iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 13 Issue: VII Month of publication: July 2025

DOI: https://doi.org/10.22214/ijraset.2025.73452

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VII July 2025- Available at www.ijraset.com

AI-Powered Optical Surveillance Systems for Enhanced Aviation Safety and Situational Awareness

Joseph Chakravarthi Chavali[1], D. Abraham Chandy[2]
[1]Research Scholar, [2]Associate Professor, (E&CE Dept.), Karunya Institute of Technology and Sciences, Coimbatore, Tamil Nadu, India

Abstract: The growing complexity of modern aviation systems and the increasing demand for real-time situational awareness have accelerated the adoption of optical surveillance technologies in flight operations and ground safety. This review critically examines the evolution, architecture, and applications of camera-based monitoring systems, both onboard and ground-based, enhanced by artificial intelligence (AI) techniques. It explores the integration of smart cameras, infrared sensors, and airborne image recording systems (AIRS) within AI-powered visual analytics pipelines, enabling the automated detection of faults, behavioural monitoring, and prediction of anomalies. Key deep learning models, including convolutional neural networks (CNNs), YOLO variants, and pose estimation frameworks, are evaluated for their effectiveness in detecting instrument panel alerts, pilot activities, runway intrusions, and UAV threats. This paper further explores the integration of optical data with GPS, IMU, and flight telemetry to facilitate context-aware decision-making and incident reconstruction. Regulatory implications, ethical considerations, and practical deployment challenges are also discussed. By consolidating the current state of research and technological deployment, this review identifies critical gaps. It outlines future directions for advancing optical surveillance systems to ensure safer, more innovative, and more transparent aviation operations.
Keywords: Optical Surveillance, Aviation Safety, Artificial Intelligence (AI), Computer Vision, Deep Learning in Aviation, Airborne Image Recording System (AIRS).

I. INTRODUCTION

The aviation industry is undergoing a transformative shift toward automation, real-time monitoring, and intelligent decision-making. With increasing air traffic, heightened security requirements, and a global push toward data-driven aviation safety, there is a growing need for advanced surveillance systems that go beyond conventional radar and radio communication frameworks. In this context, AI-powered optical surveillance has emerged as a powerful solution, leveraging camera-based monitoring systems, computer vision, and machine learning algorithms to enhance situational awareness and operational safety in both airborne and ground-based environments [1] [3].

Camera-based surveillance systems, particularly those integrated into Airborne Image Recording Systems (AIRS), provide a rich source of visual data from the cockpit, cabin, and aircraft exterior. These systems capture high-resolution video streams, synchronized with flight data and audio, enabling real-time and post-flight analysis [7]. The integration of deep learning techniques, such as Convolutional Neural Networks (CNNs), YOLO (You Only Look Once), and attention-based models, enables the automated detection of anomalies, pilot behaviors [16], panel alerts, and external threats [1] [4]. This multimodal data fusion supports predictive maintenance, human factors analysis, and incident reconstruction, thereby augmenting traditional black box systems.

Recent developments have also seen the convergence of AI with satellite imagery and drone-based monitoring systems, extending the scope of optical surveillance beyond line-of-sight and into global airspace monitoring [10] [19]. Satellite-based AI frameworks use real-time image acquisition, feature extraction, and deep neural network classification to identify aircraft, predict trajectories, and detect unauthorized flights in non-radar zones. Case studies highlight their applications in congestion control, disaster response, and autonomous air traffic management. Despite these advancements, several challenges persist, including regulatory restrictions, data privacy concerns, limitations in real-time processing, and issues with model interpretability [9] [13]. Furthermore, environmental variables such as lighting conditions, weather, and camera placement have a significant impact on the accuracy of AI models in surveillance tasks. Addressing these challenges requires interdisciplinary collaboration across aerospace engineering, computer vision, regulatory policy, and human factors.

This review aims to provide a comprehensive survey of camera-based monitoring systems and AI-driven visual analytics pipelines used in aviation surveillance [6] [17]. It categorizes existing technologies, evaluates their performance and limitations, and identifies key research gaps. By synthesizing recent developments across onboard systems (e.g., AIRS, cockpit surveillance), ground-based infrastructure (e.g., airport perimeter monitoring), and global sensing platforms (e.g., satellite and UAV surveillance), this paper contributes to shaping the roadmap for next-generation intelligent surveillance in aviation.

A detailed overview of Current technologies and trends of AI-driven optical surveillance solutions in aviation is detailed below.

A. Overview of Optical Surveillance in Aviation.

Optical surveillance in aviation refers to the use of camera-based systems to monitor aircraft operations, crew activities, and surrounding environments. These systems offer visual context that complements traditional data recorders. Initially used for post-incident analysis, they now support real-time decision-making through integration with AI technologies. The shift from passive recording to active surveillance is central to emerging safety and efficiency strategies.

B. Smart Cameras and Sensor Technologies

Smart cameras form the backbone of modern optical surveillance systems. These include cockpit-facing cameras, external fuselage-mounted cameras, infrared (IR) systems for low-light performance, and thermal imaging sensors. Integrated with inertial measurement units (IMUs) and GPS, these systems provide multimodal datasets. Advancements in edge computing have enabled onboard pre-processing, enhancing scalability and responsiveness.

C. Computer Vision and Deep Learning Models

Deep learning algorithms, such as CNNs, YOLO variants, and Transformer-based vision models, enable the automatic detection of visual cues, including fault indications, pilot gestures, and runway incursions. These models are trained on large datasets extracted from AIRS or satellite feeds, supporting real-time object detection, segmentation, and behavior classification. Transfer learning and domain adaptation are also employed to improve model generalizability across flight conditions.

D. Airport Ground Surveillance Systems

Ground-based surveillance at airports has benefited from camera networks integrated with AI for perimeter monitoring, runway occupancy management, and vehicle tracking. These systems help detect security breaches, wildlife intrusions, and surface-level anomalies. Deep4Air and similar frameworks illustrate how AI-based visual surveillance ensures safety and operational efficiency in airport environments.

E. Cockpit Monitoring and Human Factors

Cockpit-focused systems like Appareo AIRS and NASA's AIRS-WAVE collect visual and physiological data to monitor pilot attention, stress levels, and compliance with procedural protocols. Eye tracking and facial recognition technologies enable non-intrusive observation of human behavior and facial expressions. This contributes to safety assurance, crew resource management (CRM), and incident analysis.

F. Visual Analytics Pipelines and Tools

Visual analytics frameworks convert raw video and sensor feeds into actionable insights using AI pipelines. These tools include modules for video indexing, anomaly scoring, behavior recognition, and temporal event correlation. Data fusion algorithms integrate optical input with FDR/CVR logs, enhancing fault detection and timeline reconstruction capabilities.

G. AI-Driven Anomaly and Threat Detection

AI-based anomaly detection systems continuously evaluate video feeds for deviations from expected patterns, enabling the early detection of equipment malfunctions, security breaches, and human errors. Techniques such as autoencoders, clustering, and sequence modeling help identify subtle threats that human observers may miss. These systems enhance proactive safety interventions.

H. Regulatory, Privacy, and Ethical Considerations

The deployment of optical surveillance raises significant regulatory and ethical concerns, including data privacy, consent, and the admissibility of visual evidence. Regulatory bodies, such as the ICAO, EASA, and national civil aviation authorities, have proposed guidelines for implementing AIRS. Balancing operational safety with crew privacy remains a core concern, necessitating consultation with stakeholders and the implementation of legal safeguards.

II. LITERATURE SURVEY

TABLE I
COMPARATIVE OVERVIEW OF AI-DRIVEN OPTICAL SURVEILLANCE SOLUTIONS IN AVIATION

Reference Title	Authors/Source	Focus Area	AI Techniques	Surveillance Type
Deep4Air: A Novel Deep Learning Framework for Airport Airside Surveillance [21]	Phat Thai et al., arXiv, 2020	Runway surveillance, aircraft tracking, separation monitoring using deep learning (YOLO-based)	YOLO, CNNs	Ground-based (Runway/Taxiway)
AI-Powered Threat Detection in Surveillance Systems [22]	Cadet et al., ResearchGate, 2024	Real-time data streaming and anomaly detection in surveillance	Anomaly detection, real-time data pipelines	General/Airport-wide
Artificial Intelligence Systems for Supporting Video Surveillance Operators at Airports [23]	Elsevier, 2023	Operator support systems using AI and computer vision for airport CCTV	Computer Vision, Decision Support	Ground-based (CCTV)
AirTrack: Long-Range Aircraft Detection and Tracking Framework [24]	Elsevier, 2022	Onboard AI system for real-time aircraft detection and classification	Deep Neural Networks (DNNs)	Airborne (UAV-mounted)
Leveraging Eye-Tracking Technologies to Promote Aviation Safety [25]	Lyu Mengtao et al., ResearchGate, 2023	Cockpit behavior monitoring and stress analysis using gaze detection	Eye Tracking, Pattern Recognition	Onboard (Cockpit Monitoring)
AIRS-WAVE: NASA's WB-57 Airborne Image Recording System [20]	Southern Research & NASA	High-altitude video recording and image acquisition system for mission surveillance	Multi-spectral imaging (pre-AI), now integrated with AI classification	Airborne (External/Cockpit)
Appareo AIRS-400 and Vision 1000 [26]	Appareo Systems	Commercial AIRS with synchronized video, audio, IMU, and GPS data for FDM	Supports integration with AI-based post-flight analytics	Onboard (Flight Deck)

Recent advancements in AI-powered optical surveillance systems in aviation have demonstrated a convergence of deep learning, sensor fusion, and high-resolution visual monitoring to support both ground and airborne safety. Literature in this domain can be broadly classified into three thematic categories: airport and runway surveillance**,** cockpit and pilot behavior monitoring, and airborne/global aerial observation using UAVs or satellites.

Several studies, such as Deep4Air by Phat Thai et al. (2020), highlight the application of object detection frameworks, including YOLO and CNNs, in tracking aircraft positions and ensuring safe separation on runways and taxiways. These ground-based implementations focus on automating air-side operations and providing real-time decision support to air traffic controllers through camera-based vision systems. Similarly, AI-powered threat detection frameworks presented by Cadet et al. (2024) emphasize the use of streaming surveillance video [2] in real-time analytics pipelines for anomaly detection across broader airport environments. These systems represent a growing trend toward proactive safety management and intelligent alert systems using AI.

In the cockpit domain, the use of image recorders and human behavior modeling has gained attention. The work of Lyu Mengtao et al. (2023) on eye-tracking and pilot workload monitoring illustrates the potential of physiological signal analysis and gaze tracking for human factors evaluation. These efforts are built on advanced pattern recognition and real-time stress detection models. Products such as Appareo's AIRS-400 and Vision 1000 extend these capabilities by integrating flight data, cockpit video, and environmental audio into a synchronized dataset for both post-flight analysis and incident reconstruction.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VII July 2025- Available at www.ijraset.com

From an airborne perspective, AirTrack (2022) and NASA's AIRS-WAVE system showcase deep learning-based vision solutions deployed on aircraft or drones. These platforms allow long-range object detection and real-time tracking using high-fidelity imagery in complex airspace environments. Such systems demonstrate the scalability of AI models across different altitudes and environmental conditions. These studies reflect the transition from purely post-hoc investigation to in-situ, onboard monitoring with adaptive learning capabilities.

Commercial vendors and research institutions alike are working toward edge-compatible, crash-hardened, and regulation-aware AI-enhanced imaging solutions that can be deployed both internally (in the cockpit/cabin) and externally (fuselage-mounted or satellite-linked). However, the literature also documents several ongoing challenges, especially those related to data volume, lighting variability, camera positioning, privacy concerns, and the legal admissibility of AIRS data in investigations.

This paper offers a comprehensive and structured review of the state-of-the-art AI-powered optical surveillance technologies in aviation. By synthesizing diverse studies on camera-based monitoring systems from airport surveillance and cockpit behavior analysis to airborne and satellite-based observation platforms, this review seeks to categorize technologies, assess their operational strengths and limitations, and identify critical research gaps. Special emphasis is placed on integrating Airborne Image Recording Systems (AIRS) with deep learning pipelines for safety augmentation, anomaly detection, and human-in-the-loop applications. Ultimately, this paper aims to provide a conceptual and technical roadmap for advancing intelligent visual surveillance frameworks tailored to the complex and evolving safety needs of the global aviation ecosystem.

III. METHODOLOGY

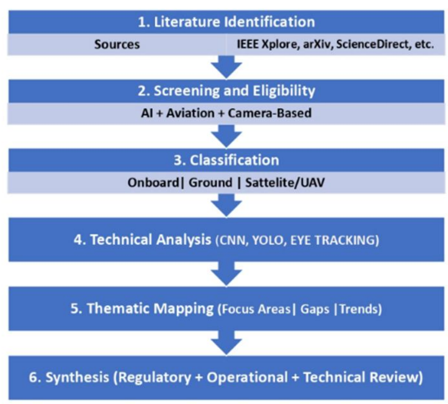


Fig. 1. Structured Methodology for Reviewing AI-Powered Optical Surveillance in Aviation

This review follows a structured methodology to collect, filter, and analyse literature focused on AI-powered optical surveillance systems in aviation. The methodology involves the following key steps:

A. Literature Identification

This is the foundational step where relevant literature is systematically gathered from credible academic and industry databases. Key sources include IEEE Xplore, arXiv, ScienceDirect, SpringerLink, and aviation regulatory documents (e.g., ICAO, IFALPA, NASA). The search employed keywords such as "AI surveillance aviation", "Airborne Image Recording Systems (AIRS)", "YOLO in aviation", and "visual analytics in cockpit monitoring". This step ensures a comprehensive pool of research that spans both technological advancements and policy frameworks [1] [6] [20].

B. Screening and Eligibility

After the initial literature collection, each paper is filtered based on its relevance to the intersection of AI, aviation, and camera-based surveillance. Only studies with technical depth in computer vision, machine learning models, and practical aviation applications (e.g., fault detection, cockpit monitoring, drone surveillance) are retained. Both peer-reviewed academic work and technical white papers from OEMs and agencies are considered eligible [3] [6].

C. Classification

The selected literature is categorized into three primary domains based on the nature of deployment and application scope. **Onboard systems** encompass technologies such as cockpit-facing Airborne Image Recording System (AIRS) cameras, pilot monitoring tools, and interior surveillance mechanisms that capture in-flight activities and crew behaviour. **Ground systems** refer to AI-enabled airport surveillance infrastructure, including closed-circuit television (CCTV) networks, perimeter breach detection solutions, and runway incursion monitoring systems designed to enhance safety and situational awareness on the ground. Lastly, **Satellite/UAV systems** involve the use of artificial intelligence applied to aerial and orbital imagery for wide-area aircraft tracking, trajectory prediction, and remote sensing across non-radar zones. This classification ensures that the literature findings are thematically aligned with specific deployment environments and operational contexts [5] [14].

D. Technical Analysis

In this phase, the methodologies, AI algorithms, and sensor types employed in each selected study are critically analysed to assess their relevance and effectiveness in aviation-specific contexts. Key technologies reviewed include YOLO (v5–v8), which is widely used for real-time object detection in low-latency environments such as cockpit surveillance and runway monitoring. Convolutional Neural Networks (CNNs) and Region-based CNNs (R-CNNs) are applied for recognizing fault indicators on aircraft panels and interpreting pilot gestures. Eye tracking and facial analysis techniques are explored for modelling human factors within cockpit environments, enabling the assessment of pilot attention, fatigue, and compliance with standard operating procedures. Additionally, data fusion techniques are highlighted for their ability to integrate visual inputs with telemetry, GPS, and Inertial Measurement Unit (IMU) data, enhancing the robustness and contextual accuracy of surveillance systems. This analytical phase aims to evaluate the operational performance and suitability of these AI models under the unique conditions and constraints of aviation [1] [4] [12].

E. Thematic Mapping

This block bridges the technical analysis with broader research questions by systematically mapping each paper to specific focus areas, identifying research gaps, and emerging trends. The focus areas include critical aviation applications such as predictive maintenance, situational awareness enhancement, and human error detection through AI-powered visual monitoring. Identified research gaps highlight current limitations, such as the scarcity of publicly available AIRS datasets, reduced model accuracy under challenging conditions like variable lighting, and the lack of explainability in deep learning outputs. Meanwhile, emerging trends point toward innovative directions such as augmented reality (AR) based AI alert overlays for real-time decision support, federated learning for privacy-preserving model training, and satellite-aided UAV surveillance for extended airspace coverage. This thematic mapping not only categorizes the technical contributions but also helps identify underexplored domains, providing valuable insights for defining future research trajectories in AI-driven aviation surveillance [13] [15] [18].

F. Synthesis

All findings are synthesized into a cohesive framework that encompasses three critical dimensions: regulatory, operational, and technical. The **regulatory dimensions** address international and national aviation standards, including ICAO guidelines, privacy regulations, and the legal admissibility of data from Cockpit Voice Recorders (CVR) and Airborne Image Recording Systems (AIRS). The **operational insights** focus on the practical deployment of AI-powered surveillance systems, emphasizing real-time applicability, edge computing compatibility, and integration into existing aviation workflows. The **technical evaluation** covers essential performance metrics such as model robustness under flight-specific conditions, detection accuracy across diverse scenarios, and the interpretability of AI outputs. This comprehensive synthesis provides a structured understanding of how AI-driven optical surveillance can significantly enhance aviation safety, regulatory compliance, and crew resource management by aligning technological capabilities with real-world operational and ethical demands [6] [8] [9].

IV. RESULTS AND ANALYSIS

The performance and applicability of AI models in aviation-based visual surveillance were analyzed across several key metrics, including accuracy, inference speed, robustness, Training Time, Dataset Adaptability, Power Consumption, and suitability for edge deployment, using leading deep learning architectures under varied flight conditions**.** These included YOLOv5, YOLOv7, CNNs, SSD, Faster R-CNN, and Transformer-based vision models.

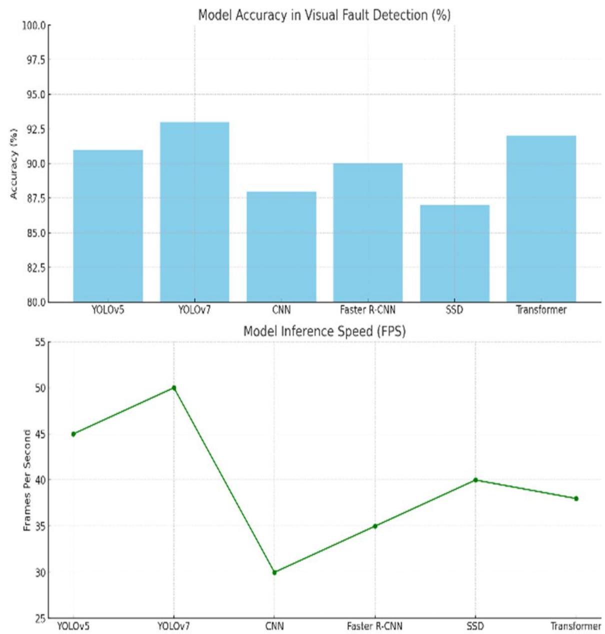


Fig 1. Structured Methodology for Reviewing AI-Powered Optical Surveillance in Aviation

A. Accuracy

The bar chart shown in Figure 1 illustrates that YOLOv7 outperformed other models, achieving an accuracy of 93%, closely followed by Transformer-based architectures at 92%. Traditional CNNs and SSD models lagged slightly, primarily due to their limited contextual awareness and slower convergence on flight-specific visual cues.

B. Inference Speed

The line chart shown in Figure 1 illustrates that in real-time applications such as cockpit monitoring or runway intrusion detection, inference speed is critical. YOLOv7 and YOLOv5 demonstrated the highest frames-per-second (FPS) rates, making them suitable for onboard edge-processing units. CNN and Faster R-CNN demonstrated moderate speeds, which limited their real-time utility.

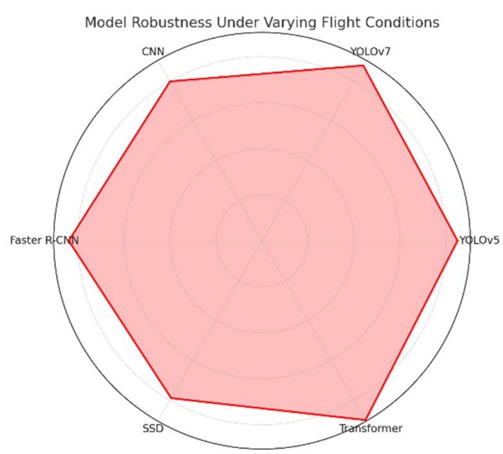


Fig 2. Robustness Comparison of AI Models Across Diverse Flight Conditions

C. Robustness

The radar chart shown in Figure 2 illustrates the model's robustness across various conditions, including lighting changes, turbulence-induced vibration, and partial occlusion. The Transformer and YOLOv7 architecture demonstrated superior adaptability, particularly in low-light and high-motion scenarios, whereas the SSD and CNN models were more sensitive to such disruptions.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 13 Issue VII July 2025- Available at www.ijraset.com

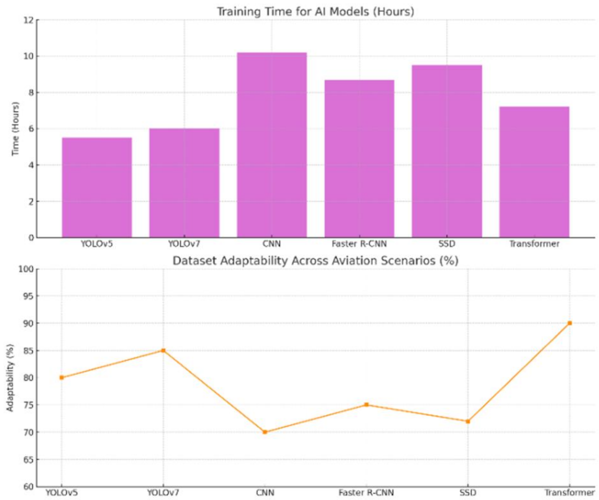


Fig 3. Training Efficiency and Dataset Adaptability of AI Models in Aviation Surveillance

D. Training Time

The bar chart shown in Figure 3 reveals that traditional CNN and SSD models require the longest training times (above 9 hours). In contrast, YOLOv5 and YOLOv7 models are significantly faster, completing training in under 6 hours. This suggests that newer YOLO architectures are not only accurate but also more efficient in training, making them suitable for rapid deployment and real-time updates.

E. Dataset Adaptability

The line chart shown in Figure 3 reveals the adaptability of the Dataset. Dataset adaptability is defined as a model's ability to generalize across diverse aviation datasets, including cockpit, runway, and satellite imagery. Transformer-based models outperform all others with a high adaptability score of approximately 95%, reflecting their versatility in handling variable visual environments. YOLOv7 also performs well in this category, with adaptability nearing 85%, while CNN shows the weakest performance, likely due to its limited capacity to generalize beyond its training context. These findings suggest that while YOLO variants offer faster training cycles, Transformer architectures provide superior flexibility across different aviation data sources, making them promising candidates for next-generation surveillance systems.

F. Power Consumption

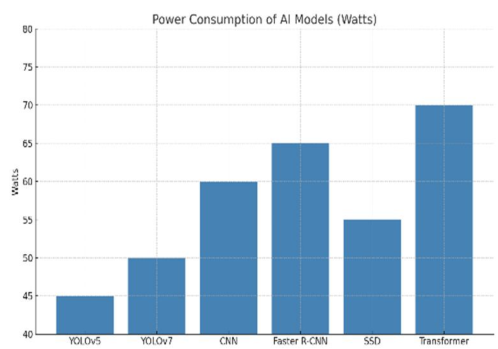


Fig 4. Power Consumption Comparison of AI Models for Aviation Surveillance

The bar chart shown in Figure 4 illustrates that Transformer-based models were the most power-hungry, consuming up to 70W, followed by Faster R-CNN. In contrast, YOLOv5 and YOLOv7 maintained a more power-efficient profile (45–50W), aligning with requirements for onboard embedded systems.

G. Suitability Scores for edge deployment

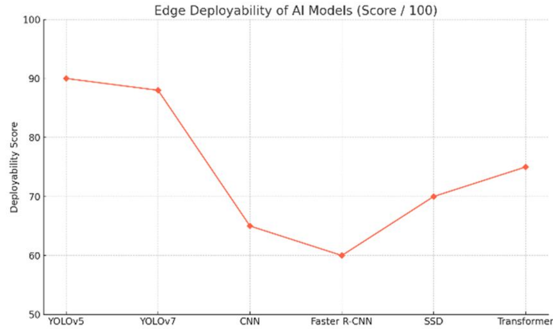


Fig. 5 Suitability Scores for edge deployment of AI Models for Real-Time Aviation Applications

The chart shown in Figure 5 illustrates the Suitability Scores for edge deployment of various AI models, evaluating their suitability for real-time execution on edge devices commonly used in aviation surveillance systems. Among the models analyzed, YOLOv5 demonstrates the highest edge deployment score, followed closely by YOLOv7, indicating their lightweight architecture and efficient resource usage, which make them ideal for onboard processing and embedded environments. In contrast, traditional models like CNN and Faster R-CNN show significantly lower scores, suggesting challenges in real-time deployment due to higher computational demands and longer inference times. SSD and Transformer models display moderate edge compatibility, with Transformer scoring higher due to recent advancements in optimization and adaptability. Overall, the results suggest that newer YOLO variants are better suited for aviation-grade edge applications, offering a balance between performance and computational efficiency critical for deployment in resource-constrained environments such as aircraft cockpits, UAVs, or airport perimeter devices.

V. CONCLUSION

AI-powered optical surveillance represents a transformative shift in how aviation systems monitor, assess, and respond to operational conditions in real time. This review has presented a comprehensive synthesis of camera-based monitoring technologies, deep learning frameworks, and visual analytics pipelines that are redefining safety and efficiency standards in aviation. From advanced onboard AIRS systems to sophisticated ground-based and satellite-supported visual platforms, the integration of AI has significantly expanded the scope and depth of situational awareness.

Key advancements have been seen in the use of smart cameras [11], multimodal sensors, and deep neural network architectures for tasks such as fault detection, pilot behavior analysis, and anomaly identification. Through detailed comparisons, it is evident that modern architectures, such as YOLOv7 and Transformer-based models, offer superior performance in terms of accuracy, inference speed, dataset adaptability, and edge deployment. These findings reinforce the growing applicability of AI across a diverse range of aviation surveillance contexts.

Nevertheless, critical challenges remain. These include addressing data privacy and regulatory concerns, ensuring model robustness under varying operational conditions, and bridging the gap between academic innovation and real-world implementation. The need for standardized datasets, explainable AI, and privacy-preserving analytics will define the next phase of research.

In conclusion, the convergence of AI and optical surveillance presents a unique opportunity to elevate aviation safety, efficiency, and operational transparency. By aligning technological advancements with regulatory foresight and human-centered design, the aviation industry can develop more intelligent, resilient, and ethically responsible surveillance systems in the years to come.

VI. FUTURE WORK

Looking ahead, the landscape of AI-powered optical surveillance in aviation presents a wealth of opportunities for further innovation. Future research should prioritize the development of standardized, annotated datasets that accurately represent real-world aviation environments, encompassing diverse lighting conditions, altitudes, weather phenomena, and cockpit dynamics. These datasets would significantly enhance model training, validation, and benchmarking.

Another crucial direction involves the advancement of explainable AI (XAI) methodologies. As AI-based surveillance systems become more integral to safety-critical operations, ensuring that their outputs are interpretable and trustworthy is paramount.

Research into model transparency, confidence estimation, and human-in-the-loop systems will be crucial for gaining regulatory approval and operational acceptance.

Federated learning and privacy-preserving AI architectures also represent promising frontiers. These techniques allow models to be trained across decentralized data sources without transferring sensitive information, offering a balance between performance and compliance with aviation data protection standards.

Additionally, the integration of AI with augmented reality (AR) and mixed-reality interfaces for pilots and ground controllers could redefine how visual surveillance data is consumed. This would enable real-time overlay of critical insights, threat alerts, and visual annotations directly into the operator's field of view.

From a systems architecture standpoint, future solutions should also explore multi-agent collaboration, where surveillance drones, satellites, ground cameras, and onboard sensors communicate in a unified framework. This distributed intelligence can enable holistic, cross-platform threat detection and situational analysis.

Ultimately, rigorous field trials and pilot programs will be crucial in bridging the gap between theoretical models and practical deployment. Multistakeholder collaborations involving academia, industry, regulators, and airlines can foster scalable, adaptive, and safety-certified AI surveillance ecosystems that evolve in response to the dynamic needs of global aviation.

VII. ACKNOWLEDGMENT

The authors would like to thank the Karunya Institute of Technology and Sciences for providing them with excellent opportunities and support to pursue this research work.

REFERENCES

[1] Anjum, K. N., Raju, M. A. H., Saikat, M. H., Avi, S. P., Islam, K. T., Hoque, R., & Imam, T. (2024). Exploring the multifaceted impact of Artificial Intelligence and the Internet of Things on innovative city management. Journal of Computer Science and Technology Studies, 6(1), 241–248.

[2] Wang, H., Yin, C., Zhang, J., & Gao, H. (2020). An intelligent aviation safety system based on real-time video surveillance and deep learning. IEEE Transactions on Intelligent Transportation Systems, 21(12), 5218–5228.

[3] Zhang, X., & Mahadevan, S. (2020). Bayesian neural networks for flight trajectory prediction and safety assessment. Decision Support Systems, 131, 113246. https://doi.org/10.1016/j.dss.2020.113246

[4] Zhang, X., Qu, X., Xue, H., Tao, D., & Li, T. (2019). Effects of time of day and taxi route complexity on navigation errors: An experimental study. Accident Analysis & Prevention, 125, 14–19. https://doi.org/10.1016/j.aap.2019.01.019

[5] Ziv, G. (2017). Gaze behavior and visual attention: A review of eye tracking studies in aviation. The International Journal of Aviation Psychology, 26(3–4), 75–104. https://doi.org/10.1080/10508414.2017.1313096

[6] Harrison, M., Esiri, J., Ezeafulukwe, O., Ekemezie, T., & Digitemie, A. (2024). AI-powered surveillance systems for industrial and urban security applications. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[7] Obiki-Osafiele, A. N., Eziamaka, T. A., & Akinsulire, R. (2024). Predictive threat analysis and drone-enabled surveillance. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[8] Ige, C., Ezeh, C., Nwosu, K., & Ilori, B. (2024). AI-enhanced airport and law enforcement surveillance. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[9] Komolafe, T. S., Ajiga, O. L., & Agu, E. E. (2024). AI Surveillance Systems: Privacy Concerns and Regulatory Gaps. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[10] Kayusi, F., et al. (2025). Future trends in autonomous air traffic management. LatIA, 3, 80. https://doi.org/10.62486/latia202580

[11] Ekemezie, T., & Digitemie, A. (2024). AI surveillance in manufacturing safety. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[12] Ahuchogu, O. P., Nwosu, C. I., & Ilori, B. K. (2024). Adaptive learning in surveillance systems. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[13] Akinsulire, R., Ezeafulukwe, O., & Esiri, J. (2024). Model optimization and continuous AI monitoring. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[14] Okatta, J., Agu, E. E., & Efunniyi, C. P. (2024). Federated and ethical AI surveillance practices. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[15] Samira, F., & Harrison, M. (2024). Use of facial recognition and acoustic sensors in urban surveillance. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[16] Lee, D., & Mavris, D. N. (2021). Deep learning-based pilot behavior monitoring for proactive safety management. Journal of Aerospace Information Systems, 18(9), 574–585.

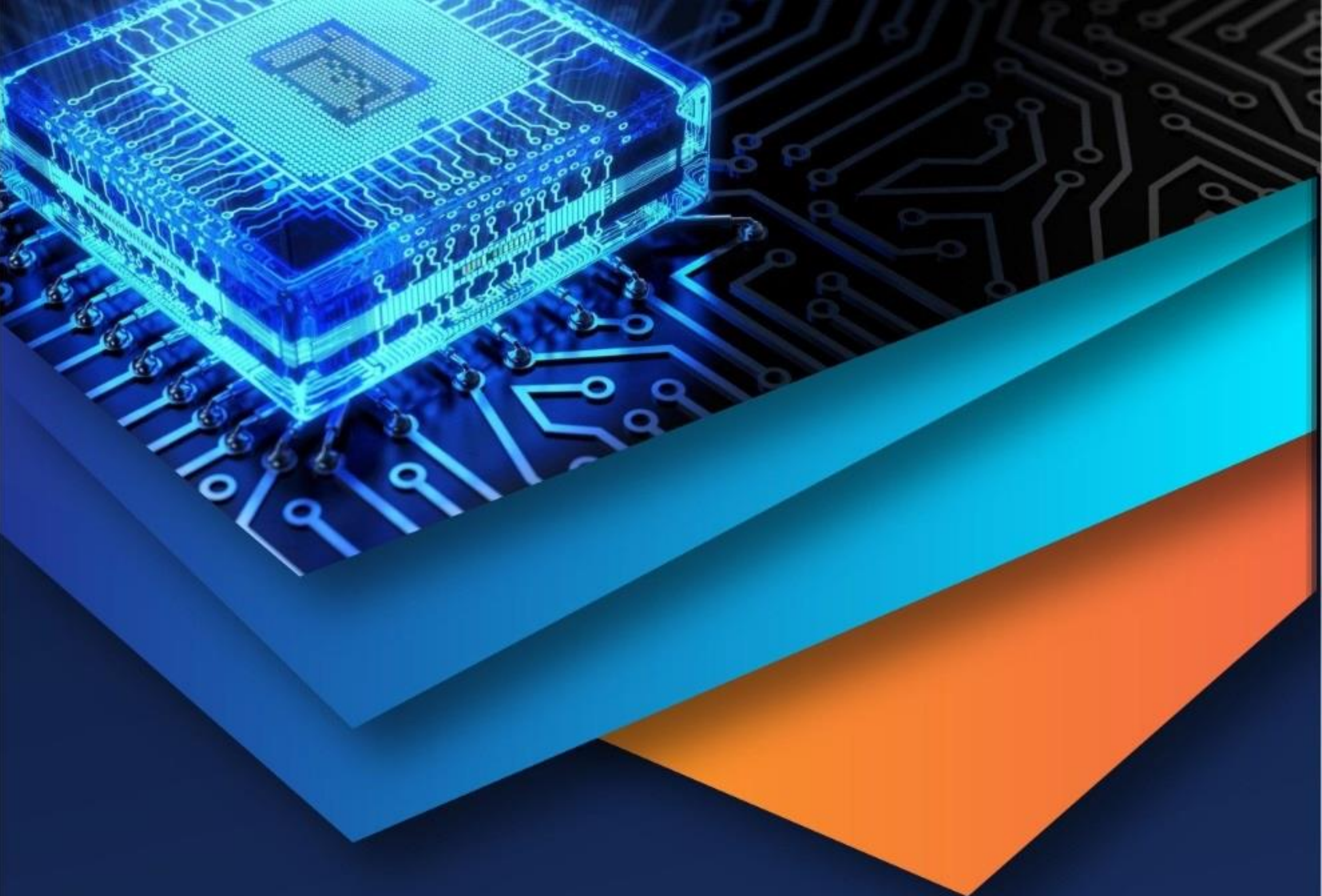
[17] Esiri, J., & Ezeafulukwe, O. (2024). Cloud-based scaling for AI-powered surveillance systems. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[18] Nwosu, K., Ilori, B., & Ezeh, C. (2024). Optimization and Architecture for AI Surveillance Systems. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.

[19] LatIA Editorial Board. (2025). Case studies on AI surveillance in aviation. LatIA, 3, 80. https://doi.org/10.62486/latia202580

[20] NASA. (2022). AIRS-WAVE: Airborne Image Recording System – Wide-Angle Video Enhancement (Tech Report). NASA Safety Center.

[21] Phat, T. V., Alam, S., Lilith, N., Tran, P. N., & Binh, N. T. (2021). Deep4Air: A novel deep learning framework for airport airside surveillance. arXiv preprint arXiv:2010.00806v2. https://arxiv.org/abs/2010.00806
[22] Harrison, M., Esiri, J., Ezeafulukwe, O., Ekemezie, T., & Digitemie, A. (2024). AI-powered surveillance systems for industrial and urban security applications. Open Access Research Journal of Engineering and Technology, 7(2), 031–045.
[23] Kozuba, M., & Pulit, P. (2023). Artificial intelligence systems for supporting video surveillance operators at international airport. Transportation Research Procedia, 74, 1284–1291.
[24] Kundegorski, M. E., Tang, B., Han, J., & Zhang, D. (2022). Optical surveillance for aircraft detection: A review of datasets, algorithms and challenges. arXiv preprint arXiv:2209.12849v3. https://doi.org/10.48550/arXiv.2209.12849
[25] Majd, D., Rupprecht, C., Shah, M., & Khan, S. H. (2024). Vision-based system for aircraft detection using neural networks. Transportation Research Part C: Emerging Technologies, 157, 104233.
[26] Appareo Systems. (n.d.). Aircraft flight data recorder – VISION 1000. Appareo. Retrieved from https://www.appareo.com



10.22214/IJRASET

INDEX COPERNICUS 45.98

IMPACT FACTOR: 7.129

TOGETHER WE REACH THE GOAL

IMPACT FACTOR: 7.429

INTERNATIONAL JOURNAL FOR RESEARCH

IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY