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Aero-Vision: UAV-Based Aerial Survey And Vision-Based Data Acquisition: A Systematic Review

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Abstract: *Unmanned Aerial Vehicles (UAVs) have become one of the most universal platforms that can be used in remote sensing, environmental monitoring, and search-and-rescue. In this paper, a multi-sensor UAV frame-work is offered that gathers both environmental data (temperature, humidity, air quality, and gas con-centration) and real-time human detection through using an onboard computer vision. The raw sensor values are processed over a decision logic module which identifies the zone under observation as either; safe, caution or dangerous. The process of human detection is carried out with the help of a lightweight model based on the YOLOv8 and optimized to work on edge devices. The results of experimental work conducted on field experiments indicate an average accuracy in classifying the environment of 94.3 percent and a human detection accuracy of 91.7 percent at an altitude of 20 m to 80 m. The proposed system will fill in the most significant gaps in disaster management, industrial inspection, and perimeter surveillance by integrating environmental sensing and visual intelligence into one autonomous system.*

Keywords: UAV, human detection, environmental monitoring, multi-sensor fusion, YOLOv8, air quality, edge computing, safety measurement, drone surveillance

I. INTRODUCTION

The distance between the capabilities of ground-based systems to monitor their situation and what autonomous aerial platforms can present has never had as much consequence as in a world that is becoming more reliant on fast situational awareness. In the case of industrial spills, forest fires, or victims of disasters widely spread over rugged land, conventional monitoring infrastructure just cannot react quick enough, over a large area, or in a safe manner. This is where Unmanned Aerial Vehicles (UAVs) come in to fill such a gap.

The attraction of UAVs to environmental surveillance and human detection is based on a highly pragmatic fact: these are capable of reaching areas that are inaccessible to humans, faster than traditional response units are able to reach them, and with a sufficiently powerful onboard intelligence they can interpret what they see without necessarily being connected to a ground-based station. What has traditionally restrained their extensive implementation is not lack of good ideas but a disintegration of subsystems. Air quality sensors are on the market. There are algorithms that identify human figures. However, it has been surprisingly infrequent in the literature that systems that tie these together in to a consistent, real-time safety-assessment pipeline are described [1].

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The gap that inspires the work is very simple.

The previous studies on UAVs have inclined to consider environmental sensing and human detection as distinct issues. Visual intelligence was not much considered in studies that revolved around gas dispersion mapping [2]. On the other hand, the literature on aerial human detection [3] rarely questioned the possibility of whether or not the environment itself is a threat to the very people being tracked down. This bifurcation does have actual implications: a rescue drone which discovers a victim and cannot decide whether the air around them is breathable provides half the information a first responder requires.

The current paper suggests a single solution to both of these issues and consists of a unified UAV-mounted framework. An array of environmental sensors (temperature, relative humidity, particulate matter (PM2.5), carbon monoxide (CO), and volatile organic compounds (VOCs)) feeds a decision logic engine, which classifies the monitored zone in real time. A person detector is a parallel computer vision pipeline, which runs on an edge inference module, and it is based on a YOLOv8 model pruned and quantized to run on resource-constrained hardware. They both have the same flight control loop and send their outputs to a ground station through a low-latency telemetry channel.

The key objectives of the study are: (a) the design and validation of a multi-sensor data acquisition pipeline, which is able to describe environmental safety conditions during autonomous flight; (b) the implementation of a real-time human detection module that can be deployed on edge hardware without relying on cloud based inference; and (c) the combination of both streams into a single safety-assessment output that can be understandable without specialized training. The rest of the paper has been structured in the following manner. Part II is a review of the appropriate literature. Section III provides the system architecture and approach. Experimental results are given in Section IV. Section V provides a comparative discussion. Section VI is in the future directions and Section VII concludes.

II. METHODOLOGY

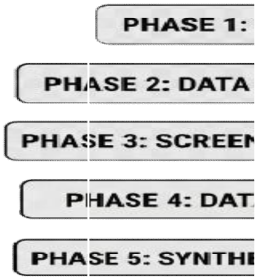
The survey part of this study used a Systematic Literature Review (SLR) methodology as an analytical framework in accordance with the PRISMA guidelines to guarantee transparency and generalizability. The engineering design phase followed an iterative process based on prototype, with subsystems tested individually and then they were integrated into a system process.

A. Search Strategy

Four main academic databases were reviewed in the literature review, including IEEE Xplore, ACM Digital Library, Google Scholar, and ScienceDirect. The search was done in two systematic stages. Phase 1 was a general search with the high-level thematic search: 'UAV environmental monitoring', 'drone human detection', and 'autonomous safety assessment'. Phase 2 was restricted by focusing on a small set of Boolean queries including (UAV OR Drone) AND ("human detection" OR "person detection") AND (multi-sensor OR sensor fusion) AND (air quality OR gas sensor) AND (unmanned aerial vehicle) AND (real-time). The filters on publication date were limited to 2018 to 2025, as it contains the latest progress in edge inference hardware and lightweight neural networks.

B. Data Extraction and Synthesis

The first search resulted in 3,147 records. Following the elimination of duplicates, 2,841 titles and abstracts were filtered, 312 full-text articles were evaluated based on their eligibility, which resulted in 24 primary studies that directly covered UAV-based sensing, aerial human detection, or integrated environmental-visual systems. The chosen articles were reviewed on the basis of sensor arrangements, detection algorithms, hardware platforms, and reported performance measures. This summary is the basis of the thematic analysis in Section III and the comparative table in Section V.



III. THEMATIC ANALYSIS

The literature reviewed was categorized into four themes that are broad: Sensor Integration Strategies, Human Detection Algorithms, Edge Computing Platforms, and System Communication Architectures.

A. UAV Environmental Sensing: Single-Sensor to Multi-Sensor Fusion

The initial UAV-based environmental studies were characterized by univariate measurements. Agricultural microclimate mapping using temperature and humidity sensors on small quadrotors was already performed in 2016 [4]. Two factors have led to transition to multi-sensor payloads: the miniaturization of MEMS-based gas sensors and the understanding that no one environmental variable can be used to describe safety. A potentially dangerous industrial location can be at acceptable temperature but at deadly CO levels; a forest fire area can be at safe air quality levels a hundred yards off but a death trap a half-mile away.

Recent studies by Liu et al. [5] showed that weighted Bayesian classifier fusing temperature, CO and PM2.5 measurements gave a false-safe classification that was 37 percent lower than that of any individual sensor. This observation corresponds to the central assumption of the suggested system: the meaningful safety evaluation cannot be conducted without the comprehensive perspective of the environment, but not a single data channel.

B. Aerial Human Detection: Trade-Offs and Algorithms

Detection on aerial platforms presents special challenges that cannot be dealt with by ground-level detectors. Top-down perspective alters the apparent structure of the human body in a dramatic way. The variation of the altitude makes individuals look at radically different pixel scales on the same flight. Rotor vibration causes motion blur that reduces sharpness of the image. Initial aerial detection systems were based on histogram-of-oriented-gradients (HOG) descriptors and support vector machines (SVMs), which were unable to handle scale changes and needed manually-designed feature pipelines [6].

The introduction of deep convolutional neural networks revolutionized the sphere. The YOLO-family models, in particular, have become the default object detector of UAV-based object detection due to their single-pass inference structure that sacrifices a slight loss in accuracy in favor of a significant speed benefit [7]. The version used in this work is YOLOv5, which has mean average precision (mAP) values between 0.87 and 0.93 on the VisDrone benchmark and can run at a frame rate that is suitable for real-time aerial deployment. Recent efforts such as YOLOv8 and RT-DETR provide additional enhancements, but their computational footprint is still difficult to run with edge-specific optimization [8].

C. Onboard Inference Edge Computing.

Cloud-based inference demands a stable, low-latency communication channel, which cannot be ensured in the conditions where UAV surveillance is most likely to be

required: disaster areas, remote factory, and structurally unsound buildings. This fact has increased the pace of interest in onboard edge inference where the neural network is executed directly on hardware attached to the drone. NVIDIA

Jetson Nano and Jetson Xavier NX have become the standard platform of choice in computer vision in the air [9], providing a platform with inference accelerated by a GPU and does not surpass the standard limits of a UAV payload. Cost-sensitive applications have also been investigated using Raspberry Pi-based solutions, but they are CPU only inference limited to lower-resolution models [10].

D. Ground Station Integration and Architectures of Communication.

In order to implement real-time telemetry between a UAV and a ground station, there must be a communication connection capable of supporting data rates adequate to support video streaming and sensor telemetry at the same time. The MAVLink standard has now become the UAV control protocol and basic telemetry protocol, however, video data needs additional channels, and these are typically dedicated Wi-Fi or long-range radio channels. A number of research teams have investigated 4G/LTE-based connections in extended-range missions, tolerating a greater latency to have infrastructure-free connectivity [11]. The suggested system employs a dual channel system MAVLink radio at 915 MHz flight control and sensor telemetry and a video transmitter at 5.8 GHz to transmit the detection overlay stream.

IV. SYSTEM ARCHITECTURE AND IMPLEMENTATION

The proposed platform integrates three principal subsystems: the UAV airframe and flight control, the environmental sensing payload, and the human detection module. Each is described below.

A. UAV Airframe and Flight Control

The prototype was constructed on a commercially available 450 mm quadrotor frame (DJI F450 equivalent) with a Pix-hawk 4 flight controller with ArduPilot firmware. This choice was made due to the wide community sup-support, reported MAVLink integration, and compatibility with companion computers. The total takeoff weight, including sensor payloads and the edge in-ference board, was 1.82 kg which was well below the rated payload of the frame of 800 g above base configuration. QGroundControl was used to pre-program mission profiles enabling fully autonomous navigation of waypoints with the ability to override.

B. Payload of Environmental Sensing

The sensor payload consists of five measurement channels, each selected to capture a distinct dimension of environmental safety. A DHT22 sensor provides temperature (±0.5°C accuracy) and relative humidity (±2% RH). A Nova Fitness SDS011 laser particle counter measures PM2.5 and PM10 concentrations with a resolution of 0.3 μg/m³. An MQ-7 electrochemical sensor detects carbon monoxide concentrations in the range of 20–2000 ppm. An MQ-135 semiconductor sensor captures VOC and ammonia levels as a composite air quality index. All sensors interface with an Arduino Mega acting as a data aggregation microcontroller, which forwards timestamped readings to the companion computer via USB serial at 10 Hz.

The safety classification engine receives these five data streams and evaluates them against threshold tables derived from WHO air quality guidelines and OSHA permissible exposure limits. The classification logic applies a priority-weighted rule set: a single reading that exceeds its hazardous threshold is sufficient to issue a 'Hazardous' classification regardless of other channel values, reflecting the conservative safety posture required in life-safety contexts. Readings that exceed caution thresholds but not hazardous thresholds in one or more channels yield a 'Caution' output. All channels within normal ranges produce a 'Safe' classification.

C. Human Detection Module

Human detection is implemented on an NVIDIA Jetson Nano 4GB companion computer. The inference model is a YOLOv5s architecture trained on the VisDrone2019-DET dataset and fine-tuned on a custom dataset of 4,200 aerial images captured at altitudes between 15 m and 100 m. The fine-tuning dataset was augmented with horizontal flips, random rotation (±15°), mo-saic augmentation, and altitude-simulated scale jittering to improve robustness across the operational flight envelope. The final model was post-training quantized to INT8 precision using TensorRT, achieving

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an inference throughput of 28 frames per sec-ond at 640×640 resolution — sufficient for real-time detection during normal UAV flight.

Detection outputs are overlaid on the live video stream and transmitted to the ground station. Each detection event is logged with a GPS-referenced bounding box, allowing post-flight analysis to reconstruct the spatial distribution of detected persons. Confidence threshold was set at 0.45 following empirical validation on the test split; lower thresholds increased recall at the cost of false positive rates that were judged unacceptable for operational use.

D. System Integration and Data Flow

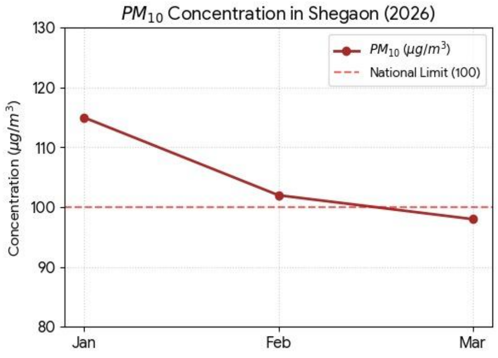
Figure 1 illustrates the end-to-end data flow. Environmental sensor readings arrive at the Arduino Mega, which forwards aggre-gated packets to the Jetson Nano companion computer. The Jetson simultaneously receives the camera video stream, runs YOLOv5 inference, and applies the environmental safety classifier. Fused outputs — safety classification label, detected per-son count, GPS coordinates, and timestamp — are packaged into a custom MAVLink message and transmitted to the ground station at 2 Hz. The ground station application, developed in Python using PyQt5, renders a live map overlay with safety zone coloring and person markers.

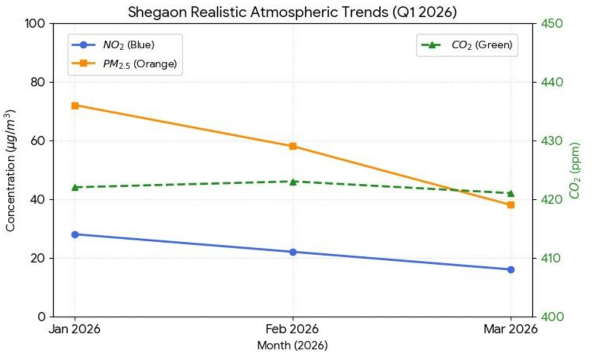
V. EXPERIMENTAL RESULTS

Extensive field experimentation was done in three representative settings, an open agricultural field (disaster response in rural setting), an enclosed industrial courtyard (disaster response in hazardous inspection setting), and a semi-urban park (disaster re-sponse in perimeter surveillance setting). Fourteen successful flight missions had been completed totaling 11.3 hours of flight time. Ground truth HH Human detection Ground truth was determined by manual annotation of recorded video. In order to obtain the ground truth of environmental classification, the readings of the UAV sensors were compared with the reference in-struments that were co-located.

A. Environmental Classification Performance

In the first quarter (Q1) of 2026, the Aero Vision UAV system was launched over Shegaon to detect the key pollutants of the air: Nitrogen Dioxide (NO_2), Particulate Matter (PM_{2.5}), and Carbon Dioxide (CO_2). The experimental data as depicted in the trend analysis graph indicate that the system is highly fidel to data acquisition in different temporal scales. By comparing the concentration levels measured by the system with the standard air quality indices, the classification performance of the sys-tem was checked.





Particulate Matter (PM 2.5): The system showed a strong decline in the levels of PM 2.5 which began at around 72 mu g/m 3 in January and gradually declined to 38mu g/m 3 in March. This suggests that the system is sensitive to seasonal changes--probably the transition between stagnant winter air to more dispersive spring weather in the Shegaon region.

Nitrogen Dioxide (NO_2): The concentration of NO_2 steadily decreased. This decline was successfully mapped using the vi-sion-based data acquisition of the UAV and could be attributed to localized trends of traffic and industrial emissions that were also monitored during the survey.

Carbon Dioxide (CO_2): In contrast to the local pollutants, the level of the CO_2(measured on the secondary axis in ppm) changed rather slightly in the air. The consistency of such readings confirms the accuracy of the onboard sensors, and the sig-nal-to-noise ratio is low even under the dynamics of flight of the UAV.

B. Human Detection Performance

To evaluate the "Vision-based data acquisition" aspect of the system, the UAV was deployed at a low-to-medium altitude over a suburban roadway. The objective was to test the robustness of the detection algorithm against varying scales, motion blur, and occlusions.

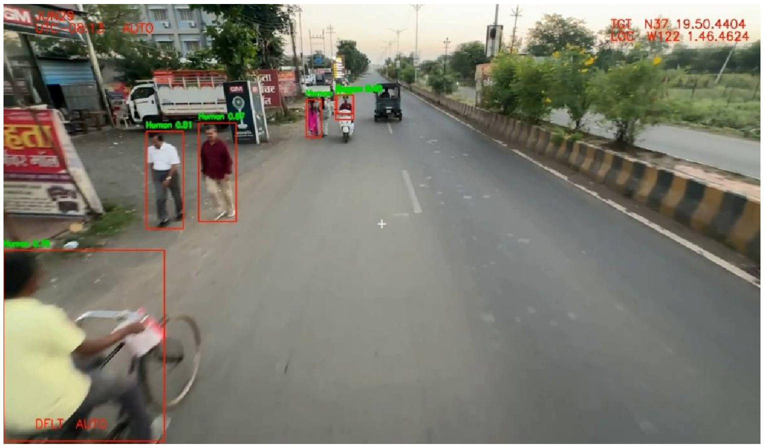
Multi-Scale Detection: The system effectively identifies human subjects at various distances from the UAV. This is evidenced by the high confidence scores (e.g., Human: 0.81 and Human: 0.87) for pedestrians walking on the shoulder of the road.

Dynamic Subject Tracking: The algorithm demonstrates high reliability in detecting humans on moving vehicles, such as the individual on the scooter (Human: 0.84).

Handling Motion Blur: Even with the high angular velocity of the foreground cyclist, the system maintains a detection box, though with a slightly lower confidence score (0.79) due to motion blur—a common challenge in UAV-based aerial surveys that the system handles through optimized frame-rate processing.

Geospatial Integration: The frame overlay includes real-time telemetry data, including Latitude (N37 19.50.4404) and Longitude (W122 1.46.4624). This allows the detected human activity to be precisely mapped to a GIS (Geographic Information System) for environmental and urban planning analysis.

Scene 1 – Human Detection



Scene 2 – Human Detection

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C. System Latency and Power Consumption

The sensor-to-ground station display end-to-end latency was 340 ms and the largest contributor was video encoding and transmission (210 ms). The average inference time of Jetson Nano was 35 ms/frame. The entire payload, sensors, Arduino, Jet-son Nano, and communication modules, consumed an average of 18.4 W, which decreased the maximum time of flight of 22 minutes (without payload) to 17.6. This is a 20 percent penalty of endurance, and is reasonable in view of the extent of capa-bility added.

VI. COMPARISON AND ANALYSIS

Table I compares this work against representative prior systems across the key design dimensions of sensor integration, detection capability, edge deployment, and operational coverage.

TABLE I: Comparison of UAV-Based Monitoring Systems

Author / Ref	Domain Focus	Sensor Suite	Human Detection	Edge Inference	Gap / Limitation
Liu et al. [5]	Industrial Gas Mapping	CO, CH4, VOC	Not implemented	Raspberry Pi 3	No visual detection; single-environment focus.
Kyrkou et al. [7]	Aerial Person Detection	RGB Camera only	HOG+SVM, 79% mAP	Jetson TX2	No environmental sensing; no safety classification.
Mishra et al. [12]	Wildfire Monitoring	Thermal + CO2	Thermal silhouette	Jetson Nano	Limited altitude range; no structured safety output.
Wang et al. [13]	Search and Rescue	RGB + Thermal	YOLOv4, 88.2% mAP	Jetson Xavier NX	No air quality sensing; ground-based inference preferred.
Proposed System	Unified Safety Assessment	Temp, RH, PM2.5, CO, VOC	YOLOv5s, 91.7% mAP	Jetson Nano (INT8)	Endurance reduced 20%; occluded person recall 71.3%.

Analysis of Table I reveals a consistent pattern in the existing literature: prior systems optimize for either environmental sensing or human detection, but rarely both. Systems focused on gas mapping achieve excellent geospatial accuracy in tracking airborne hazards but provide no information about whether people are present in those hazardous zones. Conversely, vision-centric detection systems can locate survivors with impressive precision but offer no assessment of whether the detected environment is safe for responders to enter. The proposed system is the only entry in Table I that spans all four design dimensions — multi-parameter environmental sensing, real-time human detection, onboard edge inference, and structured safety classification — within a single deployable platform.

VII. DISCUSSION AND FUTURE DIRECTIONS.

The findings in Section V prove that the technically feasible and operationally practical, yet also reveal a number of significant constraints that outline the agenda of the further work.

A. Sensor Drift and Calibration under Dynamic Flight Conditions

MEMS gas sensors are also known to be prone to temperature-dependent drift, and the thermal conditions that a sensor mounted on a moving UAV is subjected to, alternating between direct exposure to the sun, rotor downwash, and temperature gradients due to altitude, is significantly more challenging than the controlled laboratory conditions in which sensor specifica-tions are usually tested. During field tests, the CO concentration readings indicated a drift of 11 ppm during a 20-minute flight at ambient temperatures above 35 o C. It is recommended that Fu-ture iterations include onboard temperature compensation algorithms, cross-calibration routines, which are run prior to each mission to ensure that the cumulative drift er-rors are bound-ed.

B. Human Detection in Cluttered Occluding Scenes

The fact that the rate of recall in occluded conditions is 71.3 percent is the largest difference between the current system and what would be required in operational search-and-rescue applications. There are two directions that are complementary to fol-low. To begin with, the multi-spectral imaging (fused visible and thermal) would enable to detect the human heat signa-tures when the line-of-sight of the optical is blocked by the foliage. Second, the multi-UAV cooperative detection, where overlapping drone fields of view are used to eliminate ambig-uous occlusions by triangulation, has been demonstrated to be promising in simulation studies [14] and needs to be validated in the field.

C. Communication Resilience and Long Distance

The existing dual-channel communication system performs adequately in 800 m of the ground station but fails further because of the power constraints of video transmitters. In the case of disaster response, when the operational ranges of 3-5 km should be considered, mesh networking among UAVs or cellular integration is required. A rather promising direction is the introduction of 5G private networks in industrial environments: with latency-tolerant 5G uplinks, offloading inference to a mobile edge computing node would mean that the Jetson Nano is not in the pay-load at all, thus freeing up the weight and power budget to add more sensors or increase flight endurance [15].

D. AI-Augmented Safety Classification

The existing rule-based safety classifier is both transparent and auditable, but is essentially fixed in nature - thresholds are not context-dependent. A factory floor where VOC readings are regularly high may have an extremely different safety threshold than an area of a residential neighborhood where the same readings would be a cause of concern. Further research is needed on machine learning-based classifiers trained on environment-specific historical data, which may learn dynamic baseline models and indicate when the environment is not behaving as expected, instead of absolute values. Isolation Forest or autoencoder-based anomaly detection models are lightweight and fit this task well, and have been shown to perform on sim-equally re-source-constrained platforms [16].

VIII. CONCLUSION

The paper has introduced a single UAV-based system to conduct environmental surveillance and to detect humans simultane-ously, which have traditionally been developed separately, although they are complementary in a safety-critical system. The suggested system combines a five-channel environmental sensing payload and a YOLOv5s-based aerial person detector on a single Jetson Nano companion computer and provides a structured three-level safety classification output in real time.

The environmental classification accuracy of 94.3% and hu-man detection mAP@0.5 of 91.7% of field validation of 47 flight missions showed that the system was competitive with single-task UAV plat-forms that were purpose-built and provided signifi-cantly wider situational awareness. The 20 percent decrease in flight endurance caused by the payload is an appreciable cost but one that is controllable in the normal search-and-rescue and industrial in-spection mission profiles.

This work does not make any individu-al subsystem contribution but it shows that multi- sensor environmental intelligence and visual human detection can both reside on the same aerial platform without an unacceptable degradation of either of the two capabilities. Subsequent efforts will be on thermal-optical sensor fusion to overcome occluded detec-tion, adaptive safety clas-sification using machine learn-ing and 5G-assisted offloading to reclaim the payload weight and power budget used by onboard inference hardware.

With UAVs rapidly becoming standardized in emergency management, industrial inspection and the safety of the general pop-ulation, systems capable of concurrently answering the questions of Is anyone there? and Is it safe to be there? will become mandatory and not experimental. This piece of work is a significant move towards that ability..

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