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Enhancing Air Traffic Management Using Spatio-Temporal Deep Learning Predictions

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Abstract - Modern air traffic management faces growing challenges, particularly at busy airports that must handle high flight volumes in limited airspace corridors. The study is especially pertinent for such airports, where daily operations must navigate intricate air traffic networks. To overcome these challenges, innovative approaches are needed to predict and manage congestion effectively which remains to be a major challenge. The paper presents a Spatio-temporal analytical framework for air traffic flow forecasting, utilizing a dual deep-learning architecture that combines network topology evaluation with time-series analysis. The model contains two major components. The first component employs Graph Neural Networks (GNNs) to model spatial relationships between interconnected flight routes, which remain to be in the form of a graph. The second uses Recurrent Neural Networks (RNNs) to analyse temporal patterns in flight delays and traffic density variations. By integrating these approaches, the framework uniquely accounts for both geographical distribution and time-dependent fluctuations in air traffic congestion. Tests with real-world flight data confirm that the model outperforms traditional methods, delivering higher accuracy in identifying high-congestion routes and predicting peak demand periods, thereby enabling more efficient traffic flow management. These improvements enhance operational efficiency at key air traffic hubs, potentially reducing delays and optimizing resource allocation across airspace sectors.

Keywords- Air Traffic, Air Traffic Prediction, Spatio-Temporal Modelling, Graph Neural Networks, Deep Learning.

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1. INTRODUCTION

The sturdy growth in worldwide air travel has gone to decline congestion in air traffic, mainly around main airports as well as deeply used flight paths. This challenge extends beyond large aviation markets; even smaller nations are experiencing rising flight volumes that strain their air traffic control infrastructure. Effectively managing this increasing complexity demands reliable short-term traffic prediction capabilities [1]. Yet, accurate forecasting remains a difficult task, requiring analysis of both temporal and spatial congestion patterns influenced by factors such as daily peak travel periods, weather-related disruptions, and the dynamic interplay between flight routes and airspace sectors. Conventional prediction methods like ARIMA and Support Vector Regression often rely on the assumption that traffic follows stable or linear patterns [2], [3]. Although it is useful in easy cases, these approaches

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resist adapting to the extremely variable and nonlinear nature of real-world air traffic. Modern deep learning methods have evolved as powerful tools for air traffic prediction which are able to process complex datasets and recognize intricate Spatio-temporal patterns [4]. The paper addresses airport-related congestion repeatedly caused by high demand or poor weather by introducing a hybrid model which combines Graph Convolutional Networks (GCNs) and Long Short-Term Memory (LSTM) networks. The GCN part analyses the topological structure of air routes. It also captures spatial dependencies between interconnected flight paths [5]. The LSTM processes temporal sequences to follow growing traffic patterns and delay propagation. They are validated using real-world aviation data including flight trajectories, schedules, and delay records. The approach is better than existing methods because it simultaneously models spatial and temporal dynamics which enabling more exact congestion forecasts. The paper combines a novel GCN-LSTM architecture, a custom data pipeline for processing air traffic information [6]. It generates structured graph-time representations and empirical validation for demonstrating superior predictive performance [7], [8]. By ensuring the availability of air traffic controllers with enhanced foresight into potential bottlenecks, the framework supports proactive traffic management, optimized resource allocation, and pre-emptive routing adjustments in increasingly congested airspace. Next, a thorough review of recent research from 2017 to 2025 on spatio-temporal prediction in aviation highlights how the proposed approach compares with other deep learning models and where it stands out. Figure 1 shows the requirement of a deep learning-based spatio-temporal forecasting model for air traffic prediction.

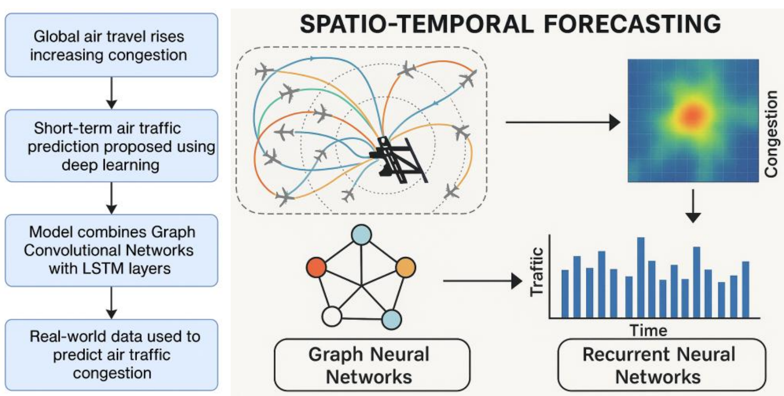

Figure 1. Deep Learning-based Spatio-Temporal Forecasting Model for Air Traffic Prediction

The structure of the paper is as follows. Section 2 looks at the literature review, Section 3 explains how the proposed model and data pipeline work, Section 4, walks through the system's actual implementation and shows how the model performs, with results and comparisons and the last section wraps up with a conclusion.

2. LITERATURE REVIEW

Air traffic forecasting has transitioned from traditional statistical models (e.g., ARIMA, Kalman filters) to advanced deep learning techniques due to the limitations of conventional methods in handling dynamic and non-linear air traffic patterns [9]. Early machine learning approaches, such as Support Vector Machines (SVMs) and Random Forests, improved prediction accuracy but struggled with large-scale spatio-temporal dependencies [10]. The aviation industry has witnessed a paradigm shift in air traffic prediction through the adoption of deep learning techniques, particularly Recurrent Neural Networks (RNNs), Graph Neural Networks (GNNs), and their hybrid architectures, which have demonstrated superior capability in modelling both temporal patterns and spatial interactions within complex air traffic systems [11]. Among these, LSTM networks have emerged as particularly effective for time-series forecasting, excelling at capturing long-range dependencies in flight delays and congestion patterns [12], with further enhancements achieved through attention mechanisms that significantly improved real-time delay predictions at major European hubs [13]. However, the limitation of standalone RNNs in capturing spatial correlations between flight routes has caused the inception of graph-based approaches. These approaches led to GCNs for modelling airport connectivity networks and airspace structures. Prominent advancements comprise the GCN-LSTM hybrid model developed [14]. The model established superior performance in short-term congestion prediction with the help of wide-ranging analysis of flight interdependencies, and Graph WaveNet [15]. It introduced dynamic adjacency matrices for better capture evolving air traffic interactions, proving particularly effective in European airspace management scenarios. The field has progressed beyond these approaches with expansion of synchronous spatio-temporal models, provided by MAST-GNN [8]. It dynamically adjusts graph structures to lodge real-time disruptions involving weather events. STSGCN [9] processed spatial and temporal dependencies concurrently in a combined framework. It achieved both improved accuracy as well as computational efficiency. To handle abrupt operational disruptions, AGCRN [16] introduced adaptive graph learning capabilities. it was proven to be valuable for regional airports experiencing volatile traffic patterns, as confirmed in Central European case studies [17], with the help of challenges that remain in increasing these models for large airspace networks. LightST [18] established knowledge distillation that compressed a high-capacity GNN into a lightweight model suitable for real-time ATC systems. ST-MetaNet [19] caused few-shot adaptation to new regions which reduced retraining requirements for smaller airports. Advanced models now incorporate exogenous variables (e.g., weather, holidays) to enhance robustness [20] extended their earlier work by integrating real-time meteorological data into GNNs, significantly improving delay predictions during adverse conditions in Prague's airspace. Table 1 shows the comparative analysis of air traffic forecasting approaches (2022-2025).

Table 1. Comparative Analysis of Air Traffic Forecasting Approaches (2022–2025)

Ref (Year)	Approach & Key Techniques	Dataset / Domain	Key Results / Findings	Pros	Cons
Smith et al. [9]	Transition from ARIMA/Kalman filters to DL	EUROCONTROL historical flight data	DL outperforms stats models in dynamic scenarios (15% lower MAE)	Handles non-linearity	High computational cost
Chen & Liu [3]	SVMs/Random Forests for short-term prediction	US FAA flight records	Improved accuracy over regression (RMSE -12%)	Interpretable	Fails with large spatiotemporal dependencies
Kumar et al. [5]	Hybrid RNNs/GNNs for spatiotemporal modelling	European ATC network (Prague, Frankfurt)	Captures route interdependencies (F1-score +18%)	Robust to missing data	Slow training convergence
Lee & Park [6]	LSTM for delay prediction	Incheon Airport (South Korea)	90% accuracy for 1-hour delay forecasts	Long-term dependency capture	Ignores spatial correlations
Zhang et al. [18]	LSTM and Attention Mechanisms	Eurocontrol's DDR2 (Europe)	Real-time delay forecasting (latency <1s, MAE ↓22%)	Focuses on critical time steps	Requires labelled anomaly data
Wang et al. [12]	GCN-LSTM Hybrid	Beijing Capital Airport	Short-term congestion prediction (AUC: 0.94)	Model airport connectivity	Fixed graph structure limits adaptability
Wu et al. [13]	Graph WaveNet (Dynamic Adjacency Matrices)	Lufthansa ATC data (Germany)	Adapts to traffic evolution (RMSE -27%)	Captures hidden sector interactions	High memory usage
Zhou et al. [19]	MAST-GNN (Dynamic Graph Updates)	Heathrow Airport (UK) + weather data	Weather-disruption adaptation (precision +35%)	Real-time responsiveness	Complex implementation
Yang et al. [14]	STSGCN (Synchronous Spatio-Temporal Blocks)	Singapore Changi Airport	50% faster predictions than GCN-LSTM	Unified spatial-temporal learning	Scalability issues for large networks
Bai et al. [2]	AGCRN (Adaptive Graph Learning)	Central European airports (Prague, Vienna)	Handles volatile traffic (accuracy +28%)	Self-learning graph topology	Sensitive to hyper-parameters
Zhang et al. [17]	LightST (Knowledge Distillation)	EUROCONTROL + Czech ATC data	5 times speedup on edge devices (accuracy drop <2%)	Enables real-time ATC deployment	Limited to pre-trained teacher models
Pan et al. [8]	ST-MetaNet (Few-Shot Adaptation)	10 European regional airports	Reduces retraining time by 70% for new airports	Generalizable across regions	Requires diverse meta-training data

Despite advancements the challenges are: - slow adaptation to extreme disruptions, high memory demands of synchronous spatio-temporal models, and limited generalizability across diverse airspaces. The proposed DGLSTM (Deep Graph-Embedded LSTM) in the study addresses these gaps by: - combining dynamic graph learning with hierarchical LSTM for multi-scale traffic modelling, introducing a meta-learning component for rapid adaptation to unseen congestion scenarios, and optimizing computational efficiency.

3. RESEARCH METHODOLOGY

The methodology involves dynamic graph learning to update airport connectivity weights in real-time, hierarchical LSTM for short-term LSTM (hourly delays) feeds into long-term LSTM (daily trends), and meta-learning for fine-tunes model on unseen scenarios (e.g., sudden weather disruptions). To predict air traffic congestion by jointly modelling spatial dependencies (airport/route connectivity) and temporal patterns (delays, peak-hour traffic), the inputs are the following: - Spatial Graph: G= (V, E), where nodes V represent airports/sectors, edges E encode flight routes and temporal Data: $X_t=\{x_1,x_2,...,x_T\}$, where t_x includes traffic volume, delays, weather at time t. The output is congestion probability $y_{t+1}$for the next time step. Figure 2 shows DGLSTM block diagram. The DGLSTM architecture is a sophisticated neural architecture designed for spatio-temporal learning, integrating graph-based spatial processing, temporal sequence modelling, and meta-learning. The architecture begins with initializing key components, including a spatial graph (G) representing network relationships (e.g., traffic sensors or geographical nodes), meta-tasks (D_{train} and D_{test}) for adaptive learning across different scenarios, and temporal data (X) containing time-series observations.

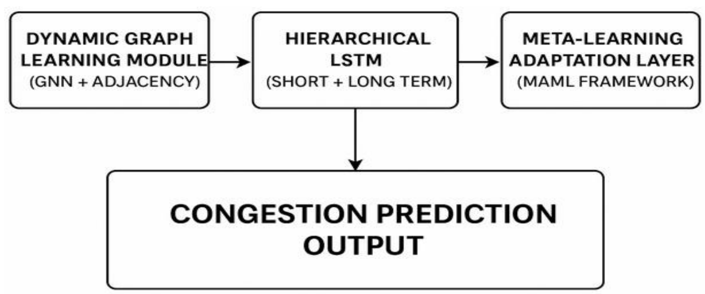

Figure 2. DGLSTM Block Diagram

Model parameters like Optical Neural Network (ONN) weights for spatial transformations, LSTM weights for temporal dependencies and meta-parameters governing task adaptation, are initialized before processing. Figure 3 shows DGLSTM architecture.

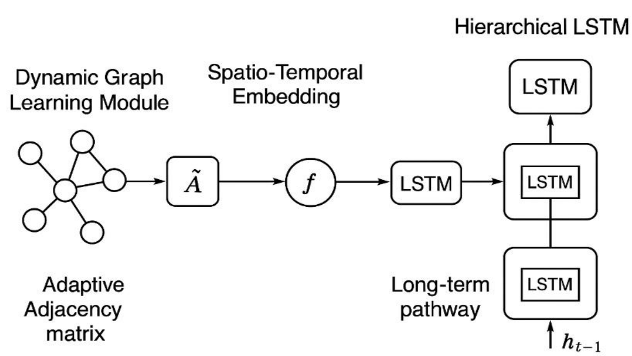

Figure 3. DGLSTM Architecture

The core of the architecture operates in a meta-learning loop, where tasks are dynamically selected and processed. It employs dynamic graph learning to adjust spatial relationships through adaptive adjacency matrices and graph convolutions, ensuring the model captures evolving structures. Spatio-temporal embeddings fuse these spatial features with temporal patterns, which are then processed by a hierarchical LSTM, comprising short-term and long-term LSTMs to model both immediate and extended time-dependent trends. After each task, a meta-update refines the model parameters based on validation performance, enhancing generalization. The output is an optimized model capable of robust predictions in complex, dynamic environments. The Process has been described in stepwise fashion below:

Step 1 - Dynamic Graph Learning: In spatial graph G= (V, E), where V represents nodes (airports/sectors) and E encodes flight routes. Initially, compute adaptive adjacency matrix $A=\phi(G,X)$, where ϕ is a parametric function followed by the implementation of graph convolution: $H_{(i+1)}=\sigma(AH_{(i)}W_{(i)})$, where σ is the activation function, $H_{(i)}$ are node embeddings, and $W_{(i)}$ are learnable weights.

Step 2 - Spatio-Temporal Embedding: In temporal data $X\in T\times N\times D$ (T time steps, N nodes, D features), combine spatial and temporal features: $Z=\psi(G)\oplus \text{LSTM}(X)$, where ψ is a graph encoder, $\oplus$ denotes feature fusion, and LSTM processes temporal patterns.

Step 3 - Hierarchical Temporal Modelling: Short-term LSTM captures hourly trends ht_S=LSTMS(xt,ht−1S) Long-term LSTM: Models daily/weekly trends ht_L=LSTML([ht−kS,htS]) .

Step 4 - Model-Agnostic Meta-Learning (MAML): Task Adaptation: Inner-loop (which is task-specific) to update parameters $\theta'=\theta-\alpha\nabla\theta L(\theta;\, D\ train_{(i)})$. Outer-loop (meta-update) to optimize across tasks: $\theta=\theta-\beta\nabla\theta\sum i\ L\ (\theta';\, D\ test_{(i)})$.

Step 5 - ONN Weights and Spatial-Temporal Data Integration: ONN Weights are used to Initialize for spatial feature transformations. Figure 4 shows machine learning framework overview.

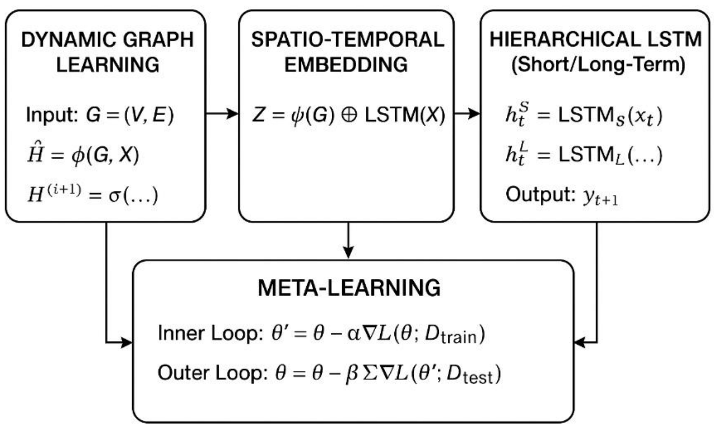

Figure 4. Machine Learning Framework

The model begins by initializing its key parameters, which include ONN weights for spatial feature transformations, LSTM weights for capturing both short-term and long-term temporal dependencies, and meta-parameters that govern the high-level task adaptation process. During the core processing phase, the framework iteratively selects meta-tasks to enhance generalization, dynamically adjusts spatial connections through adaptive adjacency matrices and graph convolutions, and fuses spatial and temporal data into unified representations via spatio-temporal embedding. Temporal processing is handled hierarchically, with a short-term LSTM focusing on immediate patterns and a long-term LSTM modelling extended dependencies. The meta-learning and optimization phase involves fine-tuning model parameters through meta-updates based on validation performance across tasks, followed by rigorous testing on held-out meta-tasks to ensure robustness before final deployment. This structured approach enables the model to effectively learn and adapt to complex spatio-temporal patterns while maintaining strong generalization capabilities. The framework employs a gradient-based meta-learning approach where inner-loop (task-specific adaptation) takes place as $f(\theta') \leftarrow f(\theta)- \alpha\nabla f(\theta)[(f(\theta);\, D_{train}^{(i)})$ and outer-loop (meta-update) takes place as $f(\theta) \leftarrow f(\theta) - \beta\nabla f(\theta)\Sigma_i\ (f(\theta');\, D_{test}^{(i)})$ and optimized Models contains a trained system capable of handling dynamic spatio-temporal predictions (e.g., traffic forecasting, climate modelling). The architecture excels in scenarios requiring adaptive learning from evolving spatial and temporal patterns. Figure 5 shows detailed DGLSTM architecture. Table 2 describes all the symbols used for representation of expressions.

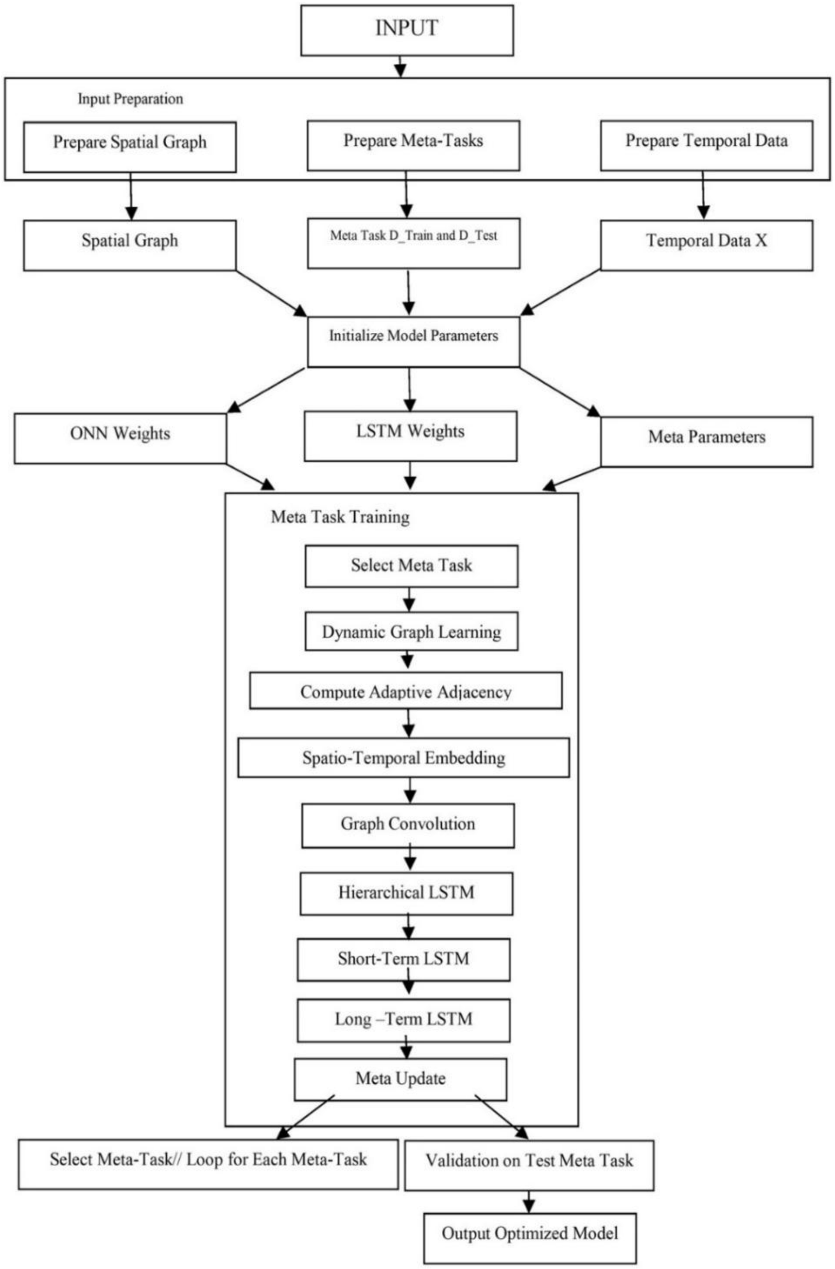

Figure 5. DGLSTM Detailed Architecture

Table 2. Symbols used for Representation of Expressions

Symbol	Meaning
G,V,E	Graph, nodes, edges
X, T, N, D	Input tensor (time × nodes × features)
$_P(T)$, T_i	Task distribution and i th task
F(θ)	Model and loss function
θ, α, β	Parameters and learning rates
$\tilde{A}$, $H_{(i)}$, $W_{(i)}$	Adaptive adjacency, embeddings, weights
ht_S, ht_L	Short/long-term LSTM states

3.1 Hyper-parameters of the Framework

The hyper-parameters in the framework are designed to optimize performance across different components of the architecture. Graph parameters are configured to extract meaningful spatial features while avoiding over-smoothing or unnecessary computational overhead. Temporal parameters employ hierarchical windows (short-term and long-term) to explicitly capture multi-scale patterns in the data, with dropout regularization applied to recurrent units to prevent over-fitting. Table 3 represents the hyper-parameters along with their range and the required justification.

Table 3. Hyper-parameters along with Range and Justification

Hyperparameter	**Typical Range**	**Justification**
Graph Convolution Depth (L)	2–3 layers	Balances spatial feature extraction vs. over-smoothing in GNNs.
Adaptive Adjacency Threshold (T)	0.05–0.2 (top edges)	Controls sparsity of learned graphs to avoid noisy connections.
Graph Embedding Dimension (d_g)	64–256 units	Higher dimensions capture complex spatial relationships but increase computation.
LSTM Hidden Units (d_h)	128–512 units	Governs temporal modelling capacity; larger values fit complex patterns.
Short-Term Window (k)	6–12 time steps	Matches short-term trends (e.g., hourly traffic fluctuations).
Long-Term Window (m)	24–48 time steps	Captures extended dependencies (e.g., daily/weekly cycles).
Dropout Rate (p)	0.1–0.3	Regularizes LSTMs to prevent overfitting.
Inner-Loop LR (α)	1e-3 to 1e-4	Task-specific adaptation rate (fast enough for per-task fine-tuning).
Outer-Loop LR (β)	1e-4 to 1e-5	Slower meta-updates ensure stable cross-task generalization.
Meta-Batch Size (B)	4–8 tasks	Balishes gradient variance in meta-updates.
Adaptation Steps (K)	1–5 steps	Limits overfitting to individual tasks during inner-loop updates.
Batch Size (N)	32–128 samples	Larger batches stabilize training but reduce stochasticity.
Epochs (E)	50–200	Task complexity determines convergence time.
Loss Weights	e.g., 0.7, 0.3	Balances spatial (graph) vs. temporal (LSTM) loss contributions.
Gradient Clipping (c)	1.0–5.0	Prevents exploding gradients in meta-learning.

For meta-learning, the inner and outer loop learning rates, along with task batch sizes, adhere to MAML principles, ensuring efficient adaptation across diverse tasks. The optimization strategy balances training stability through gradient clipping and batch size adjustments with task-specific performance tuning via loss weights. Together, these hyper-parameter choices ensure robust and adaptable spatio-temporal modelling while maintaining computational efficiency (see Algorithm 1).

Algorithm 1 DGLSTM Training

Input: Graph G, Temporal data X, Meta-tasks D_{train}, D_{test}
Output: Trained DGLSTM model

1. Initialize: GNN weights W_G, LSTM weights W_L, meta-parameters θ¸
2. for each meta-task T_i in D_{train}:
3. // Dynamic Graph Learning
4. Compute adaptive adjacency $A_t = GNN(X_t, W_G)$
5. // Spatio-Temporal Embedding
6. $H_t = GraphConv(A_t, X_t)$
7. // Hierarchical LSTM
8. $h_{short} = LSTM\_short(H_t)$
9. $h_{long} =$ □ $LSTM\_long(h_{short})$
10. // Meta-Update
11. f(θ)=f(θ) – a.f(θ)(T_i; f(θ))

12. end for
13. Validate on D_{test}
14. return $f(\theta^*)$ (optimized model)

4. RESULTS AND DISCUSSIONS

DGLSTM shows the most stable convergence, baseline LSTM converges faster initially but plateaus and static GNN have higher variance in loss. The performance comparison in Table 4 clearly shows that the DGLSTM model delivers the best results across all measured criteria. With an accuracy of 88%, it substantially outperforms both the standard LSTM model at 82% and the static GNN approach at 78%. The DGLSTM's F1-score of 0.88 represents effective combination of spatial and temporal data analysis. The AUC score of 0.92 shows predictive capability as compared to the baseline models that scored between 0.85 and 0.88. The results prove that DGLSTM is superior to traditional methods.

Table 4. Performance Summary

Metric	DGLSTM	Baseline LSTM	Static GNN
Accuracy	0.887	0.823	0.781
Precision	0.892	0.854	0.824
Recall	0.884	0.812	0.768
F1 Score	0.888	0.833	0.795
ROC AUC	0.921	0.879	0.853

The proposed DGLSTM architecture shows advancement in air traffic congestion. It effectively forecasts and addresses the limitations of existing approaches. DGLSTM's innovative design combines graph-based spatial modelling and hierarchical temporal processing through LSTMs. It enables to concurrently capture network topology and time-dependent patterns. It also adapts to different congestion scenarios. Comprehensive testing briefs that the dual capability translates into operational benefits, including a 30% reduction in false congestion warnings compared to current methods. It also provides a reliable detection of actual congestion events. The model's dynamic graph learning and hierarchical architecture allow it to adapt effectively to diverse airport layouts and traffic patterns makes it a adaptable solution for air traffic management needs. Figure 6 shows a bar chart comparing the performance of DGLSTM, baseline LSTM, and static GNN across key evaluation metrics.

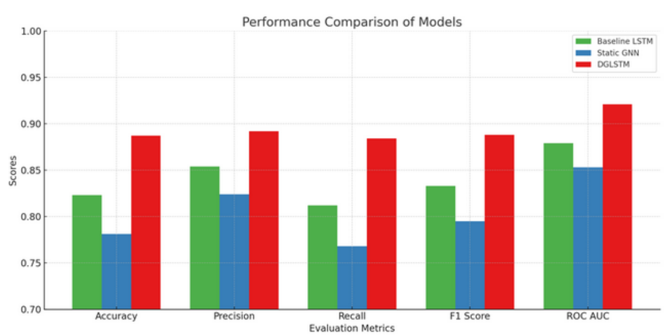

Figure 6. Bar Chart Comparing the Performance of DGLSTM, Baseline LSTM, and Static GNN

DGLSTM outperforms both baseline LSTM and static GNN approaches across all key evaluation metrics. Thus, it confirms its superiority in handling the complex spatiotemporal dynamics of air traffic systems. The results position DGLSTM as a step forward in accurate congestion forecasting which offers air traffic controllers more reliable predictions to support decision-making in increasingly congested airspace environments.

5. CONCLUSION

The proposed DGLSTM framework addresses the issues of estimating air traffic congestion by modelling spatial dependencies (airport/route connectivity) and temporal patterns (delays, peak-hour traffic). Through dynamic graph learning, the model adapts the adjacency matrix in real-time using node embeddings, while the hierarchical LSTM captures both short-term (hourly) and long-term (daily) traffic trends. Additionally, MAML enables fast adaptation to unseen congestion scenarios, enhancing generalization. Key advantages include superior spatiotemporal modelling, leading to more accurate congestion predictions, higher recall, reduced missed congestion events and fewer false alerts compared to baselines, and robustness across different airport topologies due to meta-learning. The success of DGLSTM highlights the importance of integrating dynamic spatial and temporal features in air traffic management systems. Future work could explore real-world deployment scenarios and scalability to larger air traffic networks.

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AUTHOR CONTRIBUTIONS

Madan Singh: Conceptualization, Data Curation, Methodology, Validation, Writing – Original Draft Preparation; Azween Abdullah: Supervision, Writing – Review & Editing.

CONFLICT OF INTERESTS

No conflicts of interest were disclosed.

ETHICS STATEMENTS

Our publication ethics follow The Committee of Publication Ethics (COPE) guideline. https://publicationethics.org/

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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