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AI Guardian for Aircraft Safety and Rescue: A Review of Predictive Health Monitoring, Collision Avoidance and Autonomous Emergency Response

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Abstract—Severe weather, mid-flight system failures and hazardous terrain continue to challenge aviation safety, and traditional safeguards depend heavily on pilot intervention and ground communication that may be limited during sudden emergencies. This paper reviews the concept of an AI Guardian, an intelligent framework that supports flight safety before, during and after an incident. Three capability areas are examined. First, predictive health monitoring uses deep learning on engine and flight-data telemetry to estimate remaining useful life and detect anomalies before they become failures. Second, decision support for collision avoidance and emergency handling draws on airborne collision-avoidance logic, neural-network policy compression and formal verification of safety-critical networks. Third, post-incident rescue support coordinates drones with computer vision to locate crash sites, deliver medical kits and relay location data to rescue teams. A five-layer architecture that integrates onboard sensing, edge analytics, pilot advisory, air–ground communication and rescue coordination is proposed. Research gaps, objectives, a comparison of techniques and the certification challenges set out in the EASA AI roadmap are discussed. The review concludes that AI can reduce human error and response time if it remains verifiable, explainable and subordinate to pilot authority.

Index Terms—Aviation safety, predictive maintenance, remaining useful life, collision avoidance, anomaly detection, rescue drones, explainable AI, certification

I. INTRODUCTION

Commercial aviation is among the safest forms of transport, yet accidents still occur when several small problems combine under time pressure: an engine degrades unnoticed, weather deteriorates, workload rises and communication with the ground is interrupted. Once an aircraft is down, especially over mountains, forests or water, locating survivors quickly becomes the deciding factor.

Artificial intelligence is well suited to these problems because aircraft already generate large volumes of sensor data. Learning methods can find early warning signs in that data, suggest safe actions when the crew is overloaded, and direct rescue resources once an incident has happened. The European Union Aviation Safety Agency has published a roadmap for AI in aviation [1] that emphasizes human-centric design, learning assurance and explainability, signalling that regulators expect such systems to arrive but under strict conditions.

This paper reviews the building blocks of an "AI Guardian" for aircraft safety and rescue, proposes an integrated architecture and identifies the research needed before such a system could be certified.

II. THEORETICAL BACKGROUND

1. Safety Layers In Aviation

Aviation safety follows a layered approach: design and maintenance prevent failures, onboard systems and crews manage abnormal situations, and search and rescue services respond after an accident. An AI Guardian adds intelligence to each layer, as summarized in Fig. 1.

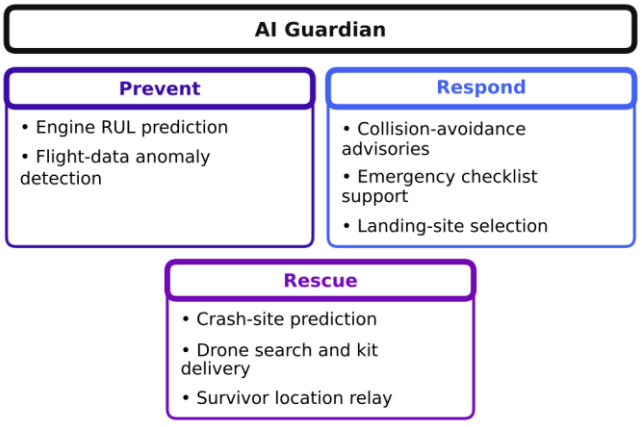


Fig. 1. Functions of an AI Guardian across the aviation safety layers.

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2. Prognostics And Remaining Useful Life
Prognostics estimates the remaining useful life (RUL) of a component from its condition data. The C-MAPSS simulation dataset of Saxena *et al.* [2] models turbofan engine degradation and has become the standard benchmark for RUL algorithms.

3. Collision Avoidance
The Traffic Alert and Collision Avoidance System (TCAS) issues resolution advisories that tell pilots to climb or descend when another aircraft comes too close [3]. Its successor family, ACAS X, derives advisories from optimized decision tables computed with methods for decision making under uncertainty [4].

III. SURVEY OF EXISTING APPROACHES

Zheng *et al.* [5] applied long short-term memory networks to RUL estimation and showed that modelling temporal dependencies in sensor sequences improves accuracy over shallow regressors. Li *et al.* [6] used deep one-dimensional convolutional networks on time windows of engine signals and obtained competitive results with fewer parameters, suggesting that compact models can serve onboard use.

For anomaly detection in operational flight data, Das *et al.* [7] proposed multiple kernel learning that combines continuous and discrete signals and demonstrated it on fleet data, uncovering operationally significant events that rule-based exceedance checks missed.

Julian *et al.* [8] compressed the very large ACAS Xu lookup tables into a set of deep neural networks that fit within avionics memory while closely reproducing the original advisories. Because neural networks are hard to certify, Katz *et al.* [9] developed Reluplex, an SMT-based verifier that proved safety properties of these collision-avoidance networks, showing a path toward formally verified AI in the cockpit.

After an accident, unmanned aerial vehicles can search large areas quickly. Erdelj *et al.* [10] reviewed UAV roles in disaster management, and real-time detectors such as YOLO [11] allow drones to identify wreckage and people in imagery. Murphy [12] documented field experience with rescue robots and stressed the importance of operator interfaces. Table I summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Author(s) / Year	Technique / Approach	Key Contribution	Limitation / Gap
[2]	Saxena et al., 2008	C-MAPSS engine degradation simulation	Standard benchmark for RUL research	Simulated, not fleet data
[5]	Zheng et al., 2017	LSTM for RUL estimation	Captured temporal degradation patterns	Requires long sequences
[6]	Li et al., 2018	Deep 1-D CNN prognostics	Accurate RUL with compact model	Benchmark-only validation
[7]	Das et al., 2010	Multiple kernel anomaly detection	Found significant events in flight data	Alerts need expert review
[8]	Julian et al., 2019	DNN compression of ACAS Xu tables	Fits collision logic into avionics memory	Approximation must be verified
[9]	Katz et al., 2017	Reluplex SMT verification	Proved properties of ACAS Xu networks	Scales to small networks
[10]	Erdelj et al., 2017	UAV support for disaster management	Roles for drones in search and rescue	Endurance and regulation limits
[12]	Murphy, 2014	Field study of rescue robots	Practical deployment lessons	Mostly teleoperated systems

IV. COMPARATIVE STUDY

Table II compares techniques used across the guardian's functions. Recurrent and convolutional networks dominate prognostics, compressed networks suit onboard decision aids, and object detectors drive drone search.

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TABLE II Comparison of Techniques Across Guardian Functions

Function	Technique	Strength	Limitation
Prognostics	LSTM / 1-D CNN	Learns degradation	Needs run-to-failure data
Anomaly detection	Kernel / autoencoder	Finds unknown events	Explanations weak
Collision avoidance	Compressed DNN	Fast, compact	Certification effort
Verification	SMT (Reluplex)	Formal guarantees	Limited scale
Rescue search	YOLO on UAV imagery	Real-time detection	Battery limits

V. RESEARCH GAPS

- **G1:** RUL models are mostly validated on simulated engine data; evidence from operational fleets is limited.
- **G2:** Anomaly detectors raise alerts but rarely explain them in terms a pilot can act on in seconds.
- **G3:** Neural decision aids are difficult to certify; verification currently scales only to small networks.
- **G4:** Integration between onboard health monitoring and post-crash rescue coordination is largely absent.
- **G5:** Human–AI teaming under high workload, including how advisories are presented, is under-studied.

VI. AIMS AND OBJECTIVES

- To review AI techniques for predictive health monitoring of aircraft systems.
- To study AI-assisted collision avoidance and emergency decision support, including verification.
- To examine drone-based search and rescue for aviation incidents.
- To propose an integrated AI Guardian architecture spanning prevention, response and rescue.
- To identify certification and human-factors challenges.

VII. PROPOSED ARCHITECTURE

The architecture in Fig. 2 places time-critical functions on board and uses ground and cloud services for fleet learning and rescue coordination.

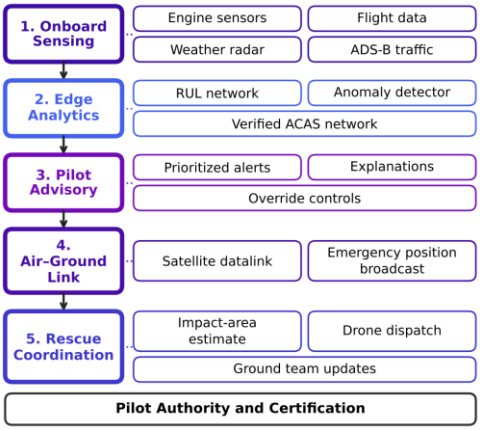


Fig. 2. Proposed five-layer AI Guardian architecture for aircraft safety and rescue.

1. Onboard Sensing Layer
Engine sensors, flight-control data, weather radar, ADS-B traffic reports and cockpit alerts are collected continuously.

2. Edge Analytics Layer
Compact neural networks estimate component health and flag anomalies; a verified collision-avoidance network evaluates traffic conflicts.

3. Pilot Advisory Layer
Advisories are prioritized and explained on cockpit displays. The crew retains authority, and every advisory can be acknowledged or overridden.

4. Air–Ground Communication Layer
Health summaries and emergency messages are transmitted by satellite or ground datalink, and the aircraft's last known position is broadcast automatically if an emergency is declared.

5. Rescue Coordination Layer
Rescue centres receive the predicted impact area and dispatch drones that search with thermal and visual detection, drop medical kits and relay survivor locations to ground teams.

VIII. PROCESS FLOW AND EVALUATION

Fig. 3 shows the guardian's operating cycle. RUL is learned as a regression from a window of sensor readings $x_{t-k} \ldots x_t$, and models are compared by root-mean-square error

$$RMSE = \sqrt{(1/N)\,\Sigma\,(RUL_i - \hat{RUL}_i)^2} \quad (1)$$

together with an asymmetric score that penalizes late predictions more than early ones, because underestimating risk is more dangerous than scheduling maintenance slightly early.

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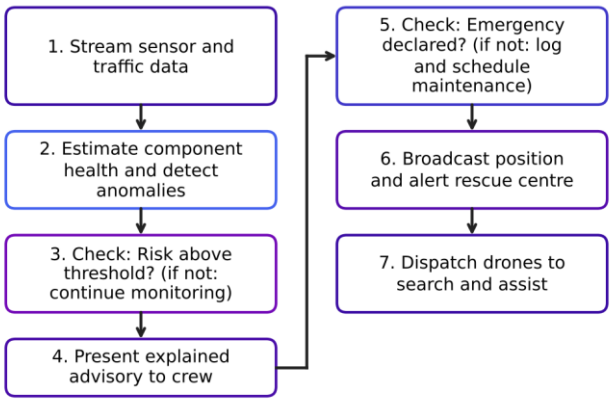


Fig. 3. Operating cycle of the AI Guardian.

A collision-avoidance policy maps the encounter state (relative position, speed and altitude rate) to an advisory, and verification checks that no input in a defined region produces an unsafe advisory.

IX. LIMITATIONS AND FUTURE SCOPE

Table III summarizes key challenges. Future work should build operational datasets shared across airlines, explainable health alerts, scalable verification tools, and simulation environments where crews can train with AI advisories before deployment.

TABLE III Challenges and Mitigation

Challenge	Mitigation
Certification of AI	Learning assurance; formal verification
Scarce failure data	Simulation, transfer learning
Pilot trust	Explained, prioritized advisories
Communication loss	Onboard decisions; automatic position broadcast
Rescue in harsh terrain	Thermal drones; multi-drone search

X. CONCLUSION

An AI Guardian can strengthen every layer of aviation safety: predicting failures before they occur, supporting crews when workload peaks and speeding rescue after an incident. The reviewed literature shows mature foundations in prognostics, neural collision avoidance with formal verification, and drone-based search. Turning these into a certified system requires operational validation, explanations that pilots trust and clear rules that keep humans in command.

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