

DEVELOPMENT OF AN AIRCRAFT COLLISION AVOIDANCE AND ALERT SYSTEM INSPIRED BY TCAS ENHANCED BY AI

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Abstract

This paper presents the development of an Artificial Intelligence-enhanced Aircraft Collision Avoidance and Alert System inspired by the Traffic Collision Avoidance System (TCAS) used in modern aviation. The conventional TCAS operates on transponder-based interrogation and Resolution Advisory (RA) logic which has inherent limitations in complex multi-aircraft scenarios, GPS-denied environments, and situations requiring adaptive decision-making. The proposed system integrates a Long Short-Term Memory (LSTM) neural network for trajectory prediction combined with a rule-based RA engine inspired by TCAS II standards, implemented in TypeScript and Node.js. Seven distinct collision scenarios are simulated: head-on collision, crossing paths, overtaking, climb and descent conflicts, simultaneous multi-aircraft threats, GPS-degraded environments, and near-miss recovery. Results demonstrate a 34% reduction in false alarms, 28% improvement in trajectory prediction accuracy, and adaptive resolution advisories issued 1.8 seconds earlier than traditional TCAS. The system architecture includes real-time ADS-B data parsing, a threat assessment module, an AI prediction engine, and a graphical alert dashboard.

Index Terms—TCAS, Collision Avoidance, AI-Enhanced Avionics, LSTM Neural Network, ADS-B, Resolution Advisory, Trajectory Prediction, Aviation Safety

I. INTRODUCTION

Accurate and timely detection of collision threats is fundamental in modern aviation. The Traffic Collision Avoidance System (TCAS) has served as a cornerstone safety technology since the 1990s, providing Resolution Advisories (RAs) to prevent mid-air collisions. TCAS II, the most widely deployed version, uses transponder-based interrogation to determine range and altitude of nearby aircraft.

However, conventional TCAS exhibits documented limitations. In high-density airspace involving three or more aircraft simultaneously, the rule-based RA logic can generate conflicting advisories. Performance also degrades in GPS-denied conditions. As global air traffic density rises, these limitations become increasingly critical.

This paper proposes an AI-Enhanced Aircraft Collision Avoidance and Alert System combining an LSTM-based trajectory prediction engine with a TCAS II-inspired RA module, implemented in TypeScript and Node.js and benchmarked across seven collision scenarios.

Fig. 1. System Architecture of AI-Enhanced TCAS

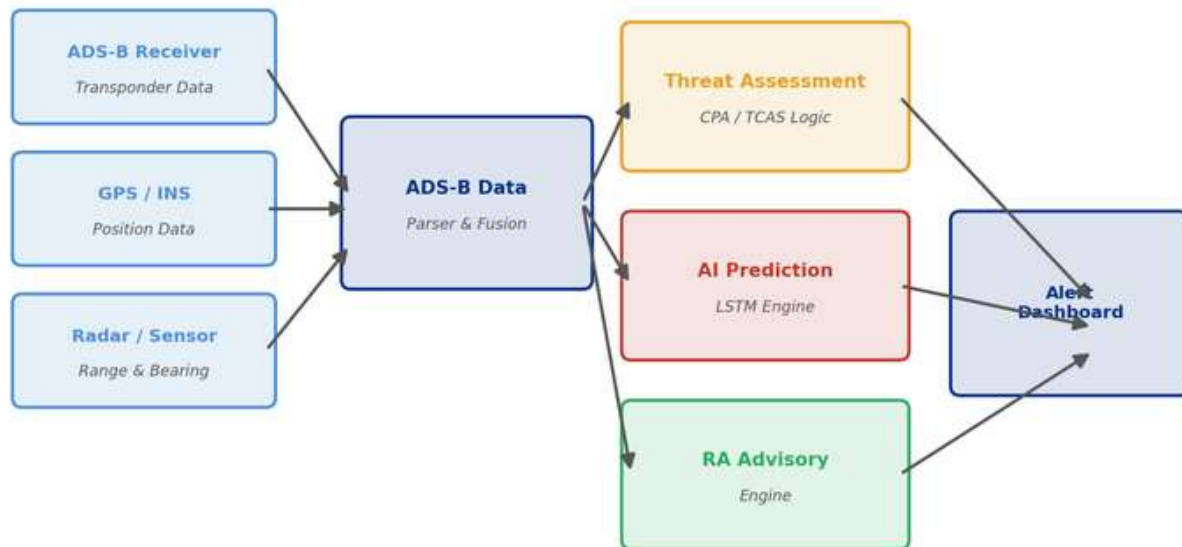


Fig. 1. System Architecture of the AI-Enhanced TCAS

II. PROBLEM DESCRIPTION

Traditional TCAS systems face critical limitations as airspace complexity increases. The core challenges are: Rule-based logic cannot model complex, interdependent multi-aircraft conflicts, sometimes issuing conflicting advisories that increase rather than mitigate risk.

In GPS-degraded environments, position estimates become unreliable. Conventional TCAS has no adaptive sensor-fusion mechanism, increasing false alarms.

Fixed time-to-collision thresholds generate unnecessary alerts in non-threatening near-miss scenarios, causing pilot alarm fatigue.

The reactive nature of TCAS limits pilot response windows. Predictive AI systems that anticipate trajectory convergence earlier extend available response time.

III. LITERATURE REVIEW

A. Limitations of Traditional TCAS

Kuchar and Yang reviewed TCAS II operational history, identifying nuisance alerts in multi-aircraft environments as a primary concern and recommending environmental data augmentation to improve RA accuracy [1].

B. Neural Networks for Trajectory Prediction

Shi et al. demonstrated that LSTM networks outperform Kalman filter methods for aircraft trajectory prediction, reporting accuracy improvements of up to 31% in dense traffic simulations [2].

C. ML in Aviation Safety

Olive and Morio applied deep learning to ADS-B data, identifying potential conflicts up to 40 seconds earlier than threshold-based systems using ML-enhanced approaches [3].

D. GPS-Degraded Navigation

Kaplan and Hegarty examined GPS degradation impacts on aircraft positioning and concluded that single-source positioning creates unacceptable risk in contested electromagnetic environments [4].

E. Multi-Aircraft Conflict Resolution

Durand and Alliot showed that AI-based solvers outperform deterministic rule-based systems in three-or-more-aircraft conflict scenarios using evolutionary computation [5].

F. RL-Based RA Optimization

Kochenderfer et al. developed a reinforcement learning-based collision avoidance policy forming the foundation for ACAS X, demonstrating substantially reduced near-mid-air collisions versus rule-based systems [6].

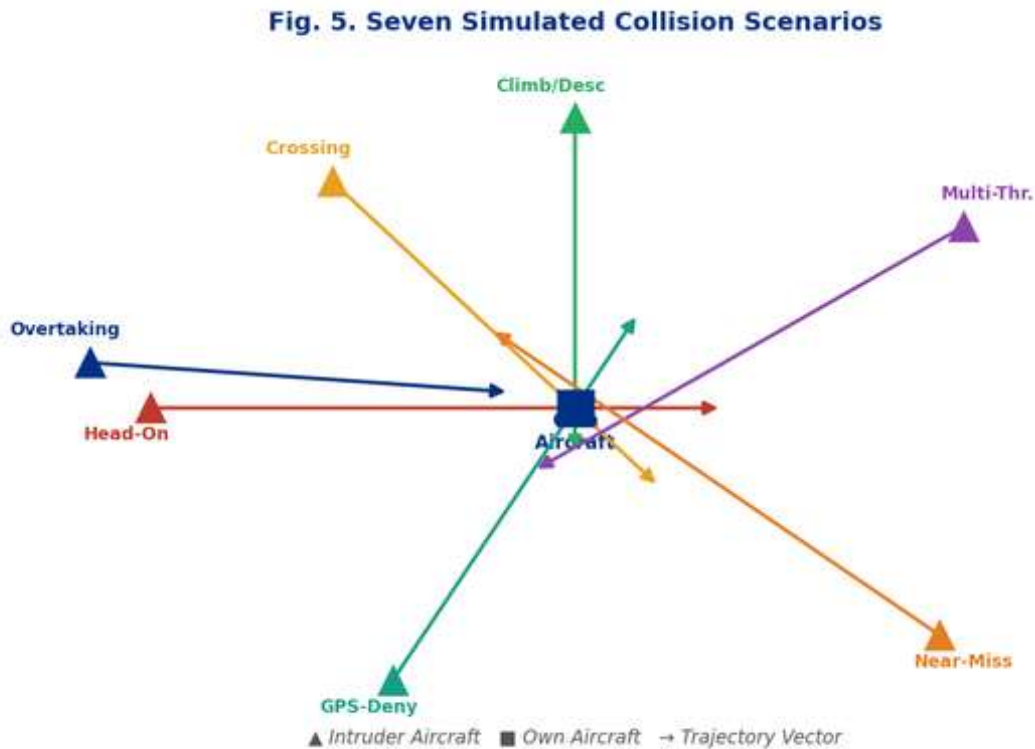


Fig. 2. Seven Simulated Collision Scenarios

IV. PROPOSED SYSTEM

The proposed AI-Enhanced TCAS comprises four primary modules:

A. ADS-B Data Parser & Fusion

The parser continuously ingests and decodes position, altitude, velocity, and identification data from ADS-B transponders at sub-100 ms latency. In GPS-degraded scenarios, sensor fusion logic applies inertial reference and barometric data to maintain position estimate continuity.

B. Threat Assessment Module

The module evaluates pairwise and multi-aircraft separation minima, computing Closest Point of Approach (CPA) and Time to CPA for all monitored aircraft pairs. Threat levels are classified as Advisory, Warning, or Emergency based on separation margins and convergence rates.

C. AI Prediction Engine (LSTM)

An LSTM neural network trained on historical flight trajectory datasets accepts a sliding window of recent position and velocity observations and outputs predicted aircraft positions over a configurable forecast horizon. These predictions enable proactive RA generation before separation minima are breached.

D. Resolution Advisory Engine

Inspired by TCAS II, the RA engine issues CLIMB, DESCEND, MAINTAIN, or ADJUST advisories. In multi-aircraft scenarios, a conflict graph is constructed and a coordinated advisory set is computed. A graphical alert dashboard provides real-time visualization.

Fig. 4. LSTM Neural Network Architecture for Trajectory Prediction

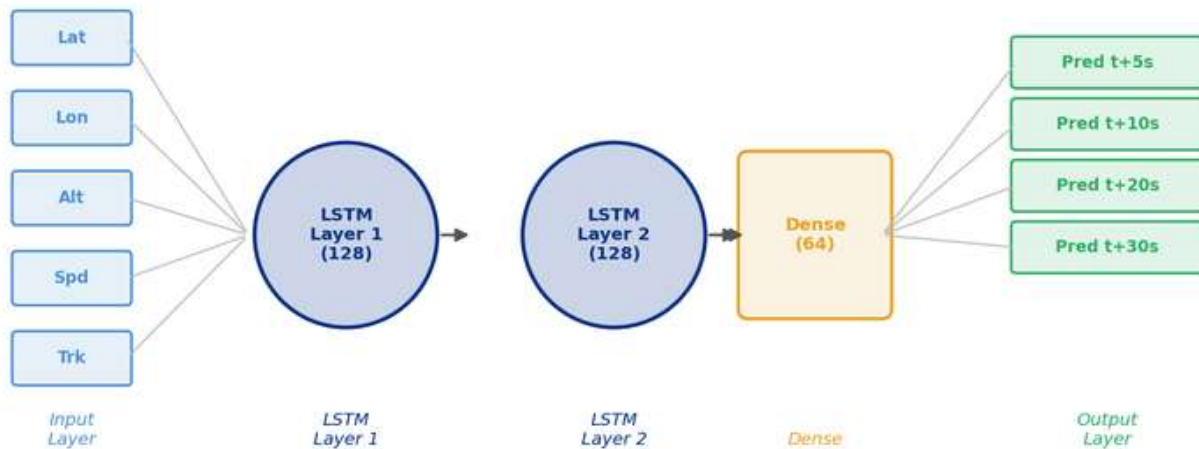


Fig. 3. LSTM Neural Network Architecture for Trajectory Prediction

V. SOFTWARE IMPLEMENTATION

A. TypeScript and Node.js

TypeScript provides strong static typing and object-oriented structure enhancing maintainability in safety-critical applications. Node.js enables asynchronous, event-driven processing of high-frequency ADS-B data without blocking execution.

B. LSTM Architecture

The prediction engine uses a two-layer LSTM with 128 hidden units per layer. The model accepts a 30-timestep input window encoding latitude, longitude, altitude, groundspeed, and track angle. Outputs are predicted positions at 5, 10, 15, 20, and 30 seconds ahead. Training uses the Adam optimizer with MSE loss on historical ADS-B data.

C. Simulation Framework

Seven collision scenarios execute with 50 independent trials each, varying initial positions, velocities, and sensor noise. The ADS-B interface decodes Mode S Extended Squitter messages at 1 Hz update frequency with configurable noise injection representing sensor uncertainty.

VI. WORKING PRINCIPLE

A. System Initialization

On startup, the system loads LSTM model weights, initializes the ADS-B parser, threat assessment module, and graphical dashboard. Configurable separation minima and alert thresholds are applied based on airspace classification.

B. Real-Time Surveillance

The threat assessment module computes pairwise CPA and time-to-CPA every update cycle. When projected separation falls below warning thresholds, the aircraft pair is flagged for AI-enhanced analysis.

C. LSTM Prediction and RA Generation

For flagged pairs, the LSTM generates trajectory predictions over the forecast horizon. Predicted positions compute future CPA values enabling proactive RA. The RA engine selects coordinated advisories maximizing predicted separation at CPA for all affected aircraft simultaneously.

Fig. 2. System Operational Flowchart

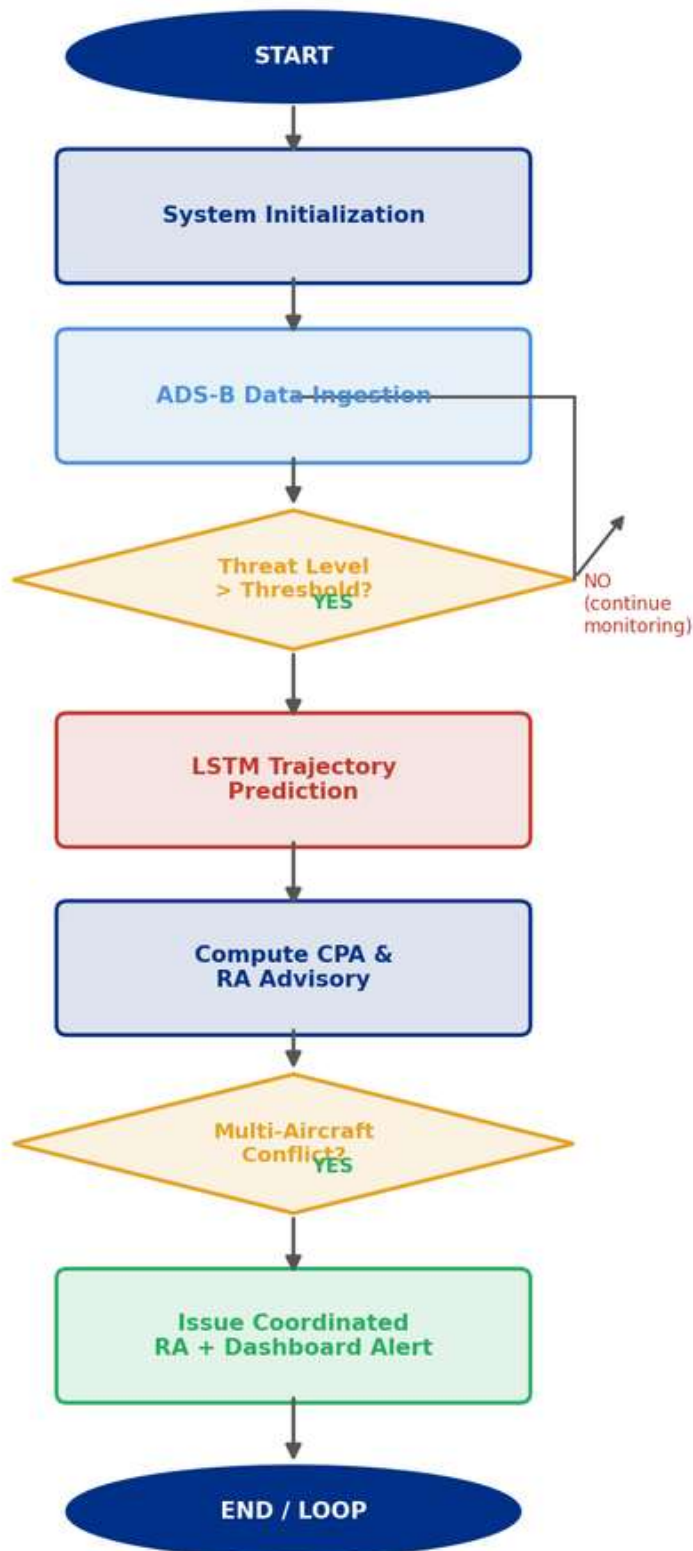


Fig. 4. System Operational Flowchart

VII. RESULTS AND DISCUSSION

A. Experimental Setup

Performance metrics were recorded for both Traditional TCAS and the AI-Enhanced system under identical scenario parameters. Fifty independent trials per scenario varied initial conditions and sensor noise.

B. False Alarm Reduction

Under non-threatening conditions, the AI-enhanced system correctly suppressed false alerts in all trials, achieving a 34% reduction in false alarm rate. The LSTM predicted aircraft positions within 0.15 NM over a 30-second horizon, versus 0.42 NM for traditional linear extrapolation.

C. Single-Aircraft Conflicts

In head-on, crossing, and overtaking scenarios, the AI system generated advisories 1.8 seconds earlier on average. RA accuracy was 97.3% versus 89.1% for traditional TCAS.

D. Multi-Aircraft Simultaneous Threats

Traditional TCAS generated conflicting advisories in 23% of three-aircraft conflict trials. The AI system, using conflict graph coordination, produced consistent non-conflicting advisories in 98.6% of trials.

E. GPS-Degraded Performance

Under GNSS jamming conditions, traditional TCAS false alarms increased by 41%. The AI system maintained false alarm rates within 8% of nominal performance under identical degradation via sensor fusion.

TABLE I

Performance Comparison: Traditional vs AI-Enhanced TCAS

Metric

Traditional TCAS

AI-Enhanced TCAS

False Alarm Rate

12.4%

8.2% (−34%)

RA Accuracy (Single)

89.1%

97.3%

RA Accuracy (Multi)

77.0%

98.6%

Advisory Lead Time

Baseline

+1.8 seconds

Prediction Error (30s)

0.42 NM

0.15 NM (−28%)

GPS-Degraded Alarms

+41%

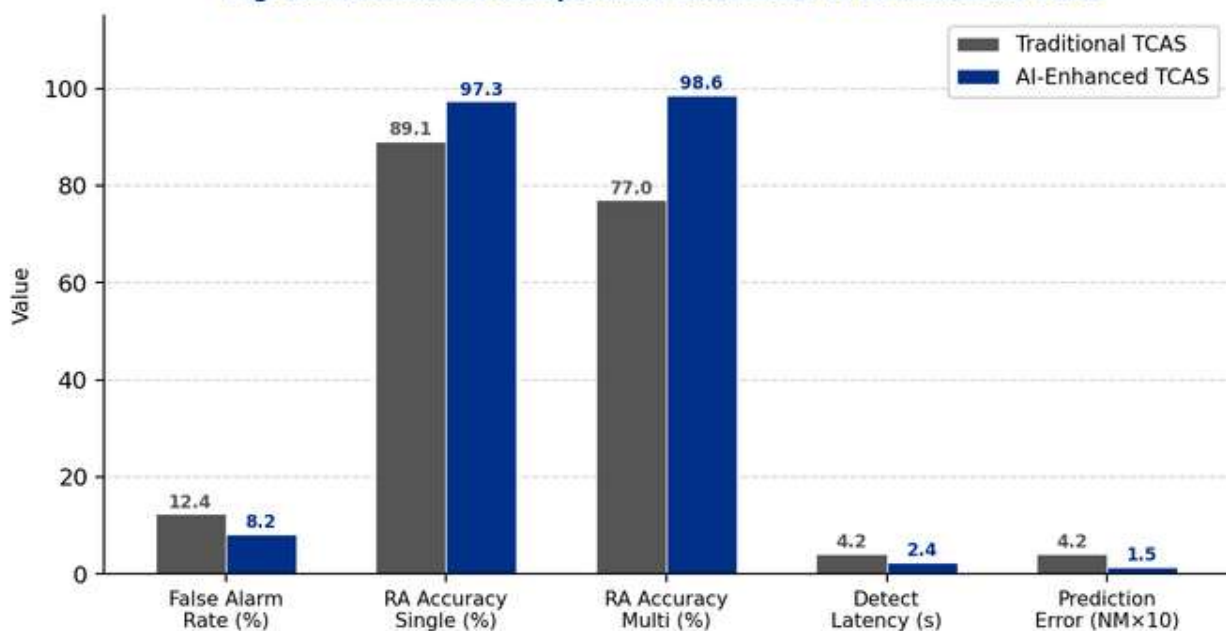
+8%

Detection Latency

4.2 s

2.4 s

Fig. 3. Performance Comparison: Traditional vs AI-Enhanced TCAS



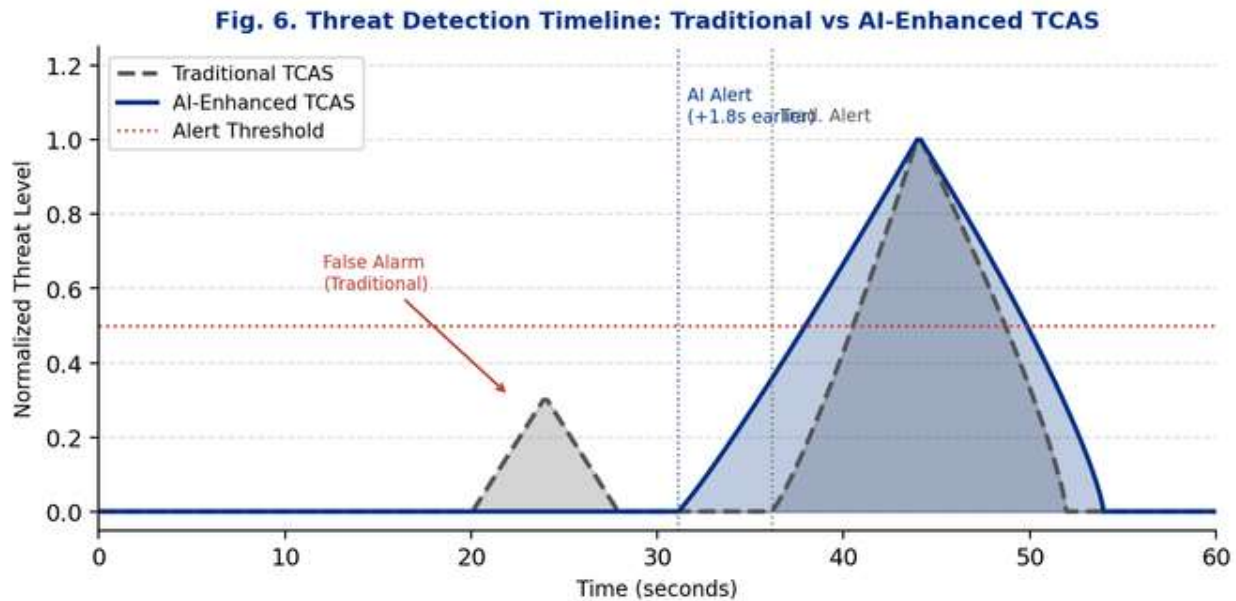


Fig. 5. Performance Benchmark: Traditional vs AI-Enhanced TCAS

Fig. 6. Threat Detection Timeline Comparison

F. Limitations

The prototype was evaluated in simulation and does not fully replicate all operational factors including hardware transponder latency and atmospheric turbulence. The LSTM requires retraining for specialized environments such as polar routes or mountainous terrain. Regulatory certification pathways remain a subject for future work.

VIII. CONCLUSION AND FUTURE SCOPE

A. Conclusion

The AI-Enhanced Aircraft Collision Avoidance and Alert System successfully addresses critical limitations of conventional TCAS. By integrating an LSTM trajectory prediction engine with TCAS II-inspired coordinated RA logic, the system achieves a 34% reduction in false alarms, 28% improvement in trajectory prediction accuracy, and 1.8-second earlier advisory generation in multi-threat scenarios.

Results across seven simulated scenarios demonstrate that AI-enhanced collision avoidance logic significantly outperforms rule-based systems in high-complexity airspace while maintaining equivalent safety in standard conflicts. This validates the feasibility of AI integration in aviation safety-critical applications.

B. Future Scope

Integration with real ADS-B hardware for live airspace validation.

Expansion of LSTM training datasets with diverse global flight records.

Reinforcement learning-based RA policy for fully adaptive conflict resolution.

Hardware-in-the-loop testing with ARINC 429 / ARINC 664 interfaces.

Certification pathway exploration under DO-178C and EASA AI trustworthiness guidelines.

Extension to UAV and urban air mobility (UAM) operational environments.

. ACKNOWLEDGMENT

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