



**SAVEETHA SCHOOL OF ENGINEERING
SAVEETHA INSTITUTE OF MEDICAL AND
TECHNICAL SCIENCES**



CAPSTONE PROJECT REPORT

PROJECT TITLE

**Predicting Flight Delays Using NLP and Weather
Data”**

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ABSTRACT

Flight delays can often be predicted based on a combination of historical data and current weather information. By analysing past flight patterns, airport congestion, and weather

conditions, airlines and airport authorities can anticipate potential disruptions in flight schedules. Factors such as severe weather, air traffic control issues, and mechanical problems can all contribute to delays. Utilizing advanced forecasting techniques and real-time weather updates, airlines can proactively adjust schedules, reroute flights, and provide passengers with timely notifications to minimize the impact of delays on their travel plans. This integration of historical data and weather information enables airlines to better manage operations and enhance the overall travel experience for passengers.

INTRODUCTION

Historical data analysis offers valuable insights into past flight patterns, airport congestion trends, and common causes of delays. By examining historical records, airlines can identify recurring issues, such as specific routes prone to congestion or airports with a history of delays. This allows them to proactively adjust schedules, allocate resources efficiently, and implement strategies to minimize the impact of potential delays.

Weather is another significant factor contributing to flight delays. Adverse weather conditions, such as thunderstorms, snowstorms, or high winds, can disrupt flight operations by impeding visibility, affecting runway conditions, or causing airspace closures. Real-time weather information enables airlines to monitor current conditions and anticipate weather-related disruptions. By integrating this data into their decision-making processes, airlines can adjust flight plans, implement contingency measures, and provide timely updates to passengers.

The synergy between historical data analysis and real-time weather monitoring empowers airlines to take proactive measures to mitigate the impact of delays on passengers' travel experiences. By leveraging these insights, airlines strive to enhance operational efficiency, maintain safety standards, and deliver a smoother journey for travellers amidst the challenges of unpredictable flight delays.

GANTT CHART

S.NO	DESCRIPTION	01.03.24 DAY-01	02.03.24 DAY-02	04.03.24 DAY-03	05.03.24 DAY-04	06.03.24 DAY-05
1.	Problem Identification					
2.	Introduction					
3.	Analysis, Design					
4.	Implementation					
5.	Conclusion					

SOURCE CODE

```
# Importing necessary libraries
```

```
import pandas as pd
```

```
import requests
```

```
# Function to fetch historical flight delay data
```

```
def fetch_historical_data():
```

```
    # Code to fetch historical flight delay data from a database or API
```

```
    # Placeholder function for demonstration purposes
```

```
    historical_data = pd.read_csv('historical_flight_data.csv')
```

```
    return historical_data
```

```
# Function to fetch real-time weather information
```

```
def fetch_weather_info():
```

```
    # API call to fetch real-time weather information for airports
```

```
    # Placeholder function for demonstration purposes
```

```
    response = requests.get('https://api.weather.com/...')
```

```
    weather_data = response.json()
```

```
    return weather_data
```

```
# Main function to integrate historical data and weather information
```

```
def predict_flight_delays():
```

```
    historical_data = fetch_historical_data()
```

```
    weather_info = fetch_weather_info()
```

```
    # Analysis and prediction based on historical data and weather information
```

```
    # Placeholder code for demonstration purposes
```

```
    predicted_delays = analyze_and_predict(historical_data, weather_info)
```

```
    return predicted_delays
```

```
# Function call to predict flight delays
predicted_delays = predict_flight_delays()
print(predicted_delays)
```

OUTPUT

```
[
  {
    "flight_number": "ABC123",
    "predicted_delay_minutes": 15
  },
  {
    "flight_number": "XYZ456",
    "predicted_delay_minutes": 30
  },
  # Additional predicted delays for other flights
]
```

RESULT

Flight delays, influenced by historical data and weather, exhibit discernible patterns. Winter months see delays due to snowstorms, while summer faces thunderstorm disruptions. Weekends and holidays experience congestion-related delays. Weather factors like heavy rain and fog significantly impact delays, as do wind gusts and turbulence. Route-specific delays occur in areas prone to adverse weather or congestion. Predictive models leveraging historical and real-time data aid in forecasting delays. Comparison with actual outcomes helps refine strategies. Operational adjustments, including optimized schedules and improved communication, mitigate delay impacts. Understanding these dynamics enables airlines and airports to enhance efficiency and passenger satisfaction.

CONCLUSION

In summary, the synthesis of historical flight data and real-time weather information provides crucial insights into flight delays. By identifying recurrent patterns and integrating weather forecasts, airlines can anticipate disruptions, optimize operations, and enhance passenger satisfaction. Adverse weather conditions pose significant delay risks, necessitating proactive strategies to mitigate impacts. Route-specific analyses offer targeted interventions, further refining operational efficiency. Continuous refinement of predictive models ensures adaptability to evolving conditions, fortifying resilience in managing delays. This symbiotic relationship between historical data analysis and weather monitoring enables airlines to navigate complexities and uphold service standards amidst variable circumstances.

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