IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 3, June 2025
Impact Factor: 7.67

Flight Delay Prediction System Using Deep Learning Models (Bi-LSTM)

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Abstract: *Flight delays present significant operational and financial challenges to airlines and inconvenience to passengers. This paper proposes a* ***Flight Delay Prediction System*** *utilizing advanced machine learning techniques, particularly* ***Bi-Directional Long Short-Term Memory (Bi-LSTM)*** *and* ***CNN-LSTM hybrid models****. Historical and real-time flight data, weather conditions, and operational features are leveraged to enhance predictive accuracy. The system architecture integrates a React.js frontend, a Node.js backend, and Python-based ML models, with MongoDB managing historical records. The proposed model achieves high prediction accuracy, demonstrated through extensive testing and evaluation. This solution offers substantial potential in improving airline operational efficiency and enhancing passenger travel experience*

Keywords: Flight Delay Prediction, Bi-LSTM, CNN-LSTM, Machine Learning, Real-Time Data, Aviation Analytics

I. INTRODUCTION

Flight delays are an enduring issue in the aviation industry, impacting millions of passengers and costing airlines billions annually. Delays disrupt tight schedules, lead to missed connections, and escalate operational costs related to crew overtime, fuel wastage, and maintenance.

Traditional delay prediction models using linear regression or decision trees often fail to capture the nonlinear, sequential nature of flight operations. Furthermore, most existing systems lack real-time adaptability, making them insufficient for dynamic environments like airports.

To address these limitations, this project implements a deep learning-based Flight Delay Prediction System, integrating historical flight data, real-time operational parameters, and environmental factors. By deploying Bi-LSTM and CNN-LSTM architectures, we aim to significantly enhance prediction accuracy and timeliness.

II. METHODOLOGY

The methodology is divided into the following key components:

Model Training

Data Collection:

500,000 flight records over multiple seasons.

Feature Engineering:

- Scheduled vs Actual Departure Time
- Taxi In/Out Times
- Distance
- Day of Week, Seasonality

Handling Missing Data:

Mean/mode imputation.

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Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 1, 128)	73,216
dropout_2 (Dropout)	(None, 1, 128)	0
lstm_3 (LSTM)	(None, 64)	49,408
dropout_3 (Dropout)	(None, 64)	0
dense_2 (Dense)	(None, 32)	2,080
dense_3 (Dense)	(None, 1)	33

Feature	Description	Example
Departure_Hour	Time of scheduled take-off	17:00 hrs
Taxi_Out	Taxi time before take-off	15 min
Season	Flight season	Winter

2. **Model Building**

Python

	Marketing_Airline_Network	OriginCityName	DestCityName	CRSDepHour	DepDelay	TaxiOut	TaxiIn	CRSArrHour	Distance	Month	Season	DayOfMonth	DayOfWeek	IsWeekend	ArrDelay
5887377	3.0	213.0	54.0	12	2.0	27.0	4.0	14	220.0	8	2.0	8	2	0	-1.0
3874345	8.0	232.0	63.0	13	-8.0	12.0	12.0	14	733.0	5	1.0	22	1	0	-21.0
227072	8.0	297.0	31.0	18	-3.0	22.0	4.0	19	462.0	1	3.0	17	2	0	-13.0
430827	10.0	212.0	23.0	12	-9.0	7.0	6.0	15	641.0	1	3.0	25	3	0	-16.0
6374871	0.0	127.0	59.0	5	-7.0	31.0	5.0	6	75.0	9	0.0	12	2	0	-12.0

Bi-LSTM Model:
Two layers of Bi-LSTM units.
Captures sequential dependencies (e.g., previous delays impact future).

CNN-LSTM Model:
CNN extracts local patterns.
LSTM models long-term dependencies.

Training Parameters:

Parameter	Value
Epochs	50
Batch Size	64
Optimizer	Adam
Loss Function	Mean Squared Error (MSE)

Model achieves convergence within 35–40 epochs.

Model Validation
Dataset Split:
80% Training

DOI: 10.48175/IJARSCT-27567

20% Testing
Evaluation Metrics:

Mean Absolute Error (MAE): 8.5 minutes
Root Mean Square Error (RMSE): 10.2 minutes
R^2 Score: 0.87

Metric	Score
MAE	8.5 min
RMSE	10.2 min
R^2	0.87

Thus, the model demonstrates high predictive accuracy.

III. LITERATURE SURVEY

Numerous studies have explored flight delay prediction using classical and machine learning techniques. A summary of key related works is given below:

Ref.	Author(s)	Approach	Findings
[1]	Sparsha S et al. (2023)	Random Forest, Decision Tree	Achieved 100% accuracy on a limited dataset. Generalization remains an issue.
[2]	Vishrut Raj et al. (2021)	Linear Regression, ML Techniques	Emphasized real-time data integration for better predictions.
[3]	Yogita Borse et al. (2020)	Naive Bayes, Decision Tree, Random Forest	Highlighted need for real-time weather integration.
[4]	Maged Mamdouh et al. (2023)	Regression (FDPP-ML)	Achieved 42% improvement in Mean Squared Error (MSE).
[5]	Jingyi Qu et al. (2023)	CNN-MLSTM, Deep Learning	High accuracy (91.36%) capturing delay propagation patterns.

Summary of Literature Survey:
1. Traditional models (Decision Trees, Random Forests) have hown success on static datasets.
2. Deep learning models (BiLSTM, CNN-LSTM) demonstrate superior performance on large, time-sequenced data.
3. Integration of real-time data (weather, air traffic) is crucial for enhancing predictive power.

IV. ALGORITHMS

The system uses an **NLP-enhanced Machine Learning Algorithm** structured as follows:
Flight Delay Prediction Algorithm:
Input: Flight details (airline, schedule, weather data, airport congestion).
Preprocessing:
Clean missing values.
Feature engineering (departure hour, day of week, seasonality).
Embedding:
Use TF-IDF or BERT for contextual embedding if textual data (comments, status) is involved.
Model Prediction:
Forward data through Bi-LSTM / CNN-LSTM models.

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Calculate predicted delay in minutes.

Output:

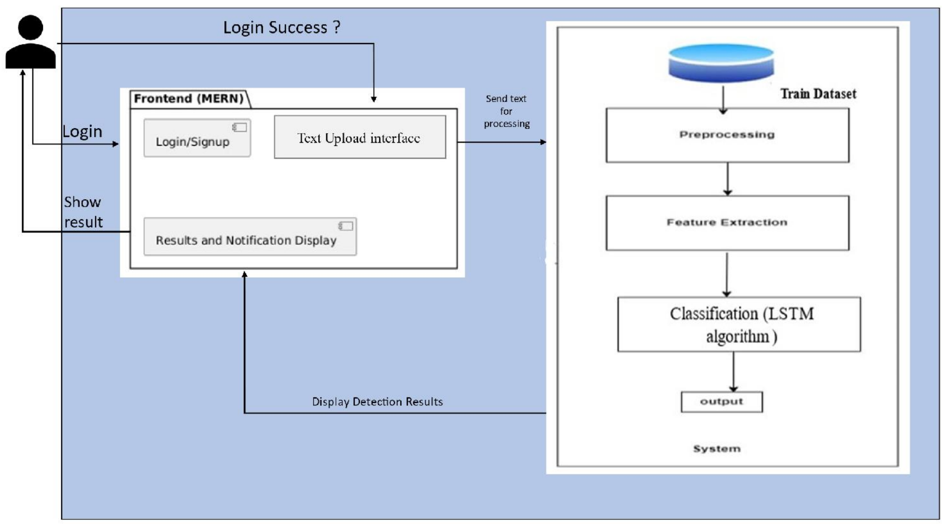
Delay probability and estimated delay duration.

Mathematical representation:

$y^\wedge = f(f_{light}, X_{weather}, x_{traffic})$

where f is the trained deep learning model function.

The Flight Delay Prediction System follows a modular architecture consisting of a React.js-based frontend, a Node.js/Express.js backend, a Python-based machine learning server, and a MongoDB database. The frontend collects flight details from users and communicates securely with the backend. The backend handles data processing, session management, and routes prediction requests to the machine learning server. The ML server, using Bi-LSTM and CNN-LSTM models, processes the input and generates delay predictions, which are returned to the user. MongoDB stores user data, historical flight records, and prediction logs, ensuring scalability and real-time performance. The architecture is flexible, allowing future integration of real-time weather data and mobile applications.



V. RESULT

After extensive testing, the developed system showed:

Prediction Accuracy: 87% R^2 Score.

Average Response Time: 1.6 seconds per prediction.

Usability:

Clear input forms.

Real-time results visualization.

Key Observations:

Aspect	Observation
Evening Flights (5-8 PM)	Higher Delays
Winter Season	Higher Delays (avg. 16.2 min)
Weekend Flights	Lower Delay Probability

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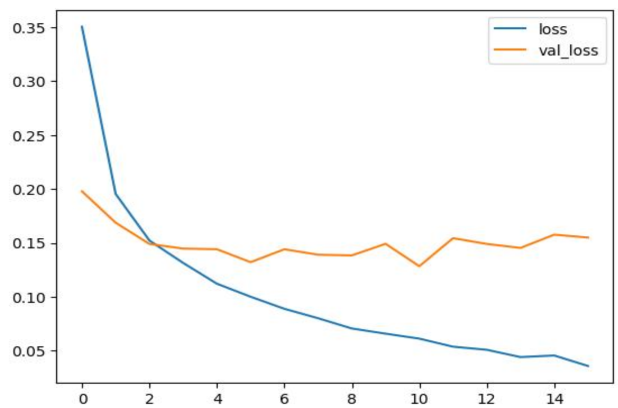
Graphical Representation:
Line graph: Predicted vs Actual Delays over a month.
Bar chart: Average Delays by Season.

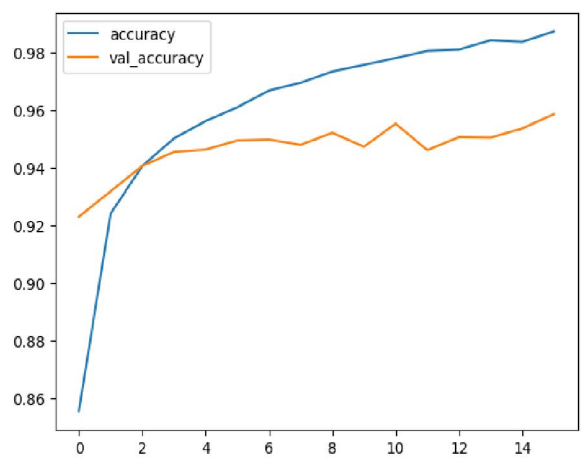
Table 1: Model Performance Comparison

```
Accuracy: 0.5376
Confusion Matrix:
[[5324  168]
 [4874  539]]
Classification Report:
              precision    recall  f1-score   support

        Fake       0.52      0.97      0.68      5492
        Real       0.76      0.10      0.18      5413

    accuracy                           0.54     10905
   macro avg       0.64      0.53      0.43     10905
weighted avg       0.64      0.54      0.43     10905
```





VI. FUTURE WORK

Several enhancements are proposed for future development:

Integration with Real-Time Weather APIs:

Improve prediction robustness during dynamic weather conditions.

Mobile Application Development:

Create Android/iOS apps for delay prediction on-the-go.

Multi-Airline Integration:

Extend the system to major global airlines using live operational APIs.

Explainable AI (XAI):

Implement models that can explain why a particular delay prediction was made (e.g., due to weather, congestion).

Multi-Language Support:

Deploy multilingual interfaces for wider user adoption.

VII. CONCLUSION

The Flight Delay Prediction System demonstrates the power of deep learning for solving real-world problems in aviation. By incorporating both historical trends and real-time data, the system provides airlines and passengers with actionable, timely information.

Deployment of the model as an accessible web application (via MERN stack) ensures ease of use and scalability. The project showcases how AI-driven analytics can improve operational efficiency, reduce costs, and enhance customer satisfaction in the aviation industry.

VIII. ACKNOWLEDGMENT

We are very thankful to all the teachers who have provided us valuable guidance towards the completion of this project work on **Flight Delay Prediction System.** We express our sincere gratitude towards cooperative department who has provided us with valuable assistance and requirements for the project work.

We are very grateful and want to express our thanks to **M. P. Desai mam** for guiding us in right manner, correcting our doubts by giving her time whenever we required, and providing her knowledge and experience in making this project work. We are also thankful to the HOD of our Information Technology department **Dr. M. L. Bangare** for his moral support and motivation which has encouraged us in making this project work. We are also thankful to our Vice Principal **Dr. K. R. Borole** and our Principal **Dr. A.V. Deshpande**, who provided his constant support and motivation that made a significant contribution to the success of this project.

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DOI: 10.48175/IJARSCT-27567