Journal of **N**onlinear **A**nalysis and **O**ptimization
Vol. 16, Issue. 1: 2025
ISSN : **1906-9685**

FLIGHT DELAY DETECTION USING DEEP LEARNING

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***Abstract* - Flight delays are one of the most significant issues in the aviation sector, resulting in money-related calamities for planes and inconvenience for passengers. with millions of flights operating annually, increasing discuss activity has led to congestion and wasteful operational aspects. delays are influenced by various variables, including climate conditions, discuss activity, specialized issues, and airplane terminal operations. in order to solve this problem, we introduce a deep learning-based demonstrate for flight delay expectation based on verifiable and real-time data. our strategy involves examining crucial variables like flight plans, climate designs, and flying machine operations. We will implement deep learning calculations, including LSTM and RNN, to separate designs and predict delays accurately. The think about refers to the comparison of the performance of different models to determine the most effective approach. the results of this research can assist carriers in making informed decisions, reducing delays, lowering costs, and enhancing traveler satisfaction through much improved operation management and planning.**
keywords-flight delays, deep learning, prediction model, air traffic congestion, weather conditions, lstm, rnn, historical data, real-time data.

I. INTRODUCTION

Air transport is a critical means of state-of-the-art mobility, promoting the growth of travelers and freight across the world. With the growing demand for discuss travel, clog in discuss activity and traveler flow has become a significant challenge. To overcome these challenges, maintaining perseverance, flexibility, and productivity within the flying system is essential. Air terminal infrastructure, supported by affordable arrive and assets, is an imperative role to play in ensuring smooth operations. Mechanical advancements and procedural refinements focus on enhancing security, efficiency, and capacity. The National Airspace Framework (NAS) focuses on reducing natural impacts while implementing these innovations. Notwithstanding the availability of advanced technologies that allow passengers to monitor their flight metrics like altitude, direction, and flight path, activity experts go ahead to struggle with reducing delays. Such delays, which stretch to a number of hours, result in turmoil and disillusionment among passengers. Important factors involved in causing delays include adverse weather conditions, airplane maintenance problems, security issues, and carrier wasteful factors.

Business travel and tourism are the primary movers of discuss activity, and both divisions are projected to evolve in totality, increasing discuss activity to 2030. This increase will help stress the discuss transport infrastructure, which is causing airspace congestion and operating inefficient elements. While building underutilized airports appear to decrease some congestion, arrive scarcity and asset limitations render expanding current airport infrastructure a more realistic and budget-friendly solution.

Flight delays, defined as the time an air ship is late or a flight is grounded, can severely impact commercial flight operations, resulting in financial losses and customer dissatisfaction. Delays also

https://doi.org/10.36893/JNAO.2025.V16.I01.021

impact airlines' marketing strategies and overall reputation. To combat this problem, researchers and analysts have gathered infinite amounts of flight data, tracked throughout entire flight journeys. Examining this data with advanced techniques, including deep learning, has the potential to predict delays accurately and provide support aircrafts improve their operations, reduce disruptions, and advance client satisfaction. The framework design for flight delay anticipation consists of information protection, where flight and weather data are gathered, information preprocessing involving cleaning and include extraction, and display preparation, in which machine learning algorithms like irregular forest, decision tree, credulous bayes, KNN, and MLP are set using the processed information. Finally, execution evaluation is done to contrast demonstrate accuracy, and results are presented in terms of charts for analysis.

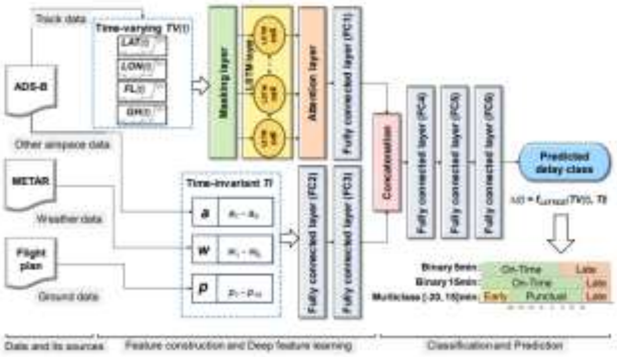

Fig.1: System architecture

II. RELATED WORK

The table below provides an extensive summary of seminal research commitments to flight delay anticipation. It outlines significant ponders, including their titles, authors, publication times, and concise explanations of their methods and findings. This summary makes a difference to obtain it existing methodologies and identify gaps for further research.

Title	Author(s)	Year	Explanation
Total Delay Impact Study	Balletal.	2010	Analyzed total delay impacts, focusing on costs and network effects.
Analysis of Performance and Equity in Ground Delay Programs	Manley & Sherry	2010	Investigated performance and equity issues in ground delay programs.
Estimating Domestic US Airline Cost of Delay	Fergusonet al.	2013	Estimated airline delay costs using a European model framework.
Stochastic Optimization Models for Ground Delay Programs	Glover & Ball	2013	Developed stochastic models addressing efficiency-equity tradeoffs.
Parallel Simulation of Agent-Based Model for Air Traffic	Kim et al.	2015	Used parallel simulation techniques for agent-based air traffic modeling.
Parallel Simulation for Aviation Applications	Wieland	1998	Applied parallel simulation techniques to aviation modeling.
Estimating Flight Departure Delay Distributions	Tu et al.	2008	Proposed statistical methods for departure delay distribution estimation.
Estimation of Delay Propagation in the National Aviation System	Xu et al.	2005	Modeled delay propagation using Bayesian networks

Table1: Literature survey

III. IMPLEMENTATION

The project was realized using Python with TensorFlow and Keras to exhibit deep learning show development. The dataset drawn from the Bureau of Transportation Insights includes 3 million records with 19 features.

1. Environment Setup:

Python, TensorFlow, Keras, Pandas, NumPy, Matplotlib, and Scikit-learn were introduced to promote show creation and examination.

2. Information Preprocessing:

The data was stacked using Pandas, and the lost values were handled using SimpleImputer of Scikit-learn. Identifying features like flight number and aircraft codes was encoded using one-hot encoding. The data was normalized to improve strides to reveal performance.

3. Show Creation:

A deep learning demonstration was created using a Consecutive neural organize with input, hidden, and output layers. The demo includes ReLU activation for hidden layers and Softmax for the output layer. The Adam optimizer was used with categorical cross-entropy loss.

4. Preparation and Testing:

The data was divided into 80% training and 20% test sets. The performance was tuned for 50 ages with a batch size of 32. Early stopping was related to prevent overfitting.

5. Demonstrate Evaluation:

The performance of the model was tested using precision, accuracy, review, and F1-score metrics. The confusion matrix provided insights into false positives and negatives.

This execution illustrates the viability of profound learning in foreseeing flight delays, helping travelers and carriers in superior arranging and decision-making.

IV. ALGORITHM

Algorithm for Flight Delay Forecast Using Deep Learning

1. Data Collection and Preprocessing

The flight delay forecast show utilize employments ADS-B, METAR, and flight arrange information from Changi Worldwide Airplane terminal. Information preprocessing comprises normalization, management of missing values, and include building. Time-invariant (e.g., course, carrier) and time-varying features (e.g., climate, discuss activity) are extracted.

2. Feature Selection and Encoding

choice are selected using relationship exploration and common data scores. Categorical choice are encoded using one-hot encoding:

One-hot encoding formula:

$$\begin{cases} 1, & \text{if category matches} \\ 0, & \text{otherwise} \end{cases}$$

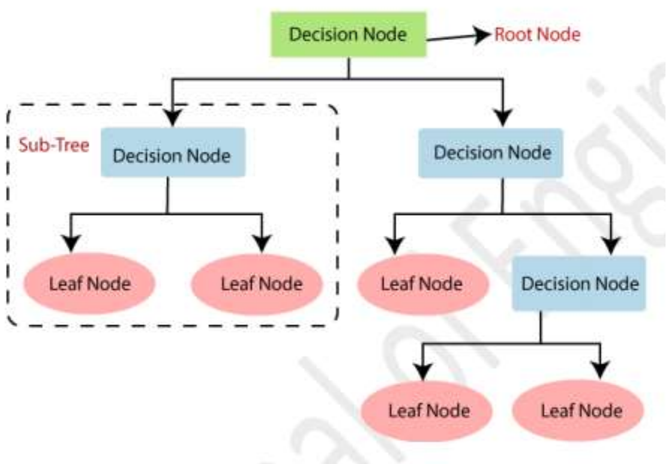

Fig.2: Decision tree architecture

3. LATTICE Model Construction with LSTM and Attention Mechanism

- The LSTM constructs consecutive flight data, observing worldly dependencies.

LSTM output: $h_t = \sigma(W_h x_t + U_h h_{t-1} + b_h)$

- Attention tool calculates consideration scores to mark relevant time steps:

steps: $\alpha_t = \mathrm{softmax}(v^T \tanh(W_a h_t + b_a))$

- The final Grid display coordinating LSTM and consideration outputs for classification.

4. **Model Training and Evaluation**

- The program is trained with twofold (on-time vs. delayed) and multiclass classification (e.g., minor, major, severe delays).
- Loss Work: Categorical Cross-Entropy:

$$\mathcal{L} = -\sum_i y_i \log(\hat{y}_i)$$

- **Optimization:** Adam optimizer with learning rate decay.

5. Show Assessment and Execution Metrics

- Accuracy:

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN}$$

- Precision, Review, F1-score, and AUC are computed to measure performance.

This systematic calculation coordinating deep learning processes, ensuring accurate flight delay predictions using real-time data and efficient show models.

V. RESULTS

The Result of the flight delay expectation models show significant differences across various calculations and input highlight sets. The evaluation includes comparisons of show exactness, developments with incorporated inborn highlights, calculation times, and the effect of the consideration mechanism.

1. Illustrate Execution Overview:

Deep models based on both time-invariant (TI) and time-varying (TV) highlights exhibited dominant precision and AUC values over models based on as it were TI or TV highlights. Notably, LSTM and GRU models achieved precision rates of 86–91% for twofold classification and 66–85% for multi-class classification.

2. Impact of TI Highlight Inclusion:

TI highlights expansion, including flight and weather information, entirely enhanced deep learning show performance. LSTM, GRU, and RNN models reported specific improvements of 42.1%, 43.2%, and 36.6% for parallel classification and even 76.5% for multi-class classification.

Model	**Binary Improvement (%)**	**Multi-class Improvement (%)**
LSTM	42.1	76.5
GRU	43.2	74.7
RNN	36.6	45.9

Table2 :Improvement Rates with TI Features Added

3. Preparing and Prediction Computation Times:

Among the models, RNN had the shortest preparing and forecast times, whereas the LSTM demonstrate took longer but promoted superior exactness. For 1000-flight preparing, times ranged from 0.07 seconds (RNN) to 0.49 seconds (LSTM), with expectation times under 0.05 seconds per flight.

Model	**Binary 15 Train (s)**	**Binary 15 Test (s)**	**Multi-class Train (s)**	**Multi-class Test (s)**
RNN	0.07	0.005	0.03	0.002
GRU	0.32	0.024	0.29	0.021

LSTM	0.35	0.026	0.34	0.026

Table 3: Computation Times for Training and Prediction

4. Centrality of Consideration Mechanism:

An addition of a consideration instrument really enhanced demonstrate execution. The LSTM show with consideration had exactness picks up of 1.8% and 3.5% for double and multi-class errands, individually. Consideration layers enabled the demonstrate to effectively record fleeting conditions in flight direction information.

These emerge highlight the importance of integrating born flight information with real-time orientation data and applying advanced deep learning techniques for accurate flight delay prediction.

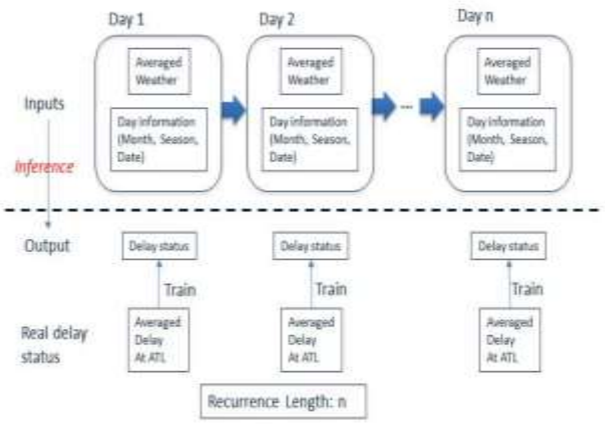

Fig. 3. Day-to-Day departure delay status model

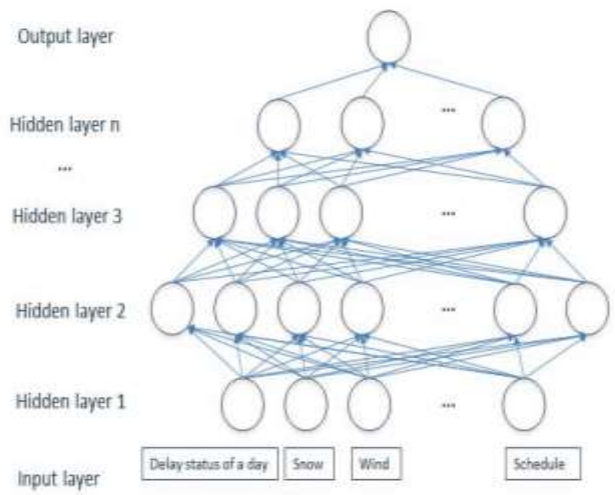

Fig. 4. Individual flight delay model

Task	**Improvement (%)**
Binary15	1.8
Multi-class	3.5

Table 4: Performance Gains from the Attention Mechanism

VI. CONCLUSION

Predicting flight delay has evolved as a critical question area, gaining significant attention owing to its impact on aircraft operations and passenger satisfaction. Several researchers have focused on enhancing show performance to achieve greater accuracy and accuracy in forecasting delays. Accurate models of flight delay forecasting are essential because timely performance directly impacts operational efficiency and customer engagement.

This research emphasizes the importance of multidimensional heterogeneous information coordination, i.e., flight plans, climate data, and discuss activity information, to enhance expectation accuracy. The integration of time-invariant (TI) and time-varying (TV) highlights is an essential role in increasing show performance. It has been observed that deep learning models, including LSTM, GRU, and RNN, collectively improve precision when TI features are integrated with TV features. The comes about show that using inclusive input highlights yields stronger expectations than using person include sets. Also, advanced techniques like include determination and consideration instruments provide help recognize the most elementary information focuses, enhancing demonstrate proficiency. Out of the machine learning models evaluated, the Multilayer Perceptron (MLP) calculation achieved the highest precision of 82%, demonstrating its ability to deal with organized information effectively. In summary, the integration of many machine learning techniques, alignment diverse information sources, and implementation of deep learning models with caution tools results in more accurate and robust flight delay predictions. The future research may focus on the integration of live information streams and exploring hybrid models to foster improvement expectation reliability and operational efficiency.

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