NATIONAL INSTITUTE OF TECHNOLOGY, WARANGAL

COMPUTER SCIENCE AND ENGINEERING

SUMMER INTERNSHIP/EPICS

IV-B.Tech. CSE(B) - INTERNSHIP PRESENTATION

DESIGN AND DEVELOPMENT OF EFFICIENT DEEP LEARNING MODELS FOR AIRCRAFT TRAJECTORY PREDICTION

RESEARCH INTERN

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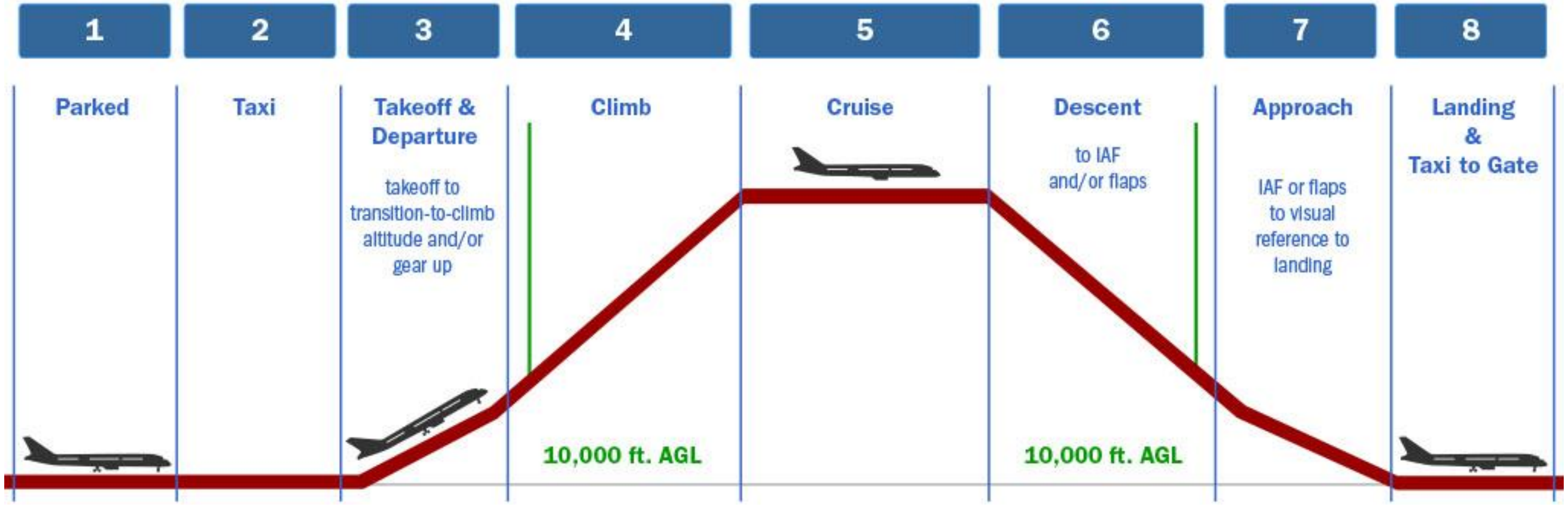
1. Introduction

Aircraft trajectory prediction is a vital component of modern aviation, helping to improve navigation safety, optimize routes, and manage air traffic. By predicting the trajectory of aircraft accurately, we can potentially reduce collisions, optimize fuel efficiency, and enhance airspace management. This project focuses on implementing an LSTM (Long Short-Term Memory) model to predict key aircraft states: acceleration, heading (turn direction), and movement (turn rate). LSTM models, known for their strength in handling temporal dependencies in sequential data, offer a promising approach to modeling and forecasting aircraft trajectories based on historical data. However, challenges in data quality and variability have posed significant obstacles in achieving reliable predictions.

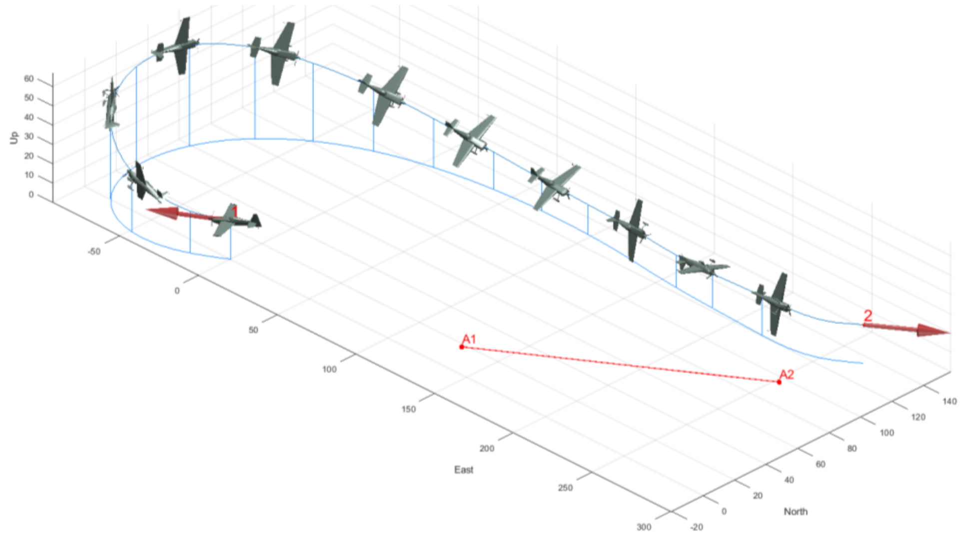
Problem Statement

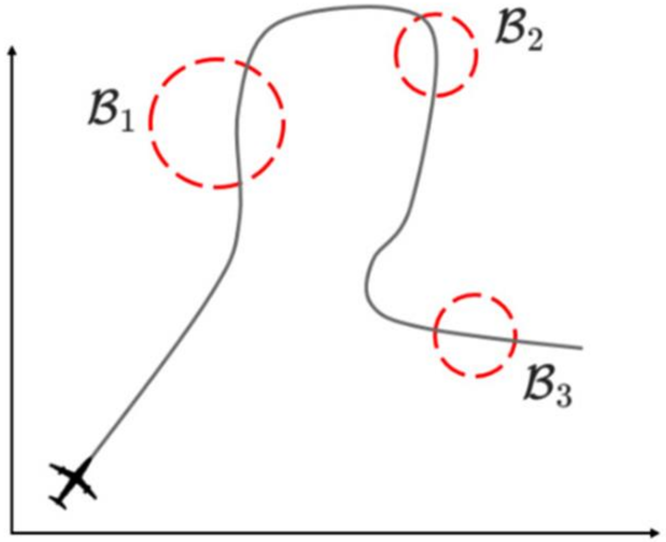
The challenge is to develop a machine learning model to accurately predict three key aspects of aircraft behavior—acceleration, heading, and turn rate. Acceleration predictions indicate changes in speed, aiding in safe spacing and fuel optimization. Heading and turn rate predictions provide insights into direction and maneuvering, which are essential for collision avoidance and efficient airspace management. This model will support air traffic controllers in enhancing safety, reducing delays, and optimizing airspace use.



Past Works

Numerous research studies have employed traditional machine learning and statistical models for trajectory prediction, such as linear regression, support vector machines (SVMs), and decision trees. However, these models often fall short in capturing the intricate temporal dependencies present in sequential data, which is crucial for accurate trajectory predictions. In recent years, researchers have explored Recurrent Neural Networks (RNNs), including LSTM and GRU architectures, for sequence modeling, achieving notable results in fields like traffic flow prediction and human activity recognition. Yet, few studies have fully applied LSTM to multi-dimensional trajectory prediction in aviation.

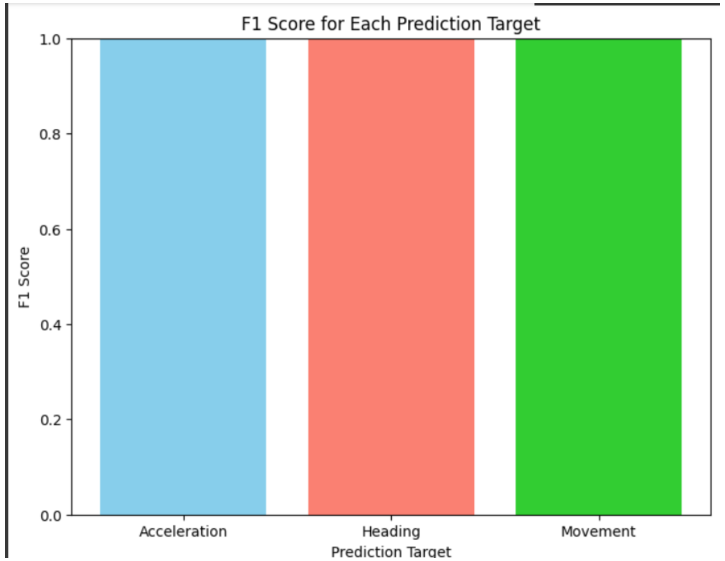




Result

According to the documentation, the expected results include achieving high accuracy in predicting acceleration, heading, and movement using the LSTM model. However, because the dataset contains constant zero values for these features, the model may produce artificially high accuracy that doesn’t fully reflect real-world performance. This limitation indicates a need for more varied data to improve the model's predictive reliability and robustness.

1. High Accuracy on Small Data: Perfect accuracy on a small dataset often means the model is overfitting, memorizing instead of generalizing.
2. Memorization : A memorizing model performs well only on training data. Regularization and cross-validation help ensure real learning.




```
Epoch [10/50], Loss: 0.0000
Epoch [20/50], Loss: 0.0000
Epoch [30/50], Loss: 0.0000
Epoch [40/50], Loss: 0.0000
Epoch [50/50], Loss: 0.0000
Test Accuracy (Acceleration): 1.0000
Test Accuracy (Heading): 1.0000
Test Accuracy (Movement): 1.0000
```

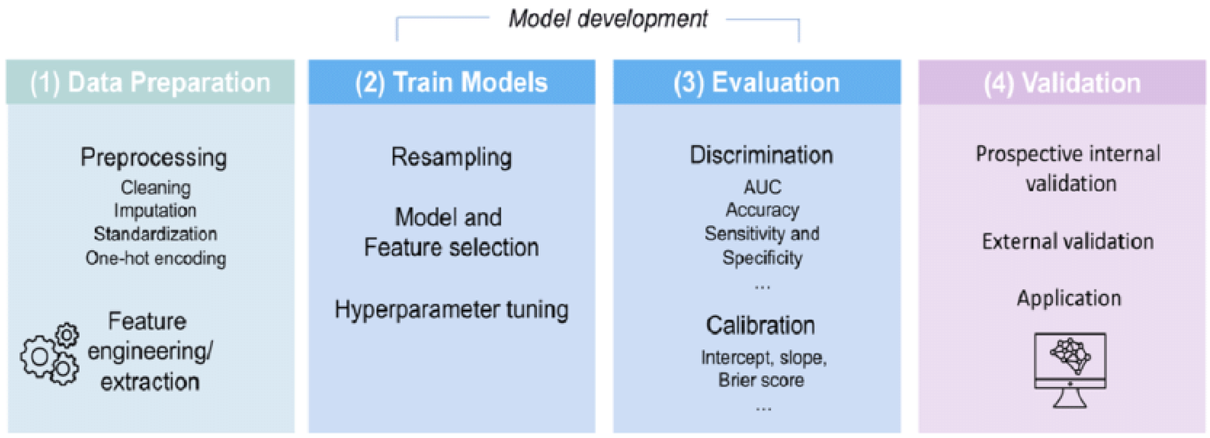
Proposed Solution

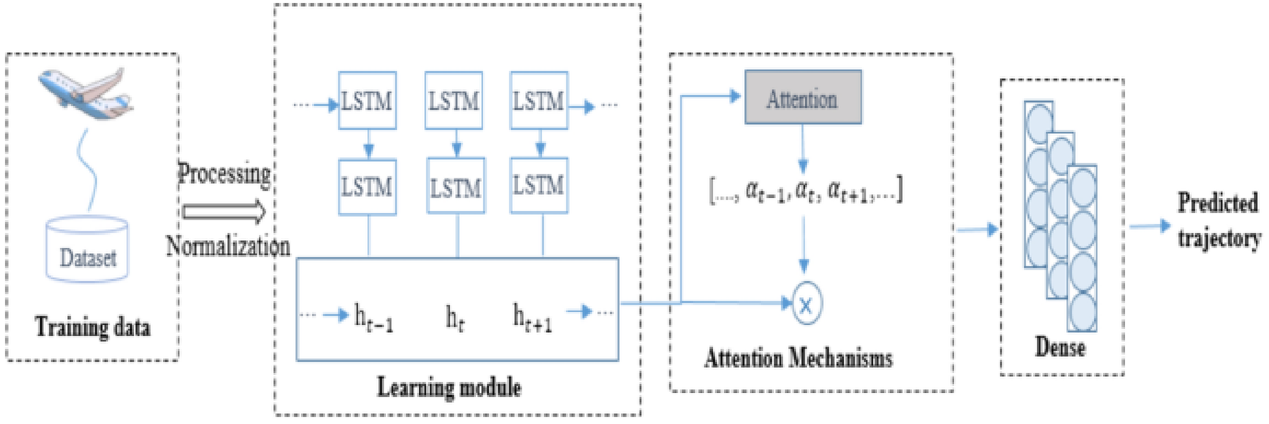
Data Preparation:
Categorical variables (acceleration, heading, turn rate) are label-encoded, while continuous variables (latitude, longitude, Cartesian coordinates, course, speed) are normalized to ensure consistency. To capture temporal dependencies, sequences are created from historical data points.

Model Architecture:
The LSTM model has three output layers, each specifically for acceleration, heading, and turn rate. This allows the model to simultaneously make distinct predictions for each aspect of aircraft movement.

Training Process:
The model is trained using cross-entropy loss for each output target, combined to form a total loss that the Adam optimizer minimizes. During each epoch, the model makes predictions, calculates the loss for each target, and updates its parameters based on the backpropagated gradients.

Evaluation: Model performance is assessed on a test set by calculating accuracy for each target (acceleration, heading, turn rate), giving insight into its prediction reliability.





Future Scope

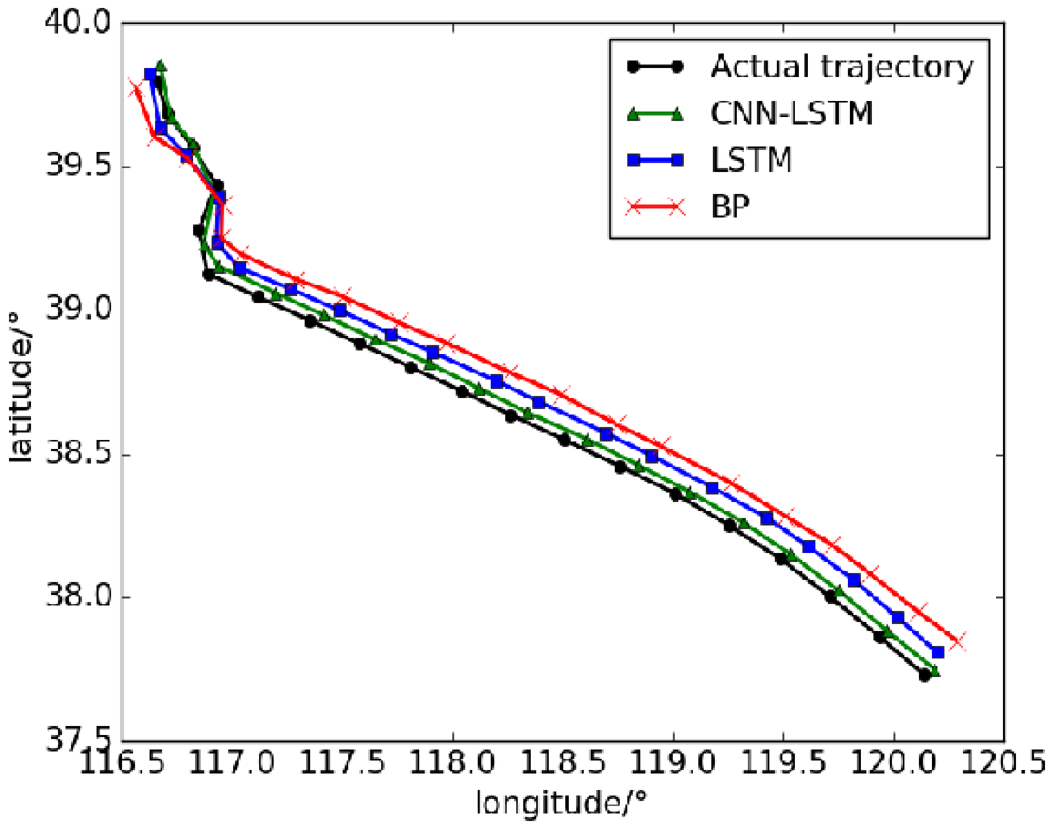
- **Check Data Quality:**
Investigate constant target values to see if they're a data issue.

- **Collect Better Data:**
Gather a more varied dataset with different values for acceleration, heading, and movement.

- **Improve the Model:**
Use dropout and try GRUs for better performance.

- **Add More Features:**
Include additional context like time of day and weather conditions.

- **Real-time Deployment:**
Prepare the model for use in air traffic management systems for real-time predictions.



(a) Prediction of latitude and longitude

References

- Tran, Phu & Nguyen, Hoang & Pham, Duc-Thinh. (2022). Aircraft Trajectory Prediction With Enriched Intent Using Encoder-Decoder Architecture. IEEE Access. 10. 17881-17896. 10.1109/ACCESS.2022.3149231.. The Trane chiller already has an automatic tube cleaning system, eliminating the need for manual cleaning.
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- Hochreiter, Sepp & Schmidhuber, Jürgen. (1997). Long Short-term Memory. Neural computation. 9. 1735-80. 10.1162/neco.1997.9.8.1735.

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