A Multi-Modal Sensor Fusion System for Detecting sUAS, Wildlife, and Aircraft near Airports

Joel Samu[1, *], Chuyang Yang[2], and David C. Morell[3]
[*] *Corresponding Author: SAMUJ@my.erau.edu*

[1] *School of Graduate Studies*
Embry-Riddle Aeronautical University
Daytona Beach, USA

[2] *School of Graduate Studies*
Embry-Riddle Aeronautical University
Daytona Beach, USA

[3] *School of Graduate Studies*
Embry-Riddle Aeronautical University
Daytona Beach, USA

***Abstract*—Airports increasingly face a low-altitude surveillance challenge that involves cooperative aircraft, authorized drones, non-compliant drones, birds, and other low slow-small targets that legacy surveillance does not observe consistently. Single-sensor approaches help in limited conditions but leave recurring blind spots in clutter, poor visibility, radio-frequency silence, and non-cooperative operations. The paper presents a systems design for an airport ground-based aerial object surveillance architecture built around multi-sensor fusion. The proposed design combines radar, electro-optical and infrared imaging, acoustic sensing, radio-frequency detection, ADS-B and Remote ID reception, LiDAR, and contextual data such as weather, NOTAMs, flight plans, and airport geospatial constraints. The architecture follows a four-stage surveillance logic of detection, classification, identification, and tracking, then routes fused results to an operator interface for alerting and decision support. Its conceptual basis draws on the Swiss cheese model and situational awareness theory: each sensor acts as an imperfect barrier, while fusion reduces the risk of single-point failure and supports perception, comprehension, and projection in airport decision-making. A requirements-driven design methodology is used to map sensor roles, define data flows, and allocate functions across sensing, fusion, storage, and human-on-the-loop operations. A structured risk assessment is embedded in the design to address false alarms, missed detections, cyber compromise, communications loss, power interruption, and operator overload. The result is a deployable, non-jamming surveillance architecture intended to improve airport situational awareness for both cooperative and non-cooperative aerial targets. The paper contributes a technically grounded framework that can support airport safety management, runway protection, and future integration with air traffic and unmanned traffic management environments.**

Keywords—aerial surveillance, airport safety, sensor fusion, drone detection, situational awareness

I. INTRODUCTION

Airports now operate in low-altitude airspace that contains crewed aircraft, authorized drones, unauthorized drones, birds, and occasional balloons or other anomalies. Legacy surveillance tools were primarily designed for cooperative aircraft and are less reliable for low-slow-small objects near the surface [1]-[3]. As a result, airport operators often face a poor tradeoff between under-detection and nuisance alerts. A missed target can expose arrivals, departures, or ground movements to conflict, while an overly sensitive system can create operator fatigue and reduce trust in alerts [1], [3].

A design problem follows from that gap. A useful airport surveillance system must detect objects in cluttered airspace, discriminate among birds, drones, and aircraft, identify cooperative targets when broadcasts are available, and maintain a track long enough to support a decision. It must also operate within airport constraints, including weather, line-of-sight blockages, communications limitations, data governance, and human workload [2], [4], [5]. The objective of this paper is to present a systems design for a multi-sensor airport aerial object surveillance architecture that supports those needs. The design is surveillance-centered, not interdiction-centered, and is intended to improve situational awareness and alert management without relying on jamming or other disruptive countermeasures [3]. Section II reviews the operational problem and theoretical basis. Section III describes the requirements-driven design methodology. Section IV presents the system architecture, sensor roles, risk assessment, and input-output definition. Section V discusses operational implications and remaining limitations. Section VI concludes.

II. BACKGROUND

A. Airport Low-Altitude Surveillance Challenge

The airport surface and its near-airfield airspace are unusually hard surveillance environments. Targets move at different scales and speeds; some emit cooperative broadcasts, while others remain silent; and clutter from terrain, buildings, vehicles, and weather can mask small returns [1], [2]. Wildlife management adds another layer because bird activity varies by season, weather, habitat, and time of day [5]. At the same time, unauthorized UAS activity near airports has become a recurring safety concern, especially where operators fail to broadcast identity or follow coordination procedures [3], [4].

The operational question is not simply whether an object exists. Airport personnel need a progression from presence detection to target understanding. They need to know whether the object is likely a bird, drone, or aircraft, whether it is compliant, where it is moving, and whether it threatens an active runway, approach corridor, or protected surface. That progression is one reason why single-sensor deployments often disappoint in practice. One modality may detect well but classify poorly, while another may identify well but only for cooperative targets [1].

B. *Sensor Tradeoffs and Need for Fusion*

Each sensor modality contributes a different piece of evidence. Radar offers wide-area detection and track initiation. EO/IR cameras add appearance and thermal cues. Acoustic sensing can confirm propeller or engine signatures. RF sensing can detect control or telemetry emissions. ADS-B and Remote ID help separate authorized traffic from anomalies. LiDAR adds short-range 3D structure and distance cues. None of these is sufficient alone, and each fails under some combination of clutter, silence, weather, or line-of-sight blockage [1], [3], [6]-[8].

TABLE I. ROLES OF THE PROPOSED SENSOR MODALITIES

Sensor	**Primary Contribution to Fused Detection**	**Main Blind Spot or Constraint Addressed by Fusion**
Radar	Long-range track initiation, azimuth, range, and velocity cues for wide-area airfield monitoring; usable in poor visibility [2].	Bird-drone ambiguity, small radar cross-section targets, and surface clutter require confirmation from other modalities.
EO/IR camera	Visual and thermal confirmation, object appearance cues, and operator-friendly imagery for decision support.	Sensitive to fog, rain, glare, darkness, and line-of-sight blockage. Thermal imagery reduces but does not remove those limits.
RF scanner	Passive detection of control or telemetry emissions and possible direction-finding cues for cooperative or semi-cooperative drones.	Silent, autonomous, or frequency-hopping targets may not be detected consistently.
ADS-B / Remote ID	Identity, position, and altitude for compliant aircraft and compliant drones, helping separate authorized traffic from anomalies.	Non-cooperative or non-compliant targets do not broadcast usable identity data [9].
Acoustic array	Passive confirmation from propeller or engine signatures; useful when RF or optical evidence is weak.	Airport ambient noise, distance, and wind reduce range and classification confidence
LiDAR	Short-range 3D shape, distance, and structural cues that support disambiguation and object localization.	Weather attenuation, added cost, and limited long-range value make LiDAR most useful as a supporting cue.

In system terms, fusion is needed because airport surveillance is an evidence aggregation problem rather than a single-sensor classification problem. A radar return that is ambiguous on its own becomes more useful when paired with EO/IR classification, acoustic confirmation, or a cooperative broadcast. Likewise, a Remote ID message is operationally stronger when it can be associated with a physically tracked object rather than accepted as an isolated broadcast [1], [8], [10].

C. *Safety-Theoretical Basis*

A layered surveillance concept is consistent with Reason's Swiss cheese model, which treats safety as the combined performance of multiple imperfect barriers rather than a single flawless defense [11]. In the airport setting, each sensor acts as one barrier, and its blind spots form the holes. Fusion reduces the likelihood that the same failure path traverses every layer simultaneously [1], [11]. Endsley's situational awareness model adds a second design lens. Level 1 concerns perception of relevant elements, Level 2 concerns comprehension of what they mean, and Level 3 concerns projection of what is likely to happen next [12]. Detection, classification, identification, and tracking map naturally onto those three levels.

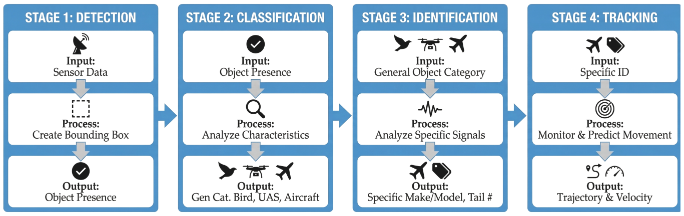

Fig. 1. Four-stage aerial object surveillance workflow, adapted from [1].

III. METHODOLOGY

A. *Requirements-Driven Design Process*

The methodology followed a design-science approach rather than an experimental comparison of deployed systems. Requirements were synthesized from three sources: recent airport surveillance literature, FAA and ACRP guidance, and operational needs implied by airport safety management practice [1]-[3], [13]. Four design steps were then applied. First, the operational problem was decomposed into detection, classification, identification, tracking, and alerting functions. Second, sensor roles were allocated to those functions based on comparative strengths and failure modes. Third, data pathways were designed for time synchronization, evidence fusion, operator display, and archival logging. Fourth, a structured risk assessment examined design vulnerabilities, including false alarms, power loss, cyber exposure, and operator overload.

This methodology was selected because airport surveillance is a system-of-systems problem. Performance depends not only on sensor capabilities but also on data integration, human decision-making, fallback behavior, and compliance with airport operating constraints. A design that performs well in isolation may still fail operationally if it produces unmanageable alert volume or cannot align cooperative messages with physical tracks [3], [14].

B. *Functional Decomposition*

The system was designed around five functional requirements. First, it must detect both cooperative and non-cooperative aerial objects within a defined airport protection volume. Second, it must classify targets into broad operational categories, at a minimum, bird, UAS, aircraft, or unknown. Third, it must identify cooperative targets when ADS-B or Remote ID information is available. Fourth, it must maintain a time consistent track with position, speed, heading, and confidence state. Fifth, it must present these outputs to an operator in a form that supports quick review and escalation. A non-disruptive operating boundary was assumed. The proposed design does not jam, spoof, or physically engage targets. That assumption keeps the architecture aligned with the regulatory and operational caution described in recent FAA work on UAS detection and mitigation [3]. The design, therefore, focuses on sensing, fusion, logging, and decision support.

C. *Data and Fusion Logic*

Raw sensor outputs are heterogeneous. Radar yields detections, range, azimuth, and motion cues. EO/IR yields image frames or thermal imagery. Acoustic sensing yields time-frequency patterns and direction-of-arrival estimates. RF sensing yields emissions, bands, and sometimes direction finding. ADS-B and Remote ID yield identity and position messages. LiDAR yields point clouds or short-range 3D structure. To make these usable together, the design assumes a common data layer in which all observations are time-stamped, georeferenced, normalized, and assigned confidence values before fusion.

Fusion then proceeds in two passes. The first pass is track-centric. It associates near-simultaneous observations that could refer to the same object and creates a fused track object. The second pass is inference-centric. It combines class evidence, cooperative identity data, contextual information, and motion history to update class label, identity status, and alert priority. That logic is consistent with airport research showing that classification quality improves when multiple cues are combined rather than treated independently [1], [6], [8], [10], [15].

IV. DESIGN OF SYSTEM

A. *System Architecture*

The layered functional architecture is shown in Fig. 2, and its external system interfaces are summarized in Fig. 3. The sensing layer collects radar, EO/IR, acoustic, RF, ADS-B/ Remote ID, and LiDAR observations. Contextual data, including weather, NOTAMs, flight plans, airspace constraints, and airport geospatial layers, are entered into the same processing environment. The fusion layer performs acquisition, preprocessing, sensor fusion, object detection, and AI/ML assisted classification. A separate data management layer preserves raw sensor data, processed outputs, and detection logs for post-event review and future model refinement. The interface layer delivers real-time display, alert management, and system controls while retaining human-on-the-loop review for alert escalation.

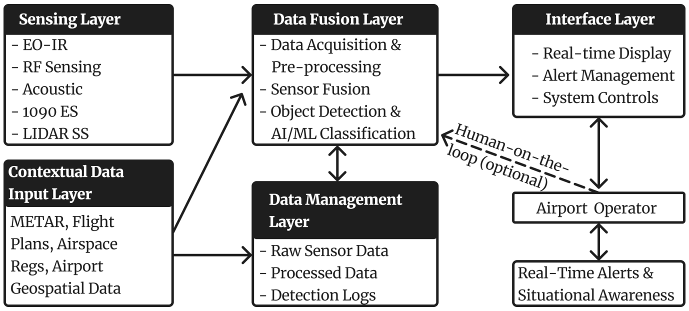

Fig. 2. Layered functional architecture for the proposed system.

The layered design separates sensing, fusion, data management, and operator interaction. That separation matters because airport operations need traceability. Operators should be able to review not only that an alert exists, but also which modalities supported it, whether the track aligns with cooperative broadcasts, and how confidence changed over time. Stored data then supports after-action analysis, model tuning, and audits of false alarms or missed detections.

The contextual data input layer is not auxiliary. Weather, NOTAMs, flight plans, local geofences, and airport surface geometry all help interpret the same detection differently. A small target near a runway threshold during active departures does not carry the same operational meaning as a cooperative track near a designated drone corridor or a bird flock during changing weather.

The interface layer should not expose raw feeds as competing alarms. It should present one fused common operational picture with drill-down access to evidence, alert rationale, and log history. That design supports airport duty managers who must act quickly, but still need enough context to coordinate with ATC, operations personnel, or outside agencies.

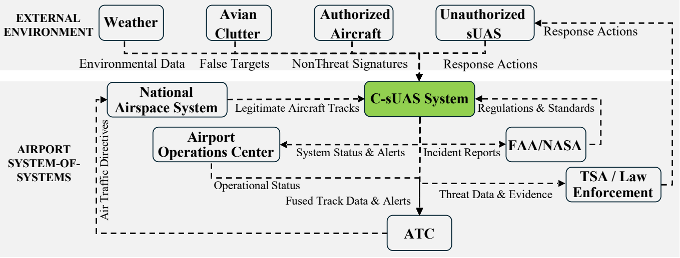

Fig. 3. System context and interfaces for the proposed system architecture.

Figure 3 places the surveillance architecture inside the broader airport system-of-systems. The airport operations center, ATC, FAA or NASA stakeholders, and TSA or law-enforcement users do not all consume the same products. A well-designed interface passes fused track alerts, operational status, and incident evidence to the appropriate stakeholder while treating weather, avian clutter, and authorized traffic as contextual discriminators rather than direct threats [2], [3], [13].

B. *Sensor Roles and Fusion Workflow*

Radar is the primary track-initiation sensor because it supports wide-area detection and motion estimation. It is especially useful when visibility is poor or when optical systems are degraded [2]. Even so, radar alone struggles with bird-drone ambiguity and low-altitude clutter [1], [6], [8], [16]. EO/IR sensors are used as confirmation sensors. They refine classification using appearance, texture, and thermal cues, though their performance degrades in fog, heavy rain, and line-of-sight obstructions [1], [7]. Acoustic sensing adds passive confirmation from propeller or engine signatures. It is most useful when optical evidence is weak or when emissions-based sensing is silent, but its range can collapse in noisy airport conditions [1], [14]. RF sensing adds non-cooperative value when a drone is transmitting control or telemetry signals. ADS-B and Remote ID act as cooperative identity layers and can quickly separate authorized aircraft or compliant drones from unknown tracks [9], [17], [15]. LiDAR is treated as a supporting cue for short-range disambiguation and 3D localization rather than a primary long-range sensor [1].

The fusion workflow follows the four stages in Fig. 1. Detection establishes object presence. Classification assigns a broad class. Identification attaches a cooperative identity when available. Tracking maintains temporal continuity, predicts motion, and supports alert prioritization. Cross-cueing connects these stages. For example, a radar or RF cue can direct an EO/IR camera toward a probable target sector, while a cooperative broadcast can help associate a physical track with an authorized operation. Alert logic then uses the fused result, not the single-sensor output, as the basis for operator notification.

Track management uses confidence-weighted association. A target with strong radar motion cues, weak EO evidence, and no cooperative broadcast may remain classified as unknown or probable UAS until additional evidence arrives. A target with coherent radar, EO/IR, and Remote ID evidence can be flagged as cooperative and monitored at a lower alert level. This graduated logic is meant to avoid both overreaction and blind acceptance.

C. Risk Assessment

Because surveillance systems can fail in ways that are operationally costly, risk assessment was treated as a design task rather than an afterthought. FAA airport SMS guidance supports structured hazard analysis during system planning [13]. Table II summarizes representative hazards for the proposed architecture. False alarms and missed detections remain the two dominant technical risks. Cyber compromise, communications loss, power interruption, and operator overload are secondary but still serious because each can disable or degrade the surveillance chain.

TABLE II. RISK ASSESSMENT FOR THE PROPOSED SYSTEM

Hazard	L^a	S	R	Representative mitigation
Clutter or multipath nuisance alerts	2	3	6	Confirm across sensors; tune thresholds.
Missed detections in fog, rain, or partial outage	2	4	8	Overlap sensors; monitor health; use fallback tracking.
Sensor or operator network compromise	2	4	8	Segment networks; encrypt; log access; patch.
Field-sensor link outage	2	3	6	Buffer locally; use redundant links where available.
Remote-node power loss	2	3	6	Provide backup power and restart diagnostics.
Alert overload at the operator display	3	3	9	Tier alerts and show only fused evidence.

L = likelihood, S = severity, and R = L x S using a qualitative FAA-style airport risk matrix [13].

Redundancy, local buffering, confidence thresholds, role based access control, and fused alert presentation reduce both nuisance alerts and silent failure modes. Human factors mitigation is also needed because even an accurate system can fail operationally if alerts are presented in a cluttered manner or if severity is not clearly differentiated.

D. Required Input and Expected Output Data

Table III summarizes the minimum inputs and core outputs of the proposed system. Fig. 4 adds a sample location map (Daytona Beach International Airport: KDAB) for a two node multi-sensor deployment, showing how airport performance depends on both structured data and local placement of sensing assets. In that limited case-study role, the airport is used to translate the generic architecture into a site-specific notional layout rather than to claim validated field performance.

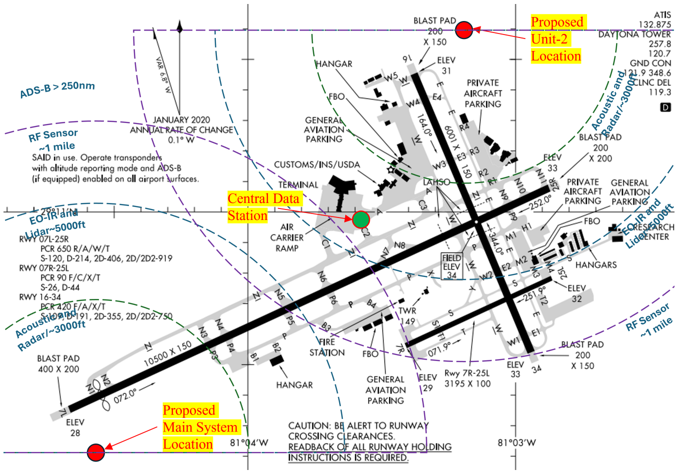

Fig. 4. Sample location map for a two-node multi-sensor deployment with approximate coverage envelopes and a central data station. The map is illustrative only and not a surveyed installation drawing.

Figure 5 presents two runway-edge perspectives placed one above the other. Together, they show how a perimeter-mounted post can preserve sight lines to threshold, infield approach, and perimeter-road activity from opposite viewing angles.

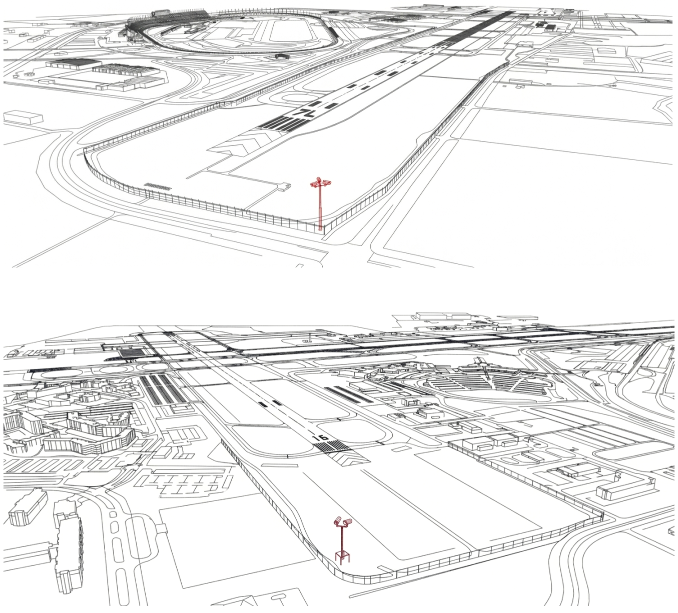

Fig. 5. Runway-edge perspectives illustrating opposite line-of-sight coverage from perimeter-mounted posts.

The sample siting map in Fig. 4 is illustrative rather than prescriptive. A primary node near a runway-end fence line and a secondary node on the opposite side create overlapping radar and RF sectors while preserving EO/IR, LiDAR, and acoustic line of sight to threshold, perimeter-road, and infield access approaches. The exact geometry will vary by airport, but overlapping fields of regard and a central aggregation point are the key design choices.

Through Endsley's framework, such siting decisions mainly protect Level 1 perception by reducing occlusion, glare, and ground clutter before fusion advances to Level 2 comprehension and Level 3 projection [12]. Local commissioning should still test nodes against terminal structures, fences, vegetation, service-vehicle traffic, and known wildlife corridors before finalizing alert thresholds.

TABLE III. INPUT DATA AND EXPECTED OUTPUT DATA

Category	Key elements
Sensor inputs	Radar tracks; EO/IR images; acoustic spectra and bearing cues; RF observations; ADS-B/Remote ID messages; LiDAR range or point-cloud cues.
Context inputs	Weather; NOTAMs; runway and taxiway status; geospatial layers; protected surfaces; local geofences; flight plans or expected traffic windows.
State variables	Time-synced observations; fused track ID; class probabilities; association confidence; cooperative identity flags; track history; predicted motion.
Outputs	Presence alert; target class; cooperative status; identity when available; trajectory and velocity; alert priority; operator display item; archived event log.

Each fused track should preserve time, location, velocity, class, cooperative status, confidence, and alert priority, while retaining anonymous continuity when identity data are absent.

E. Interactions with Experts from Industry and Academia

Throughout the concept development process, airport operators, state aviation personnel, FAA stakeholders, and academic subject matter experts reviewed the architecture. These discussions were informal design feedback rather than a formal interview study, yet three themes recurred: airports preferred surveillance and alerting over restricted countermeasure concepts, local siting and geofencing mattered as much as sensor choice, and phased deployment was more credible than an all-at-once buildout. Reviewers also stressed the need for referenceable event logs and concise alert explanations for duty managers. That feedback reinforced the emphasis on fence-line placement, stored evidence, and human review.

Across those reviews, a consistent message emerged: detection performance alone is not enough. Airport managers wanted alerts that fit existing coordination chains with operations, ATC, and security partners, while academic reviewers focused on timestamping, confidence scoring, and referenceable evidence rather than opaque alarm streams. That feedback strengthened the emphasis on fused displays, audit-ready logs, modular siting, and phased commissioning tailored to local hazard corridors.

V. DISCUSSION

The implications of the proposed architecture extend beyond raw detection range. For airports, the more consequential question is whether fused surveillance improves day-to-day decisions without creating new workload, cost, privacy, or sustainability burdens. The following subsections consider those tradeoffs in operational terms.

A. Operational Benefits

Operationally, the architecture raises runway-edge awareness during landing, takeoff, and ground movement by combining broad-area cueing with close-in confirmation. Radar and cooperative-broadcast feeds reduce search space, EO/IR and acoustic sensing help resolve ambiguous objects, and archived logs support replay, shift handover, and post-event Documentation. Compared with isolated sensors, the fused workflow is more likely to provide duty managers with a single graded alert with traceable evidence rather than several conflicting alarms [3], [13]. ADS-B and other aircraft transponder signals can also support a broader airport operational context, including estimating aircraft operations, fleet mix, and movement patterns at airports with limited conventional surveillance coverage [18]–[20].

A phased rollout is also operationally attractive. Airports can start with corridors where runway thresholds, perimeter roads, or wildlife crossings generate recurring uncertainty, then add RF, acoustic, or LiDAR layers only where ambiguity remains. That staged approach fits mixed-fleet airports and allows procedures, geofences, and alert thresholds to mature alongside local operations, rather than forcing an all-at-once deployment [2], [4].

B. Economic Benefits

Economic value comes less from direct revenue than from avoided disruption and a more selective response. Better discrimination between birds, compliant aircraft, and probable drones may shorten precautionary closures, reduce responder callouts, limit pilot go-arounds, and lower the labor burden of manual event reconstruction. Archived fused evidence can also reduce the time spent reconciling separate sensor logs after an incident [4], [13].

Over time, the same data architecture may support airport business cases for authorized low-altitude services, such as infrastructure inspection, perimeter survey, or managed drone deliveries, because compliant operations can be separated from anomalies rather than treated as generic threats. That does not guarantee revenue, but it gives airports a cleaner basis for approving and monitoring future UAS activity [2]. The modular layout also helps airports control capital exposure. A fielded program can begin with one runway-end corridor, one perimeter road, or one wildlife hotspot, then expand only where logs show recurring ambiguity or operational value. That staged path is more credible for regional airports than an airport-wide buildout on day one, and it helps tie spending to measured risk rather than vendor coverage claims.

C. Social Benefits

Social benefits center on public confidence, local legitimacy, and responsible adoption of technology. Passengers, nearby communities, airport tenants, and public-safety users are more likely to trust low-altitude operations when airports can show that unusual activity is detected, explained, and escalated through a human-reviewed process rather than through opaque automation alone [12], [13]. The architecture may also support a more balanced social response to drones near airports by distinguishing between compliant and non-compliant activity, rather than treating all small UAS operations as inherently hostile. It also gives airports a clearer basis for explaining why one event warranted escalation while another was monitored as a compliant or low-risk activity.

D. Environmental Benefits

Environmental gains are indirect but still material. More precise identification may prevent unnecessary runway holds, taxi delays, or airborne spacing adjustments, thereby reducing fuel burn and emissions. Better classification can also support targeted wildlife-management decisions by separating bird activity from drone activity, rather than prompting broad responses to every ambiguous return [5]. A surveillance-first architecture also reduces pressure for indiscriminate countermeasures that could interfere with wildlife behavior, nearby communications systems, or other airport equipment.

Environmental value also appears in more selective wildlife action. When airports can distinguish persistent bird activity from likely drone activity, they can direct dispersal or habitat response measures more precisely instead of applying broad interventions across the field. More selective action reduces avoidable vehicle movement, unnecessary holds, and secondary disturbance elsewhere on the airfield.

E. Limitations and Future Validation

The paper presents a system design, not a validated field deployment. Detection range, classification accuracy, false alarm rate, latency, and operator workload still need to be quantified under real airport conditions. Future work should focus on airport-specific trials, synchronized multimodal datasets, human factors testing, and degraded-mode evaluation under partial outages, link loss, and mixed-clutter events.

F. Validation Roadmap

Future validation should proceed in stages: local hazard mapping, synchronized multimodal data collection, fusion and alert tuning, and human-factors evaluation under realistic airport conditions. Performance should be assessed using both technical measures, such as detection probability, class error, and track continuity, and operational measures, such as alert acceptance time, operator agreement, and post-event review quality.

VI. CONCLUSION

The current paper presents a requirements-driven multi-sensor airport aerial object surveillance architecture that fuses radar, EO/IR, acoustic sensing, RF detection, ADS-B, and Remote ID, LiDAR, and contextual airport data inside a decision-support workflow. By embedding risk assessment, stored evidence, and human-on-the-loop alerting, the design remains operationally grounded rather than purely algorithmic; field validation is still required, but the framework is suitable for local airport tailoring and future ATM or UTM integration as low altitude traffic grows more complex.

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REFERENCES

[1] J. Samu and C. Yang, “Airport ground-based aerial object surveillance technologies for enhanced safety: A systematic review,” *Drones*, vol. 10, no. 1, p. 22, 2025, doi: 10.3390/drones10010022.

[2] National Academies of Sciences, Engineering, and Medicine, *Airports and Unmanned Aircraft Systems, Vol. 2: Incorporating UAS into Airport Infrastructure, Planning Guidebook, ACRP Report 212.* Washington, DC, USA: The National Academies Press, 2020, doi: 10.17226/25606.

[3] Federal Aviation Administration, UAS Detection and Mitigation Systems Aviation Rulemaking Committee Final Report. Washington, DC, USA, 2024.

[4] National Academies of Sciences, Engineering, and Medicine, *Current Landscape of Unmanned Aircraft Systems at Airports, ACRP Synthesis 104*. Washington, DC, USA: The National Academies Press, 2019, doi: 10.17226/25659.

[5] National Academies of Sciences, Engineering, and Medicine, *Airfield Turf and Vegetation Management Practices, ACRP Synthesis 128*. Washington, DC, USA: The National Academies Press, 2023, doi: 10.17226/27251.

[6] J. Liu, Q. Xu, and W. S. Chen, “Classification of bird and drone targets based on motion characteristics and random forest model using surveillance radar data,” IEEE Access, vol. 9, pp. 160135-160144, 2021.

[7] D. Gradolewski et al., “A runway safety system based on vertically oriented stereovision,” *Sensors*, vol. 21, no. 4, p. 1464, 2021.

[8] R. Heidger, V. Lambercy, and D. Lambers, “Tracking analysis of drone detection systems at airports: Methodology and results,” in Proc. Int. Radar Symp. (IRS), 2021, pp. 1-10.

[9] Federal Aviation Administration, “Remote Identification of Drones,” 2025. [Online]. Available: https://www.faa.gov/uas/getting_started/remote_id

[10] V. De Luca et al., “A platform for safe operations of unmanned aircraft systems in critical areas,” *Engineering*, vol. 49, pp. 314-331, 2025.

[11] J. Reason, Managing the Risks of Organizational Accidents. Aldershot, U.K.: Ashgate, 1997.

[12] M. R. Endsley, “Toward a theory of situation awareness in dynamic systems,” *Human Factors*, vol. 37, no. 1, pp. 32-64, 1995.

[13] Federal Aviation Administration, Safety Management Systems for Airports, Advisory Circular 150/5200-37A. Washington, DC, USA, 2023.

[14] G. Lykou, D. Moustakas, and D. Gritzalis, “Defending airports from UAS: A survey on cyber-attacks and counter-drone sensing technologies,” *Sensors*, vol. 20, no. 12, p. 3537, 2020.

[15] P. Pothana et al., “Air traffic trends and UAV safety: Leveraging automatic dependent surveillance-broadcast data for predictive risk mitigation,” *Aerospace*, vol. 12, no. 4, p. 284, 2025.

[16] P. Molchanov, R. I. A. Harmanny, J. J. M. de Wit, K. Egiazarian, and J. Astola, “Classification of small UAVs and birds by micro-Doppler signatures,” *Int. J. Microw. Wireless Technol.*, vol. 6, no. 3-4, pp. 435-444, 2014.

[17] J. H. Mott, Z. A. Marshall, M. A. Vandehey, M. May, and D. M. Bullock, “Detection of conflicts between ADS-B-equipped aircraft and unmanned aerial systems,” *Transp. Res. Rec.*, vol. 2674, no. 1, pp. 197-204, 2020.

[18] C. Yang, J. H. Mott, B. Hardin, S. Zehr, and D. M. Bullock,“Technology assessment to improve operations counts at non-towered *airports,” Transportation Research Record*, vol. 2673, no. 3, pp. 44–50, 2019.

[19] C. Yang and J. H. Mott, “Using transponder signals to model aircraft performance at non-towered airports,” in *2021 IEEE Aerospace Conference*, 2021, pp. 1–8.

[20] C. Yang, J. Mott, and D. M. Bullock, “Leveraging aircraft transponder signals for measuring aircraft fleet mix at non-towered airports,” *International Journal of Aviation, Aeronautics, and Aerospace*, vol. 8, no. 2, p. 1, 2021.