

He emphasized the importance of marine rescue, whether by ships or drones, but this research has not been implemented practically, except for a preliminary concept, and it is also dedicated to the marine field only, not including land or urban rescue, and it did not address the battery and payload limitations of small drones in a long marine path.[26].

∗Corresponding author Noof Ali Khashusha

Email addresses: master.student2410@qu.edu.iq

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6. **AI-based Drone Assisted Human Rescue**

   The use of human sounds (screams, distress signals) to detect missing persons has been developed, but there are significant difficulties in distinguishing between noise and screams that have not been fully addressed. Also, battery life and processing power when using microphones and AI forms on board the drone are not adequately addressed.[39].

7. **TagTeam Wearable-Assisted Human-Drone Teams**

   The research focused on indirect communication between humans and drones using wearable devices, but did not investigate the energy consumption and safety of wearables, nor did it demonstrate the integration of person detection algorithms with human-derived signals.[21].

8. **Improving Person Detection with Displacement Vector**

   The research confirmed the reduction of false positives using sequential images, but the system was not tested under large realistic SAR conditions and did not integrate multiple sensors such as temperature or IoT[23].

9. **Thermal Image Tracking for SAR**

   The research was based on Kalman + YOLO for thermal tracking, but the research was affected by the short tracking time in difficult environments and did not collect multi-sensor information (visible + thermal) to improve accuracy[29].

10. **Transponder (wi-fi &LoRa)**

    The system is only presented with a preliminary evaluation in forests. There are no large real-world experiments or comparisons with other location determination methods (GPS/5G) and Integration with vision detection algorithms is not addressed[17].

11. **visible-thermal Object detection with Transformers**

    The VIP-Det proposal is based on Transformers, but it has not been tested in SAR experiments or on limited power devices such as the Jetson Nano. The research focuses on theoretical performance and datasets[29].

12. **Real-Time SAR with YOLO (Small-Object Detection)**

    Despite the improved performance on the Heridal dataset and its operation on the Jetson Nano, the research did not test multi-sensor integration (thermal + visual) and did not test power issues on long missions[27].

13. **Autonomous Human Identification**

    It was tested on the TensorFlow network for human recognition, but the research was not tested in emergency conditions (fires/night) and did not test additional sensors such as thermal imaging[30].

14. **Dual-Stage UAV Processing (Edge +cloud)**

Not tested in field SAR. Faced with the challenges of relying on a fixed internet connection (Wi-Fi/4G) which is unreliable in disaster areas[28].

15. Autonomous SAR Drone (Libya)

He emphasized the use of YOLOv4-tiny + Raspberry Pi but did not compare with newer algorithms (YOLOv5/8), nor did he provide large field experiments outside of local environments[31].

16. Object Detection from UAV Thermal Infrared Images

Focus on YOLO with TIR (infrared) imagery but not comprehensive due to lack of public parameter dataset, which limits generalizability in multiple SAR scenarios[32].

17. CloudTrack (open-vocabulary Tracking)

It is based on verbal descriptions (such as the color of a shirt), but requires a strong connection to the cloud, which limits its use in environments with weak connectivity, and it has not been tested in real SAR missions[33].

18. Autonomous SAR & Fire Detection Drone

It was based on Bayesian path planning + RestNet for recognition, but had difficulties organizing multiple aircraft and was not tested in highly realistic SAR conditions.[23]

19. Enhancing Hajj & Umrah with AI

A comprehensive evaluation of AI techniques in crowd management, but not specifically focused on detecting missing persons by aircraft or SAR[34].

20. Automatic Person Detection with CNNs

Although a number of algorithms (YOLO, Faster R-CNN) were compared, the study was limited to the VisDrone and SARDbuild datasets only, and was not tested in real conditions with elements such as weather or terrain.[18].

21. Drone Detection & Surveillance (Anti-Drone)

The research here focused on detecting unauthorized aircraft using (GPS + YOLOv5) and did not focus on searching for missing persons or supporting SAR. [35]

22. Dynamic Monitoring & Tracking

OpenPose+ Face Recognition is used for surveillance, but it is more geared towards security and surveillance in residential complexes and has not been tested for SAR missions.[36].

23. Drone & Remote Sensing for Missing People (Italy)

It did not provide a scientific system or a new algorithm, but rather focused on Italian regulations and experiments[37].

5. Challenges and Future Direction

5.1 Technical Challenges

5.1.1 Power and Battery Life

- Most studies confirm that the limited power of a drone limits its flight time and ability to perform search and rescue missions for extended periods[20], [26].
- The thermal camera and various sensors drain more power, which adds another burden to the battery[29].
- Putting complex AI models on devices like the Raspberry Pi or Nano increases power consumption and heat[17], [33].

5.1.2 Communication and Networking

- Communication is unsatisfactory when there is an environmental disaster and the infrastructure is prone to failure, like in the case of drones and surface teams[20], [38].
- In some segments of the flight (especially in the case of covering large or rough terrains), the absence of a reliable wireless connection may result in data throughput failure[26], [28].
- The integration of multiple networks like 5G/4G, LoRa, and multi-hop connections among drones is still a scientific problem[28], [38].

5.1.3 System accuracy and person recognition

- The small size of the target in aerial photographs leads to a decrease in detection accuracy, especially when the aircraft is at high altitude[17], [23].
- Conditions such as environmental darkness, fog, and smoke, as well as obstacles to the line of sight, severely detract from the capabilities of computer vision[19], [27], [29].
- Visionim was developed on the YOLO or CNN models and still requires enhancements to aid its use with the fully and partially sighted[17], [19].
- The increase in false positives continues to be a problem and adversely impacts the confidence in the system [23].

5.2 Future Direction

5.2.1 Improved energy consumption

Developing higher-capacity batteries or field wireless charging systems and relying on lightweight AI algorithms to reduce resource consumption[17], [26].

5.2.2 More flexible networks

Using multi-drone mesh networks for greater coverage [26], [38] and reducing connectivity loss, as well as combining 5G, LoRa, and satellites to provide uninterrupted connectivity in disasters [38], and designing smart communication protocols that balance energy consumption with the need for instant data transmission [20]

5.2.3 Better detection and tracking accuracy

Preparing hybrid models that combine thermal and visual data using techniques such as Transformers or Prompt Tuning, in addition to creating modern datasets such as the POP dataset, which is useful in observing partially obscured victims under rubble and trees[19], [27].

5.2.4 Combining different components

Integrating drones, sensors, and wearables (smart watches) to improve positioning accuracy[20], [21] and also splitting tasks between on-board analysis and analysis in cloud servers to reduce latency[28].

6. Conclusion

This review has shown that drones have become a fundamental pillar in the field of security surveillance and search and rescue operations, due to their potential to provide capabilities in collecting data in real time and accessing difficult and dangerous environments present significant challenges. Moreover, there are still clear obstacles hampering the transition of these theoretical capabilities into practical applications. The primary issues include limited energy, battery life, weak communication in harsh conditions such as disasters, as well as low detection accuracy and tracking difficulties when targets are small or environmental obstacles like fog and smoke are present. To overcome these challenges, previous research has explored several practical approaches. These involve improving energy solutions, such as providing high-density batteries or employing field wireless charging systems, and designing lighter, less resource-intensive algorithms. In terms of communication, comprehensive solutions include building resilient networks through collaboration between aircraft and integrating technologies like 5G, LoRa, and satellites to ensure continuous connectivity under all conditions. Regarding detection accuracy, it is believed that hybrid models combining thermal and visual images, based on transformers and contextual learning methods, will greatly enhance the quality of results—especially when using advanced databases tailored for partial concealment scenarios. Additionally, integrating aircraft with wearable devices and field sensors will provide more comprehensive data, while distributing the processing burden between edge systems and the cloud, in order to reduce response time and improve performance efficiency.

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References

[1] A. S. Laliberte and A. Rango, 'Texture and scale in object-based analysis of subdecimeter resolution unmanned aerial vehicle (UAV) imagery', *IEEE Transactions on Geoscience and Remote Sensing*, vol. 47, no. 3, pp. 761–770, 2009, doi: 10.1109/TGRS.2008.2009355.

[2] Z. Liu *et al.*, 'VisDrone-CC2021: The Vision Meets Drone Crowd Counting Challenge Results'. [Online]. Available: http://www.aiskyeye.com/.

[3] I. H. Laradji, N. Rostamzadeh, P. O. Pinheiro, D. Vazquez, and M. Schmidt, 'Where are the Blobs: Counting by Localization with Point Supervision'.

[4] S. Dumenčić, L. Lanča, K. Jakac, and S. Ivić, 'Experimental Validation of UAV Search and Detection System in Real Wilderness Environment', *Drones*, vol. 9, no. 7, Jul. 2025, doi: 10.3390/drones9070473.

[5] J. Redmon, S. Divvala, R. Girshick, and A. Farhadi, 'You Only Look Once: Unified, Real-Time Object Detection'. [Online]. Available: http://pjreddie.com/yolo/

[6] S. Ren, K. He, R. Girshick, and J. Sun, 'Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks', Jan. 2016, [Online]. Available: http://arxiv.org/abs/1506.01497

[7] N. D. Nguyen, T. Do, T. D. Ngo, and D. D. Le, 'An Evaluation of Deep Learning Methods for Small Object Detection', *Journal of Electrical and Computer Engineering*, vol. 2020, 2020, doi: 10.1155/2020/3189691.

[8] H. Zhang, J. Wu, Y. Liu, and J. Yu, 'VaryBlock: A novel approach for object detection in remote sensed images', *Sensors (Switzerland)*, vol. 19, no. 23, Dec. 2019, doi: 10.3390/s19235284.

[9] M. Ibraheam, K. F. Li, F. Gebali, and L. E. Sielecki, 'A Performance Comparison and Enhancement of Animal Species Detection in Images with Various R-CNN Models', *AI (Switzerland)*, vol. 2, no. 4, pp. 552–577, Dec. 2021, doi: 10.3390/ai2040034.

[10] T. Ahn, J. Seok, I. Lee, and J. Han, 'Reliable Flying IoT Networks for UAV Disaster Rescue Operations', *Mobile Information Systems*, vol. 2018, 2018, doi: 10.1155/2018/2572460.

[11] L. Da Van, L. Y. Zhang, C. H. Chang, K. L. Tong, K. R. Wu, and Y. C. Tseng, 'Things in the air: tagging wearable IoT information on drone videos', *Discover Internet of Things*, vol. 1, no. 1, Dec. 2021, doi: 10.1007/s43926-021-00005-8.

[12] S. Yeom, 'Moving people tracking and false track removing with infrared thermal imaging by a multirotor', *Drones*, vol. 5, no. 3, Sep. 2021, doi: 10.3390/drones5030065.

[13] J. Keller, D. Thakur, M. Likhachev, J. Gallier, and V. Kumar, 'Coordinated path planning for fixed-wing UAS conducting persistent surveillance missions', *IEEE Transactions on Automation Science and Engineering*, vol. 14, no. 1, pp. 17–24, Jan. 2017, doi: 10.1109/TASE.2016.2623642.

[14] R. Austin, 'UNMANNED AIRCRAFT SYSTEMS UAVS DESIGN, DEVELOPMENT AND DEPLOYMENT'.

[15] W. Giernacki, M. Skwierczyński, W. Witwicki, P. Wroński, and P. Kozierski, 'Crazyflie 2.0 Quadrotor as a Platform for Research and Education in Robotics and Control Engineering'.

[16] Y. Blei, M. Krawez, N. Nilavadi, T. K. Kaiser, and W. Burgard, 'CloudTrack: Scalable UAV Tracking with Cloud Semantics', May 2025, [Online]. Available: http://arxiv.org/abs/2409.16111

[17] F. Ciccone and A. Ceruti, 'Real-Time Search and Rescue with Drones: A Deep Learning Approach for Small-Object Detection Based on YOLO', *Drones*, vol. 9, no. 8, p. 514, Jul. 2025, doi: 10.3390/drones9080514.

[18] S. Sambolek and M. Ivasic-Kos, 'Automatic person detection in search and rescue operations using deep CNN detectors', *IEEE Access*, vol. 9, pp. 37905–37922, 2021, doi: 10.1109/ACCESS.2021.3063681.

[19] Z. Song *et al.*, 'An infrared dataset for partially occluded person detection in complex environment for search and rescue', *Scientific Data* , vol. 12, no. 1, Dec. 2025, doi: 10.1038/s41597-025-04600-0.

[20] S. H. Alsamhi *et al.*, 'Multi-Drone Edge Intelligence and SAR Smart Wearable Devices for Emergency Communication', *Wirel Commun Mob Comput*, vol. 2021, 2021, doi: 10.1155/2021/6710074.

[21] A. Brasoveanu, M. Moodie, and R. Agrawal, 'Textual evidence for the perfunctoriness of independent medical reviews', in *CEUR Workshop Proceedings*, CEUR-WS, 2020, pp. 1–9. doi: 10.1145/nnnnnnn.nnnnnnn.

[22] X. Yu, L. Qin, X. Chen, L. Wu, and B. Zhang, 'Design and Development of An Onboard Intelligent Device based on Jetson NX', in *2023 4th International Conference on Computer Engineering and Intelligent Control, ICCEIC 2023*, Institute of Electrical and Electronics Engineers Inc., 2023, pp. 555–559. doi: 10.1109/ICCEIC60201.2023.10426728.

[23] M. K. Vasić and V. Papić, 'Improving the Model for Person Detection in Aerial Image Sequences Using the Displacement Vector: A Search and Rescue Scenario', *Drones*, vol. 6, no. 1, Jan. 2022, doi: 10.3390/drones6010019.

[24] M. L. Hoang, 'Smart Drone Surveillance System Based on AI and on IoT Communication in Case of Intrusion and Fire Accident', *Drones*, vol. 7, no. 12, Dec. 2023, doi: 10.3390/drones7120694.

[25] A. N. Alhawsawi, S. D. Khan, and F. U. Rehman, 'Enhanced YOLOv8-Based Model with Context Enrichment Module for Crowd Counting in Complex Drone Imagery', *Remote Sens (Basel)*, vol. 16, no. 22, Nov. 2024, doi: 10.3390/rs16224175.

[26] J. P. Queralta, J. Raitoharju, T. N. Gia, N. Passalis, and T. Westerlund, 'AutoSOS: Towards Multi-UAV Systems Supporting Maritime Search and Rescue with Lightweight AI and Edge Computing', May 2020, [Online]. Available: http://arxiv.org/abs/2005.03409

[27] R. Chen, D. Li, Z. Gao, Y. Kuai, and C. Wang, 'Drone-Based Visible–Thermal Object Detection with Transformers and Prompt Tuning', *Drones*, vol. 8, no. 9, Sep. 2024, doi: 10.3390/drones8090451.

[28] O. Ntousis, E. Makris, P. Tsanakas, and C. Pavlatos, 'A Dual-Stage Processing Architecture for Unmanned Aerial Vehicle Object Detection and Tracking Using Lightweight Onboard and Ground Server Computations', *Technologies (Basel)*, vol. 13, no. 1, Jan. 2025, doi: 10.3390/technologies13010035.

[29] S. Yeom, 'Thermal Image Tracking for Search and Rescue Missions with a Drone', *Drones*, vol. 8, no. 2, Feb. 2024, doi: 10.3390/drones8020053.

[30] K. Jayalath and S. R. Munasinghe, 'Drone-based Autonomous Human Identification for Search and Rescue Missions in Real-time', in *2021 10th International Conference on Information and Automation for Sustainability, ICIAfS 2021*, Institute of Electrical and Electronics Engineers Inc., Aug. 2021, pp. 518–523. doi: 10.1109/ICIAfS52090.2021.9606048.

[31] Z. A. Elashaal, Y. H. Lamin, M. K. Elfandi, and A. A. Eluheshi, 'Autonomous Search and Rescue Drone'.

[32] C. Jiang *et al.*, 'Object detection from UAV thermal infrared images and videos using YOLO models', *International Journal of Applied Earth Observation and Geoinformation*, vol. 112, Aug. 2022, doi: 10.1016/j.jag.2022.102912.

[33] S. Vasavi, G. H. Raj, T. Sahithi, and Y. Suhitha, 'Onboard Processing of Drone Imagery for Military Vehicles Classification Using Enhanced YOLOv5', *Journal of Advances in Information Technology*, vol. 14, no. 6, pp. 1221–1229, 2023, doi: 10.12720/jait.14.6.1221-1229.

[34] A. A. Shah, 'Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000. Enhancing Hajj and Umrah Rituals and Crowd Management through AI Technologies: A Comprehensive Survey of Applications and Future Directions', doi: 10.1109/ACCESS.2024.Doi.

[35] K. S. Bhavishya, K. Y. Reddy, G. S. Vamsi, and I. S. Krishnachaithanya, ‘Drone Detection and Surveillance’. [Online]. Available: www.ijfmr.com

[36] C. B. Yao, C. Y. Kao, and J. T. Lin, ‘Drone for Dynamic Monitoring and Tracking with Intelligent Image Analysis’, *Intelligent Automation and Soft Computing*, vol. 36, no. 2, pp. 2233–2252, 2023, doi: 10.32604/iasc.2023.034488.

[37] M. G. Pensieri, M. Garau, and P. M. Barone, ‘Drones as an integral part of remote sensing technologies to help missing people’, *Drones*, vol. 4, no. 2, pp. 1–10, Jun. 2020, doi: 10.3390/drones4020015.

[38] A. Calabrò and E. Marchetti, ‘Transponder: Support for Localizing Distressed People through a Flying Drone Network’, *Drones*, vol. 8, no. 9, Sep. 2024, doi: 10.3390/drones8090465.

[39] N. Papyan, M. Kulhandjian, H. Kulhandjian, and L. H. Aslanyan, ‘AI-based Drone Assisted Human Rescue in Disaster Environments: Challenges and Opportunities’, Jul. 2024, doi: 10.1134/S1054661824010152.