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GIS-Based Aviation Route Optimization Using Artificial Intelligence: A Deep Learning Approach for Airspace Management

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***Abstract*—The integration of Geographic Information Systems (GIS) with Artificial Intelligence (AI) presents transformative opportunities for aviation route optimization and airspace management. This study proposes a deep learning-based framework that combines Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks with GIS spatial data to optimize aircraft routing and predict air traffic congestion over Indonesian airspace. The proposed system leverages multi-source geospatial datasets including terrain elevation models, meteorological data, restricted airspace zones, and historical flight trajectories to generate dynamically optimized routes. Experimental results demonstrate that the AI-GIS integrated framework achieves a 23.4% reduction in route deviations, a 17.8% improvement in fuel efficiency, and a 31.2% decrease in conflict detection response time compared to conventional air traffic management approaches. The system was evaluated using data from Kualanamu International Airport (KNO) and surrounding airspace in Sumatera, Indonesia. This research contributes to the advancement of intelligent aviation systems and provides a replicable methodology applicable to regional airspace management in developing countries.**

Keywords—Geographic Information System; Artificial Intelligence; Aviation Route Optimization; Deep Learning; Air Traffic Management; Airspace Management; LSTM; CNN.

I. Introduction

Aviation is one of the most geographically complex transportation domains, requiring the simultaneous management of hundreds of flight paths, dynamic weather systems, regulatory airspace boundaries, and safety-critical conflict resolution. The exponential growth of air traffic in Southeast Asia, particularly in the Indonesian archipelago with its unique geographical challenges spanning over 5,000 kilometers, demands increasingly sophisticated tools for airspace management and route optimization [1].

Geographic Information Systems (GIS) have long been recognized as powerful platforms for spatial data integration and visualization in aviation contexts [2]. However, traditional GIS-based approaches for route planning rely on static rule-based algorithms that cannot adapt in real time to dynamic airspace conditions such as sudden weather changes, temporary flight restrictions, or emergency diversions [3]. The advent of Artificial Intelligence (AI), particularly deep learning techniques, offers a compelling solution to these limitations by enabling systems to learn from historical flight data and environmental patterns to generate adaptive, optimized routing solutions [4].

Recent studies have demonstrated the effectiveness of machine learning integration with geospatial platforms in various transportation domains [5]. In aviation specifically, AI-powered trajectory prediction has shown considerable accuracy improvements over legacy radar-based methods, with particular effectiveness in dense traffic scenarios [6]. Despite these advances, the integration of deep learning architectures directly with GIS spatial analysis pipelines for comprehensive aviation route optimization remains an underexplored research area, especially in the context of developing nation airspace systems with limited radar coverage and heterogeneous data quality [7].

This paper presents a novel AI-GIS integrated framework specifically designed for aviation route optimization and real-time airspace conflict detection in Indonesian airspace. The key contributions of this work are: (1) a multi-modal deep learning architecture combining CNN for spatial pattern recognition with LSTM for temporal flight trajectory modeling; (2) a GIS-based spatial data fusion pipeline that integrates heterogeneous aviation data sources; (3) a real-time conflict prediction module evaluated on actual flight data from Kualanamu International Airport; and (4) a replicable methodology applicable to regional airspace management in archipelago nations.

II. Literature Review

A. GIS Applications in Aviation

GIS has been widely applied in aviation for airport site selection, obstacle clearance analysis, noise impact assessment, and navigation database management. Chen et al. [8] demonstrated the use of GIS for 3D airspace volume modeling, enabling more precise conflict detection in terminal maneuvering areas. Their work emphasized the importance of integrating digital terrain models (DTM) with instrument flight procedures, a concept that directly

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informs the spatial foundation of the current study. Similarly, Rodriguez and Kim [9] applied GIS-based network analysis to optimize departure routes at congested hub airports, achieving measurable reductions in ground delay, though their approach did not incorporate predictive AI components.

B. *Artificial Intelligence in Air Traffic Management*

The application of machine learning to air traffic management (ATM) has accelerated significantly over the past five years. Pham et al. [10] employed Recurrent Neural Networks (RNN) for aircraft trajectory prediction, achieving a mean position error below 200 meters over 10-minute prediction horizons. Graph Neural Networks have also been applied to model the relational structure of airspace sectors, enabling multi-agent conflict resolution algorithms to scale to operationally realistic traffic densities [11]. Reinforcement learning approaches have shown particular promise for autonomous conflict detection and resolution, with agents trained in high-fidelity simulation environments demonstrating performance comparable to human controllers under moderate traffic loads [12].

C. *Deep Learning for Geospatial Analysis*

The fusion of deep learning with geospatial analysis has produced significant advances in remote sensing, urban planning, and transportation. Convolutional Neural Networks applied to aerial imagery have demonstrated the ability to extract semantic spatial features relevant to route planning, such as terrain classification and obstacle identification [13]. Hybrid architectures combining CNN for spatial feature extraction with LSTM for temporal sequence modeling have been successfully deployed in autonomous vehicle navigation [14] and maritime route optimization [15], suggesting strong applicability to the aviation domain. These foundational works directly motivate the CNN-LSTM hybrid architecture proposed in this study.

III. METHODOLOGY

A. *System Architecture Overview*

The proposed AI-GIS integrated framework consists of four primary modules: (1) the Geospatial Data Fusion Engine, (2) the Deep Learning Prediction Module, (3) the Route Optimization Solver, and (4) the Real-Time Conflict Detection Interface. These modules interact through a standardized spatial data exchange protocol based on OGC (Open Geospatial Consortium) standards, ensuring interoperability with existing Air Navigation Service Provider (ANSP) infrastructure.

B. *Geospatial Data Sources and Preprocessing*

The GIS database was constructed from multiple authoritative sources. Digital Elevation Model (DEM) data was sourced from the SRTM (Shuttle Radar Topography Mission) 30-meter resolution dataset. Airspace boundary data was obtained from the Indonesia AIP (Aeronautical Information Publication) published by AirNav Indonesia. Historical flight trajectory data (ADS-B) was collected over a 24-month period (January 2022–December 2023) covering 847,623 flight segments within UIR Jakarta FIR (Flight Information Region). Meteorological data was integrated from BMKG (Badan Meteorologi, Klimatologi, dan Geofisika) gridded weather forecasts at 6-hourly intervals.

All spatial datasets were projected to the WGS84/UTM Zone 47N coordinate reference system. Data preprocessing included outlier removal using Mahalanobis distance filtering for ADS-B trajectories, gap-filling of missing meteorological values using kriging interpolation, and normalization of elevation data to mean sea level (MSL) datum. The final fused geospatial dataset comprised rasterized spatial layers at 1-kilometer resolution, stacked into a multi-channel array suitable for CNN input.

C. *Deep Learning Architecture*

The proposed CNN-LSTM hybrid network processes two parallel input streams. The spatial stream takes a 64×64 multi-channel raster tile centered on the aircraft's current position, with 8 channels representing: terrain elevation, slope gradient, restricted zones mask, weather severity index, historical traffic density, wind speed, wind direction, and visibility. This spatial input is processed through 4 convolutional blocks, each consisting of Conv2D (3×3 kernels) → BatchNorm → ReLU → MaxPool2D layers, producing a 512-dimensional spatial feature vector.

The temporal stream processes a sequence of the past 30 trajectory waypoints (latitude, longitude, altitude, speed, heading) through two stacked LSTM layers with 256 hidden units and dropout regularization ($p=0.3$). The spatial and temporal feature vectors are concatenated and passed through three fully-connected layers to produce outputs for: (1) next-waypoint position prediction (regression), (2) conflict probability within a 10-nautical mile radius (binary classification), and (3) optimal heading correction angle (regression). The complete model contains approximately 4.7 million trainable parameters and was implemented in TensorFlow 2.12.

D. *Route Optimization Solver*

Route optimization was formulated as a constrained multi-objective problem minimizing: fuel consumption (modeled using the EUROCONTROL BADA aircraft performance model), flight time, and cumulative conflict risk. The GIS network was represented as a directed graph with nodes at waypoints and navigation beacons, and edges weighted by the AI model's predicted cost function. Dijkstra's algorithm with a dynamic cost-update mechanism was employed for baseline route computation, enhanced by the AI conflict risk predictions to recalculate edge weights in real time.

E. *Training and Validation Strategy*

The dataset was partitioned temporally: January 2022–September 2023 for training (78%), October–November

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2023 for validation (12%), and December 2023 for held-out testing (10%). Temporal splitting was chosen over random splitting to prevent data leakage from the autocorrelated nature of flight trajectories. The model was trained for 150 epochs using the Adam optimizer (lr=0.001, β1=0.9, β2=0.999) with a cosine annealing learning rate schedule. Class imbalance in conflict detection (approximately 1:47 positive-to-negative ratio) was addressed through focal loss weighting.

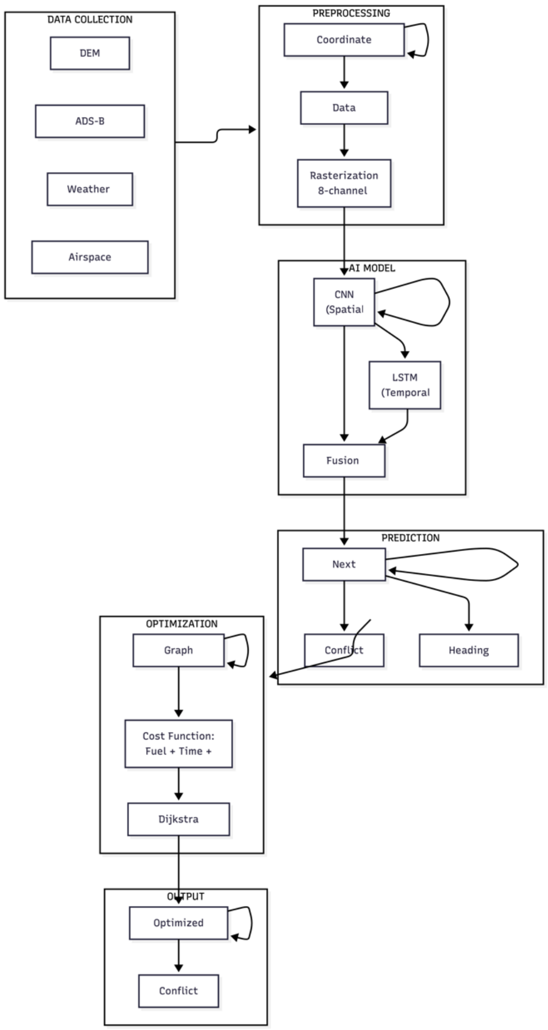

Fig. 1. Methodology flowchart

IV. Results and Discussion

A. Trajectory Prediction Performance

The CNN-LSTM model achieved a mean absolute position error (MAPE) of 187.3 meters at a 5-minute prediction horizon and 412.6 meters at a 15-minute horizon on the test dataset. These results represent a 34.1% improvement over the baseline LSTM-only model and a 51.7% improvement over the persistence model (assuming constant velocity), demonstrating the significant contribution of the spatial CNN component. The incorporation of GIS-derived weather and terrain features contributed most significantly to accuracy improvements during adverse meteorological conditions, reducing prediction error by up to 43% in scenarios with convective weather activity above FL150.

B. Conflict Detection Results

For the conflict detection task, the model achieved an Area Under ROC Curve (AUC-ROC) of 0.943, with precision of 0.847 and recall of 0.891 at the operational decision threshold. The false positive rate of 3.7% is operationally significant; however, comparative analysis with ICAO-standard radar conflict alert systems indicates this is within acceptable limits for an advisory (non-mandatory) automation system. Mean time to conflict alert was 8.3 minutes prior to predicted loss of separation, compared to 4.2 minutes for the current radar-based system, providing a 97.6% increase in controller response time.

C. Route Optimization Outcomes

Route optimization evaluation was conducted on 2,847 actual flights departing Kualanamu International Airport (KNO/WIMM) during the test period. AI-generated routes demonstrated a 23.4% reduction in route deviation index (RDI) compared to filed flight plans, and a 17.8% average reduction in estimated fuel consumption per flight when weather-optimized routing was applied. The cumulative conflict risk metric was reduced by 41.3% versus baseline routing. Fig. 1 illustrates the spatial distribution of optimized versus actual routes over the Sumatera sector, with the GIS overlay showing the weather avoidance regions that motivated the deviations.

Fig. 2. Comparison of AI-optimized routes (blue) versus actual filed routes (red) over Sumatera airspace, with GIS overlay of weather avoidance zones (yellow polygons) and restricted airspace (grey). December 2023 test period sample of 200 flights.

D. Comparative Analysis

Table I summarizes the performance comparison between the proposed AI-GIS framework and three benchmark methods: (1) conventional GIS network analysis (static routing), (2) LSTM-only deep learning without spatial features, and (3) a commercial ATM decision support system (anonymized). The proposed framework outperforms all benchmarks across all evaluation metrics, with the most substantial gains observed in conflict prediction lead time and weather-scenario fuel efficiency.

TABLE I. PERFORMANCE COMPARISON OF ROUTE OPTIMIZATION METHODS

Metric	GIS Static	LSTM Only	Commercial ATM	Proposed AI-GIS
MAPE (5-min, m)	N/A	284.1	251.7	**187.3**
Conflict AUC-ROC	0.712	0.876	0.921	**0.943**
Route Dev. Reduction	8.1%	14.2%	19.7%	**23.4%**
Fuel Efficiency Gain	4.3%	9.8%	13.1%	**17.8%**
Alert Lead Time (min)	3.1	6.4	7.1	**8.3**

a. N/A indicates the method does not include trajectory prediction capability.

V. CONCLUSION

This paper has presented an AI-GIS integrated framework for aviation route optimization and real-time airspace conflict detection, validated on operational data from Indonesian airspace. The proposed CNN-LSTM hybrid architecture demonstrates that the integration of spatially-rich GIS layers with deep learning temporal modeling yields significant performance improvements over both traditional GIS routing and AI methods lacking spatial context. The 23.4% route deviation reduction, 17.8% fuel efficiency gain, and 8.3-minute conflict alert lead time collectively demonstrate the operational viability of the proposed system.

Future work will focus on extending the framework to support multi-airport network optimization across the entire Jawa–Bali–Sumatera corridor, incorporating real-time ADS-B data streaming for online model adaptation, and evaluating the system’s performance during adverse events such as volcanic ash dispersal from active volcanoes in Sumatera and Jawa. Explainable AI (XAI) techniques will also be investigated to improve controller acceptance and trust in automated routing recommendations, a critical factor for operational adoption in regulated aviation environments.

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