

Design for drone detection: a multi-modal, cost-effective drone detection system

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Abstract: Recent drone technology development has shown increased technological agility through the use of commercial-off-the-shelf components. It is therefore important to design drone detection technology using the same agility and price. This study presents the design and development of a multi-modal drone detection system using cost-effective sensors and machine learning, while exemplifying a technology design methodology. The system can replace a monolithic central detector with a distributed network of small, enabling flexible deployment and lower costs than traditional solutions.

Keywords: drone detection, low-cost sensors, wayfaring, rapid prototyping, decision-making

1 Introduction

Unmanned aerial vehicles (UAVs), commonly referred to as drones, have become increasingly accessible and capable over the past decade (Ahmed et al., 2022). Rapid advances in battery technology, miniaturized electronics, and control systems have enabled small drones to achieve long ranges, high agility, and robust autonomous flight (Mohsan et al., 2023; Yogi and Kumar, 2024; Zhao et al., 2025). While these developments have unlocked new opportunities across domains such as inspection, logistics, agriculture, and filmmaking, it has also introduced new challenges in safety, privacy, and security. Critical infrastructure, airports, and urban environments are now exposed to the potential misuse of drones, whether intentional or accidental, creating a growing demand for reliable and scalable drone detection systems (CISA, 2025). Recent geopolitical situations have put drones at the forefront of technology development (Bendett and Nersisyan, 2024).

To combat drone misuse, counter-unmanned aerial systems (C-UAS) are being developed and deployed. Traditional systems using radars have demonstrated strong performance in controlled settings; however, these are costly to acquire and maintain (Molchanov, 2014). In addition, many existing systems are designed around fixed requirements and well-defined threat profiles, making them less suited for changing drone types and counter-drone detection design. For small organizations, municipalities, or temporary deployments such as events and construction sites, investing in specialized, proprietary detection systems is often economically infeasible. This creates a gap between the increasing need for drone detection and the practical ability to deploy solutions that are both effective and affordable. Therefore, this paper aims to develop a cost-effective drone detection platform using agile, iterative development, enabling the system to rapidly adapt to changing requirements, building on the wayfaring approach presented by Steinert and Leifer (2012), where low-cost probes and rapid iterations are used to explore uncertain design spaces. The paper first presents relevant prior work, then presents the methodology and results of the sensor platform, and concludes with a case and design discussion.

Based on these objectives, this study investigates the following research questions:

Research question 1: Which low-cost sensing modalities emerge as stable and detectable for drone detection when explored through a wayfaring-inspired development process within the current technological context?

Research question 2: To what extent can the information gathered by the identified sensing modalities support autonomous drone detection?

Research question 3: What design implications emerge from the iterative exploration of sensing modalities for distributed drone detection?

1.1 Relevant work

A wide range of sensing technologies has been applied in C-UAS, including radar, optical imaging, thermal imaging, acoustic imaging, acoustic sensing, and radio frequency (RF) monitoring (Gonzalez-Jorge et al., 2024). High-resolution radar systems, particularly Frequency-Modulated Continuous-Wave (FMCW) radar, have shown reliable performance in long-range drone detection due to their precision and robustness against lighting conditions. However, despite this effectiveness, the availability of radar modules capable of detecting smaller objects at greater range and angular resolution at a low cost is limited, making them incompatible with rapid prototyping and low-budget system development (Molchanov, 2014).

Lidar systems represent another sensing modality that offers accurate range measurements as well as object profiling capabilities. However, they are not commonly used in C-UAS (Gonzalez-Jorge et al., 2024). Low-cost lidar modules, in particular, have been shown to degrade in performance at longer distances, making them less suited for drone detection in open environments (Salhi and Boudriga, 2020). Small multirotor drones typically have minimal reflective cross-sections, and their geometries can exhibit stealth-like behaviour, further reducing lidar effectiveness (Patel et al., 2018). Preliminary tests conducted prior to the experiments described in this report, using a 16-segment Leddar M16 module (“Leddar M16 Sensor Module,” n.d.), confirmed these limitations: the sensor failed to produce meaningful returns from a stationary first-person-view (FPV) drone at a distance of 10 m.

Optical sensing using visible-light cameras has gained attention due to the widespread availability of consumer-grade imaging devices and the rapid development of convolutional neural network architectures. Models such as the You-Only-Look-Once (YOLO), particularly the YOLOv8, have demonstrated the capability to detect drones at modest distances when trained on larger and diverse datasets, although their performance remained highly sensitive to lighting conditions, background clutter, and occlusions (Yilmaz and Kutbay, 2024). Thermal infrared imaging has also been investigated as a complementary modality. Svanström et al. (2021) demonstrated that a low-resolution FLIR Boson sensor combined with a YOLO detector could achieve detection performance comparable to visible-light systems while maintaining robustness to lighting variations and enabling night-time operation.

Acoustic sensing approaches exploit the distinctive spectral signatures produced by drone propellers, which commonly manifest as harmonic components ranging from approximately 200 Hz for smaller multirotor drones up to 24 kHz for larger platforms. These signatures have been shown to persist under various conditions, although their detectability decreases with range and is influenced by environmental noise (Dumitrescu et al., 2020).

RF monitoring systems, especially those based on software-defined radios (SDR), offer the ability to detect control and telemetry transmissions on the 2.4, 5.2 and 5.8 GHz ISM bands used by DJI drones, which represents 70% of the civilian market in the United States (“DJI Mini 4 Pro - Specs - DJI,” n.d.; “HackRF One - Great Scott Gadgets,” n.d.; “Mavic Pro - Product Information - DJI,” n.d.; Elias et al., 2025). Because RF-based detection does not rely on optical visibility or thermal contrast, it is particularly well-suited for environments with cluttered terrain, challenging lighting conditions, or partial occlusions.

Collectively, prior work indicates that optical, acoustic, and RF sensing each offer unique advantages for low-cost drone detection. Optical, thermal, and acoustic modalities provide spatial information but depend on environmental conditions, whereas RF sensing performs well across a broader range of operational scenarios. These findings have contributed to a growing emphasis on hybrid and sensor-fusion-based approaches that leverage complementary strengths across multiple sensing principles.

2 Method

The study employed a two-part methodological design. First, a multimodal sensing experiment was conducted using visible-light, thermal infrared, acoustic, and RF sensors to characterize each modality’s ability to capture drone-induced signatures. Second, a dedicated classification dataset was collected for machine learning evaluation, focusing on modalities that produced structured, parameterizable features suitable for automated drone/no drone detection.

2.1 Experimental setup

The multi-sensor test platform was deployed at two outdoor locations. One site was used for the visible-light and thermal imaging experiments, and the other was used for the acoustic and RF measurements.

For the optical and thermal experiments, the sensor rig was placed in an open wooded area outside an urban environment. This location was chosen because it provided a long, unobstructed line of sight suitable for long-range imaging while still presenting meaningful visual interference from natural backgrounds such as trees, sky transitions, and terrain. A Nikon D750 DSLR and a 9th-generation iPad were used for visible-light imaging, while a Hikmicro Thunder TH35 and a FLIR One Pro were used for thermal infrared measurements.

For the acoustic and RF experiments, a second site near a small settlement was selected to introduce realistic environmental interference. Here, the sensor rig was mounted approximately 10 m above ground level to ensure line-of-sight access to the drones, but the environment also introduced deliberate sources of occlusion and noise such as road traffic, Wi-Fi and Bluetooth activity, and general urban acoustic clutter. A Røde VideoMic was used for acoustic sensing, and a HackRF One with a monopole antenna was used for RF monitoring. This location did not offer the long-range visibility required for optical testing, and therefore, no optical data were collected there.

Two grey coloured consumer drones served as test targets at both locations: a DJI Mini 4 Pro and a DJI Mavic Pro.

Optical and thermal data collection

All visible-light and thermal sensor data were recorded at distances ranging from 25 m to 350 m, allowing evaluation of detectability across a broad range of visual conditions. For each distance, images were collected with different variations in the background. The collected datasets were later used for annotation and object detection evaluation.

Acoustic and RF data collection

For the acoustic and RF experiments, the sensor rig was brought to a small settlement and elevated approximately 10 m above ground level. The same DJI Mini 4 Pro and DJI Mavic Pro used for the optical datasets were employed here, both operating on the 2.4 GHz ISM band.

Recordings were conducted at distances of 10 m, 25 m, 50 m, and 75 m. At each distance, both sensors collected two 30-second samples, resulting in paired acoustic and RF datasets for each measurement point. The drones were flown at the same altitude as the sensor rig to ensure consistent line-of-sight exposure, and the operator was positioned directly underneath the drone for every test distance to maintain comparable transmission geometry.

To characterize the environmental noise profile, two 30-second baseline recordings were collected before each drone test at every distance. These recordings established the noise floor for both the acoustic and RF measurements under the specific ambient conditions present during each trial. After the baselines were recorded for a given distance, the drone was flown and two 30-second measurement recordings were captured using the Røde VideoMic and the HackRF One. This procedure, baseline followed by drone-flight recordings, was repeated independently for all test distances, ensuring consistent reference conditions and enabling reliable comparison between baseline and drone-induced signatures across the full measurement campaign.

2.2 Data processing and dataset preparation

Visible-light and thermal sensor data

Optical and thermal images were manually annotated in Roboflow, where bounding boxes were created for each drone instance and exported in YOLO format. The preprocessing performed in Roboflow included annotation, normalization, and dataset splitting before training a YOLOv8 object detection model.

RF signal processing

RF data were recorded using a HackRF One SDR connected to a laptop running DragonOS. The in-phase/quadrature (I/Q) samples were processed using an energy-detection approach implemented in GNU Radio (v3.10.9.2). The incoming samples were first transformed into the frequency domain using a Fast Fourier Transform (FFT), after which a magnitude-squared operation was applied. Equation 1 defines the computation of the average energy level across FFT frames, where N denotes the total number of samples and $X(n)$ represents the energy at the n -th frequency bin.

$$Y = \frac{1}{N} \sum_{n=1}^N |X(n)|^2 \quad (1)$$

GNU Radio handled FFT sizing, the Blackman–Harris window, and frame overlap. Post-processing was performed in Python 3.10.0, where the mean and standard deviation in dB domain of the energy were extracted from each 30-second segment. These values were used to compare baseline and drone-induced RF energy levels.

Acoustic signal processing

Acoustic recordings were captured using a Røde VideoMic, stored in MOV format, and converted to WAV (44.1 kHz, 16-bit) prior to processing. Python was used to compute the FFT of each 30-second segment, enabling identification of harmonic peaks associated with multirotor propeller rotations. Magnitude-squared averaging was applied to the FFT magnitudes, analogous to the RF energy-detection pipeline. Formula 2 shows the signal-to-noise ratio (SNR) used to quantify detectability, where the average noise power was derived from the baseline recordings for each distance.

$$SNR(dB) = 10 \log_{10} \left(\frac{AVG \text{ signal power}}{AVG \text{ noise power}} \right) \quad (2)$$

2.3 Machine learning classification and sensor fusion

In the multimodal sensing experiments described above, all datasets contained drone-present conditions, as the purpose of this stage was to characterize each modality's ability to produce measurable drone signatures rather than to perform binary detection. The visible-light and thermal datasets consisted exclusively of images containing drones, while the acoustic and

RF datasets relied on baseline subtraction to isolate drone-induced features. Because supervised "drone"/"no drone" classification requires balanced positive and negative examples, a separate dataset was collected for the machine-learning analysis. Only the acoustic and RF modalities produced stable, parameterizable signal features suitable for this task, and were therefore included in the classification dataset.

Dataset construction and post-processing

A separate data collection was conducted specifically for machine-learning classification using the same sensor hardware: a HackRF One for RF measurements and a Rode VideoMic Rycote microphone for audio. In this collection, only a DJI Mini 4 Pro was used, operating on the 2.4 GHz ISM band. The drone was flown at distances ranging from 5 m to 25 m from the sensor rig. The sensor rig was positioned between the drone and the drone operator, with a fixed 10 m distance from the operator to ensure reproducible geometry and line-of-sight conditions.

RF data were captured using the *hackrf_sweep* command sweeping 2.3–2.6 GHz sequentially, producing frequency-domain power measurements in dB. Audio was recorded simultaneously at 44.1 kHz. After collection, the continuous recordings were segmented into uniform 1-second clips. Each clip was manually labelled as "drone" or "no drone" based on the DJI flight log. RF recordings containing missing or corrupted sweep frames were removed or linearly interpolated to maintain consistent dimensionality across samples.

To ensure balanced training conditions, the dataset was constructed such that the "no drone" class constituted approximately 49–51% of all samples for each modality. Stratified sampling was applied to preserve this balance across the dataset partitions. All datasets were divided into a 60% training set, 20% validation set, and 20% test set.

For RF clips, each 1-second segment was converted into an averaged magnitude spectrum, followed by extraction of statistical descriptors (mean, standard deviation, band-energy samples, and coarse spectral-shape metrics). For audio, magnitude-squared FFT averages were computed, harmonic peaks linked to blade-passing frequencies were retained, and a segment-level SNR (Formula 2) was included. All features were standardized to zero mean and unit variance before model training.

Separate machine-learning models were trained for the RF and audio datasets. For audio, a Random Forest classifier, support vector machine (SVM), and convolutional neural network (CNN) were evaluated; for RF, Random Forest, SVM, CNN, deep neural network (DNN), and recurrent neural network (RNN) models were evaluated. Classical models were implemented in scikit-learn, with hyperparameters tuned using grid search. Neural-network models were implemented in PyTorch and optimized using Adam with early stopping based on validation loss.

Final performance was evaluated on the held-out test set using precision, recall, and F1-score. Where precision measures the proportion of correct predicted detections, while recall measures the proportion of actual drone events detected. The F1-score combines these measures into a single metric, where values closer to 1.00 indicate stronger classification performance. Weighted averaging was applied to ensure equal contribution from the "drone" and "no drone" classes. The weighted average metric was computed using Equation 3, where $K_{no\ drone}$ denotes the number of "no drone" samples in the dataset and K_{drone} denotes the number of "drone" samples. The metric for each class ($M_{no\ drone}$ and M_{drone}) was weighted according to its proportion in the dataset.

$$M_{weighted\ average} = \frac{K_{no\ drone}}{K_{no\ drone} + K_{drone}} * M_{no\ drone} + \frac{K_{drone}}{K_{no\ drone} + K_{drone}} * M_{drone} \quad (3)$$

Sensor fusion

A late-stage sensor fusion model was implemented to combine the predictions from the acoustic and RF classifiers. The probability outputs from the best-performing unimodal models were concatenated into a two-dimensional meta-feature vector. A logistic regression model was then trained as a meta-learner to integrate these outputs and produce the final "drone"/"no drone" prediction. The fusion classifier was trained and evaluated using the same train-validation-test split as the unimodal models.

3 Results

3.1 Visible-light and thermal imaging results

Across all tested distances (25–350 m), the YOLOv8 detector was unable to identify the drones in any of the visible-light or thermal images. This outcome was consistent for both platforms and across all background conditions, including sky-facing and forest-facing perspectives. The drones occupied only a small number of pixels at longer ranges, and the

combination of background clutter, illumination variability, and limited object scale resulted in no detectable visual features for the model to extract.

Thermal imaging exhibited similar limitations. Although the thermal sensors captured temperature differences in the scene, the drones did not produce a sufficiently distinct thermal signature to be segmented from background elements such as warm trees or terrain reflections. As a result, no detectable thermal contrast was observed across the tested distances.

3.2 RF detection results

Figure 1 shows the RF energy detected from the tests with the DJI Mini 4 Pro, operating on the 5.2 GHz band (left) and the 2.4 GHz band (right). The red points represent the averaged measured energies for each 30 s recording, while the blue vertical lines indicate the corresponding standard deviation. The dashed line (“Baseline Mean”) shows the average RF energy measured during baseline recordings with no drones in the airspace, and the shaded region (“Baseline StdDev”) represents the standard deviation of these ambient measurements.

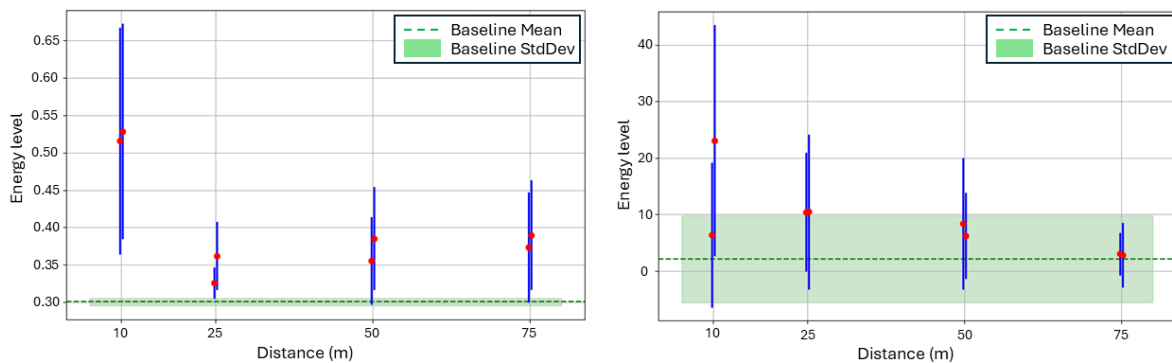


Figure 1. Energy with distance of DJI Mini 4 Pro at 5.2 GHz on the left and 2.4 GHz on the right

Figure 2 shows the corresponding RF energy results for the DJI Mavic Pro operating on the 2.4 GHz band.

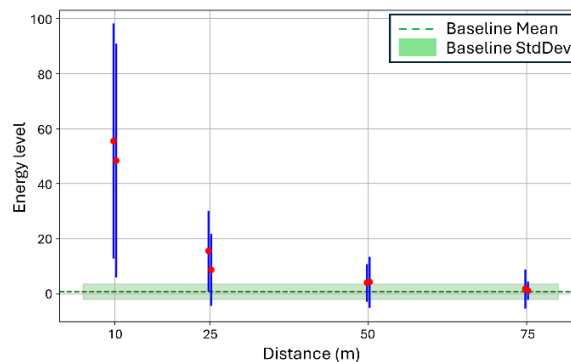


Figure 2. Energy with distance of DJI Mavic Pro at 2.4 GHz

Across both figures, the mean RF energy of every drone-present recording remained above the baseline mean at all tested distances. The standard deviation bands, however, show several instances where portions of the measured energy distribution fell below the baseline mean.

For the DJI Mini 4 Pro operating at 5.2 GHz (Figure 1 left), this occurred in the recordings at 25 m, 50 m, and 75 m. When operating at 2.4 GHz (Figure 1 right), the standard deviation dipped below the baseline mean for all tested distances except for one of the 10 m measurements. In the DJI Mavic Pro results (Figure 2), the standard deviation fell below the baseline mean for one of the 25 m measurements and for both measurements at 50 m and 75 m.

3.3 Acoustic detection results

Figure 3 and Figure 4 show the frequency-domain acoustic signatures for the DJI Mavic Pro and DJI Mini 4 Pro, respectively, recorded at a distance of 10 m from the microphone. In both figures, the blue curve represents the magnitude spectrum of the drone-present recording, while the orange curve shows the ambient noise profile recorded at the same test location with no drone present. The red curve illustrates the difference between the drone-present and baseline spectra, highlighting the harmonic components introduced by the drone’s propeller system.

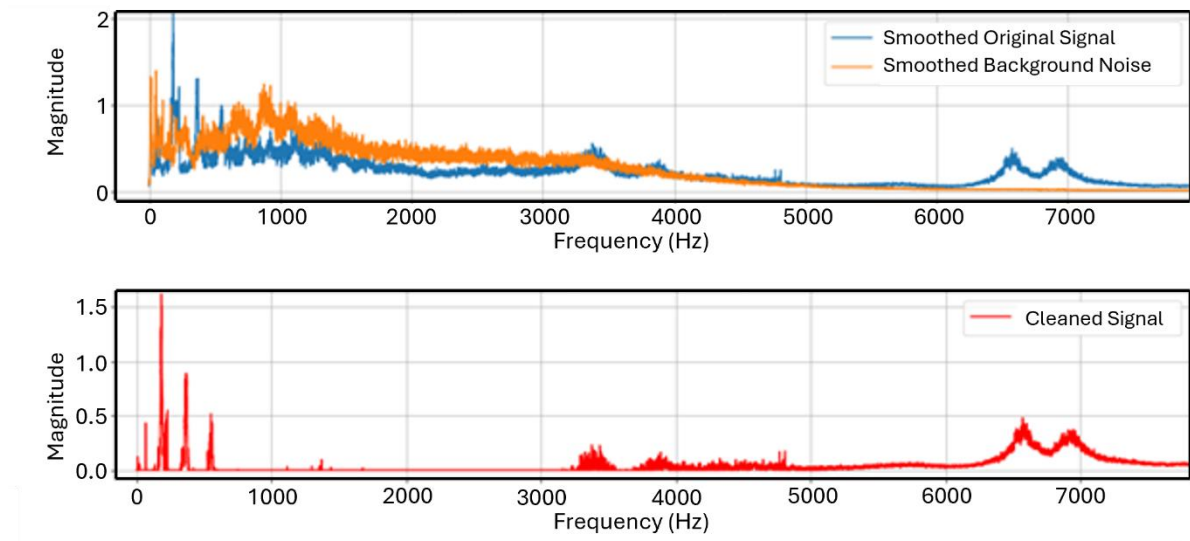


Figure 3. Frequency domain comparison of acoustic data of DJI Mavic Pro 10 m from the test station

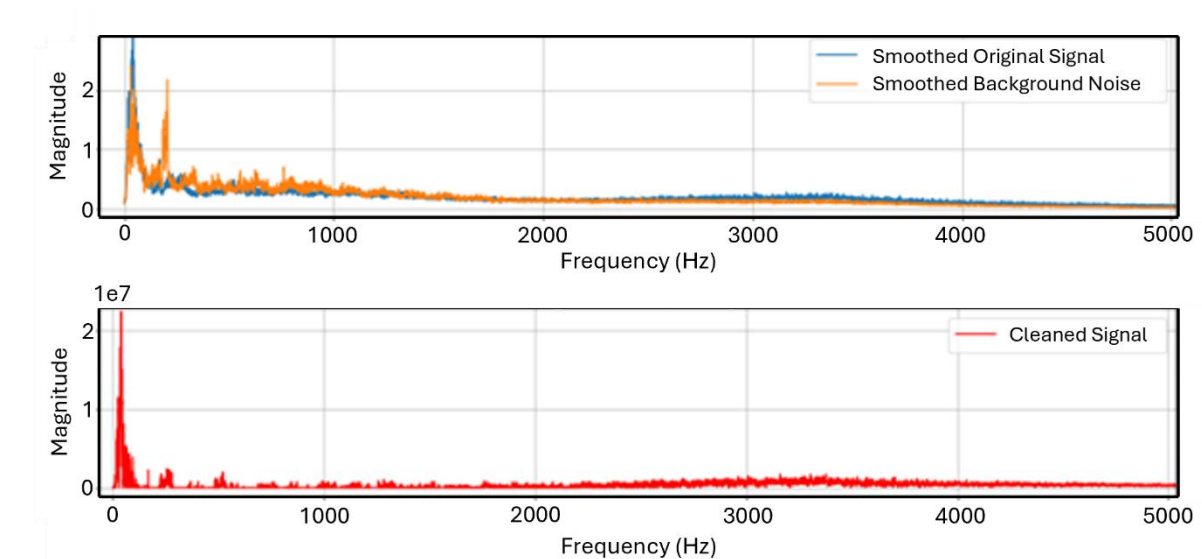


Figure 4. Frequency domain comparison of DJI Mini Pro 10 m from the test station

For the DJI Mavic Pro acoustic data (Figure 3), a distinct magnitude spike can be seen between 6.5-7 kHz. As a result of this, a focused inspection was conducted on this frequency section alone. Across all tested distances, the magnitude in this frequency section exceeded the corresponding baseline noise level, resulting in an SNR greater than 1 for all ambient noise recordings. For the DJI Mini 4 Pro acoustic data (Figure 4), no traceable distinct amplitude spike through increasing distance was present.

3.4 Machine learning classification and sensor fusion results

For both acoustic and RF, the Random Forest classifier achieved the highest performance among the tested models. Tables 1 and 2 summarize the per-class precision, recall, and F1-scores for the acoustic and RF classifiers, respectively.

Table 1. Random Forest classifier for acoustic data

Class	Precision	Recall	F1-score
No drone	0.93	0.96	0.95
Drone	0.96	0.93	0.95
Weighted average	0.95	0.95	0.95

Table 2. Random Forest classifier for radio frequency data

Class	Precision	Recall	F1-score
No drone	0.95	0.98	0.97
Drone	0.98	0.95	0.96
Weighted average	0.97	0.96	0.96

The fusion classifier, which integrates the unimodal Random Forest outputs through a logistic regression meta-learner, achieved a weighted averaged F1-score of 0.96, matching the RF-only model while improving robustness. Table 3 summarizes the fusion results.

Table 3. Sensor fusion model

Class	Precision	Recall	F1-score
No drone	0.97	0.95	0.96
Drone	0.95	0.97	0.96
Weighted average	0.96	0.96	0.96

4. Discussion

4.1 Drone detection discussion

The visible-light and thermal imaging results showed that the YOLOv8 detector did not identify the drones at any tested distance. While low colour contrast and background clutter may contribute to detection difficulty, these factors alone are unlikely to explain the outcome, as the detector also failed when the drone was flown against a clear sky background with less visual complexity. A more plausible explanation relates to how visual information is represented. Although optical and thermal sensors produce numerical pixel values, individual pixels do not contain drone specific meaning in isolation and only become informative when interpreted through spatial relationships such as edges, contours, or coherent shape features. These relationships are highly sensitive to illumination, background variation, and viewing geometry, and under the tested conditions the drones likely did not form sufficiently stable spatial structures for reliable detection. As a result, simple handcrafted features or baseline comparisons were not viable, and machine learning became the only practical approach for quantifying detection performance. Together, these findings suggest that the tested optical and thermal sensing hardware did not provide the spatial fidelity required for robust drone detection within the evaluated range.

The RF measurements demonstrated that the average spectral energy during drone flights remained consistently above the ambient baseline for all tested distances. This indicates that drone operation produced measurable and repeatable changes in the RF environment using low-cost hardware. The standard deviation bands revealed instances where portions of the measured energy overlapped with the mean baseline distribution, a behaviour that increased with distance due to path loss and normal short-term variability in transmission power. Importantly, despite these fluctuations, the 30 second averaged RF energy remained above the baseline mean for every distance and for both drone platforms, meaning that all averaged drone recordings exhibited an SNR greater than one. Further testing with varied geometries and operator placements would provide additional insight into short term RF variability, but the overall results support the viability of RF sensing for distributed detection systems.

The acoustic results highlight similar potential for low-cost microphones, particularly for drone platforms with strong harmonic signatures. For the DJI Mavic Pro, a distinct spectral feature was observed in the 6.5 to 7 kHz region. A focused inspection of this band across all recorded distances showed that the magnitude in this region exceeded the ambient noise floor for every baseline comparison up to 75 m, resulting in an SNR greater than one for all measurements. This persistent narrowband feature suggests that the Mavic Pro produces characteristic harmonic content that can serve as a reliable acoustic indicator of drone presence. However, this feature was not observed for the DJI Mini 4 Pro, indicating that

narrowband acoustic detection is more effective for larger or louder drones, and that small multirotor platforms may require alternative acoustic strategies such as broadband analysis or microphone arrays.

In the classification dataset, the acoustic and RF sensors were evaluated for discrimination between "drone" and "no drone" conditions. The unimodal Random Forest models produced weighted averaged F1-scores of 0.95 for the acoustic data and 0.96 for the RF data, indicating that the signal patterns detected in the initial sensing experiment support automated classification. The fusion model which combined the unimodal outputs using a logistic regression meta learner, achieved the same weighted averaged F1-score as the RF model and reduced cases in which one modality produced uncertain predictions. These results show that the acoustic and RF modalities provide complementary information that can be used to support automated drone detection. Future work includes generating larger datasets with harder detection cases for higher model accuracy across environments, and testing this data in a graph convolutional network (Song et al., 2022).

4.2 Design implications for distributed drone detection

In an era of rapid technological development, drone evolution and drone detection resemble a strategic exchange rather than a linear race. Drone platforms are continuously redesigned to reduce detectability, whether through changes in propeller noise, communication behaviour, airframe geometry, or visual camouflage. In such a setting, development agility becomes essential. This work therefore began with a broad exploration of sensing modalities, informed by field tests and literature, and progressed iteratively through a *wayfaring*-inspired process (Steinert & Leifer, 2012). Machine-learning development was carried out in parallel with the sensing experiments to enable rapid adjustment when certain modalities did not provide detectable information for the tested conditions.

The acoustic and RF results in this study indicate that these modalities produced the most stable and interpretable signatures for the tested commercial drones. However, this does not generalise to all drone types. Some operational contexts involve platforms that minimise acoustic output or do not rely on radio communication, including tethered FPV systems or preprogrammed routes. In such cases, RF indicators may be absent, and acoustic cues may be weak or intentionally altered. These examples highlight the need for a design process that supports continuous re-evaluation of sensing assumptions. Within a *wayfaring* approach, sensing modalities are not selected once and fixed, but are revisited as drone designs, behaviours, and environmental constraints evolve. The iterative method used here therefore serves as a framework for adapting detection strategies, rather than as an endorsement of any single sensing modality.

A modular and cost-effective detection architecture also allows systems to be distributed across multiple nodes rather than concentrated in a single long-range unit. Distributed sensing reduces dependence on one sensor configuration, increases spatial coverage, and provides flexibility when the operating environment is diverse or unpredictable. The results presented in this study suggest that a low-cost system based on commercially available components may support such a distributed approach, provided that sensing choices are continually reassessed as part of an adaptive development process.

5. Conclusion

The agile *wayfaring* design methodology presented in this study demonstrates that a drone detection system can be developed rapidly using off-the-shelf components. The multimodal field tests showed that only the acoustic and RF modalities produced stable and interpretable signatures for the tested commercial drones, while the visible-light and thermal sensors did not produce consistent cues under the given hardware and environmental conditions. The subsequent classification and fusion analyses suggest that acoustic and RF signals can support automated detection when combined with simple machine-learning models.

More broadly, the study illustrates how an exploratory and iterative development process can help adapt sensing strategies as technological and operational conditions change. Although acoustic and RF sensing were effective for the commercial drones examined here, other drone types may operate with minimal acoustic output or without radio communication, which would require reassessment of the sensing approach. The *wayfaring* method provides a means for navigating such uncertainty by allowing sensing choices to be refined as new evidence emerges.

In rapidly evolving domains such as drone detection, reliance on a single, specialised sensing solution may limit long-term effectiveness. When new drone designs diminish the relevance of existing features, systems that require extensive redevelopment or hardware modification may struggle to remain viable. A modular and easily adaptable sensing architecture, combined with an iterative design process, offers an alternative by enabling sensing components to be reconfigured or replaced as operational needs evolve. This approach may reduce redevelopment effort and shorten adaptation cycles, which is important in environments where both drone technologies and countermeasure tactics change quickly.

To answer the presented research questions:

Research question 1: Which low-cost sensing modalities emerge as stable and detectable for drone detection when explored through a wayfaring-inspired development process within the current technological context?

The results indicate that RF and acoustic sensing emerged as the most stable and detectable modalities for the tested commercial drones within the current technological context and experimental conditions. RF measurements consistently produced elevated energy levels above the environmental baseline across all tested distances, while acoustic sensing captured identifiable harmonic features for certain drone platforms. In contrast, visible-light and thermal imaging did not provide sufficiently stable signatures for reliable detection under the tested conditions. These findings suggest that the suitability of sensing modalities depends not only on sensing principles and operational conditions, but may also evolve alongside developments in drone technology, sensing hardware, and machine-learning capabilities.

Research question 2: To what extent can the information gathered by the identified sensing modalities support autonomous drone detection?

The information extracted from the identified sensing modalities supported autonomous drone detection through machine-learning classification. The RF and acoustic signals contained distinguishable patterns that enabled reliable separation between “drone” and “no drone” conditions. The classification results suggest that low-cost sensing data can provide sufficient information for automated decision-making, while sensor fusion further reduced uncertainty associated with individual sensing sources.

Research question 3: What design implications emerge from the iterative exploration of sensing modalities for distributed drone detection?

The results suggest that the effectiveness of sensing modalities varies across sensing principles and operational conditions. As previously highlighted, drone technologies and associated detection methods continue to evolve rapidly. The sensing modalities identified as effective in this study may therefore not remain optimal indefinitely as drone characteristics, sensor capabilities, and machine-learning techniques develop over time. This highlights the importance of iterative exploration and reassessment of sensing strategies, where candidate technologies can be continuously evaluated and refined as new technological opportunities emerge. Such an approach aligns with the wayfaring perspective adopted in this work, where uncertainty is addressed through exploration and successive learning cycles.

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