Adverse Weather Airplane Safety: Innovations with Machine Learning

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***Abstract*—Adverse weather plays a crucial role in ensuring safety by causing passenger flight cancellations. Misinformation can lead to fatalities, while improper maintenance may cause sudden, unpredictable flight cancellations, resulting in significant losses for both passengers and airline authorities. In this study , we predicted logistic regression model and correlation matrix to give a proper explanation of flight cancellation reasons.We also used random forest regression and SHAP to identify the features that most significantly affect flight cancellations. To research, we took the help of Kaggle data, ' 2015 Flight Delays and Cancellations' to work and give a predictive model to estimate the future probabilities of flight cancellation, specially due to adverse weather. The model shows 99.9% accuracy, which gives a point of trust to predict the target feature. It describes every feature co-efficient related to the target feature.**

***Index Terms*—Adverse Weather, Safety, Aviation safety,Logistic Regression,Random Forest Regression**

I. INTRODUCTION

In every country, adverse weather conditions, including monsoons, cyclones, thunderstorms, and dense fog, badly affect the rapidly growing aviation industry. This condition seriously impacts aviation safety, particularly in regions where turbulence, low visibility, and unpredictable weather are making flying very complicated. At the global level, aviation accidents are connected with weather conditions; that is why such challenges should be overcome at any price.Various case studies highlight factors associated with adverse weather, which often cause disruptions among airlines due to sudden weather-related issues.Flights were canceled due to extreme weather conditions like precipitation, wind, and temperature extremes[30].This causes sudden flight cancellations, leading to passenger inconvenience.There has been some recent work to address which factor caused a lot of adverse weather and flight delays. It included decision trees, random forests, and multilayer perceptron (MLP).The present study discusses the impact of adverse weather conditions on flight safety and reviews the recent technological advances in weather monitoring, navigation systems, and operational procedures with Machine Learning (logistic regression, linear correlation) mainly and random forest regression for further study to search for important features.The paper not only presents safety protocols but also the effects of weather disruption on loss and preparedness for disasters. It puts forward some innovative solutions, such as AI-based weather prediction models, enhanced vision systems, and automation of flight resource allocation to improvise safety measures.

Identify applicable funding agency here. If none, delete this.

II. LITERATURE REVIEW

The reviewed studies highlight various advancements to aviation challenges. Vijayanandh Raja et al. (2021) developed an octocopter with a CD-duct for saltwater dispersion to enhance visibility, ensuring stability and material resilience via MATLAB, CATIA, and ANSYS Workbench analyses [1]. Feiteira (2021) employed data mining techniques to predict reasons of flight delays at Atlanta Airport, finding weather as a critical factors, with Random Forest outperforming other models [3]. Borsky and Unterberger (2019) analyzed weather-induced departure delays, identifying up to 23-minute disruptions due to precipitation and wind [4]. Fultz and Ashley (2016) revealed weather's contribution to 35 percent of fatal general aviation accidents, emphasizing trends in time and geography [5]. Fujita and Caracena (1977) examined downbursts and wind shear as causes of weather-related aircraft accidents, introducing the "spearhead echo" phenomenon [7]. Balakrishnan's study on resource allocation during adverse weather proposed market-based slot trading mechanisms for efficient landing slot management [9]. Barata et al. (2024) highlighted early 20th-century advancements in aircraft navigation tools by Portuguese navigators [11]. Fukui and Nagata (2014) critiqued the U.S. DOT's tarmac delay rule for increasing cancellations and delays [13]. Balaban et al. (2024) proposed a POMDP-based framework for robust route planning during adverse weather, outperforming deterministic methods [14]. Arthur et al. (2004) compared NASA's EVS and SVS systems, demonstrating improved situational awareness in low visibility conditions [15]. These studies collectively underscore progress in UAV(unmanned Aerial Vehicle) design, aviation safety, and operational efficiency under challenging conditions.Thammisetty Venkata, ,Naga Radha Parameswari and K. Chandra Prasad (2024) [18] demonstrated that random forest regression outperformed logistic regression and decision trees in predicting machine failures and flight delays with the lowest error metrics. Somani et al. (2021) [19] found CART to be the most accurate for flight delay classification, achieving 99.15 percent accuracy. Manowon and Boonma (2023) [20] developed a batch data pipeline using Apache Airflow and identified random forest regressor as the most effective model for delay prediction. Eikelenboom and Santos (2023) [21] introduced an ML-based integrated disruption solver that reduced recovery costs and computation times during airline disruptions. Ballakur and Arya [22] applied LSTM and Bi-LSTM for quantifying delays, showing effectiveness despite dataset limitations. Henriques and Feiteira (2018) [23] utilized SMOTE to manage imbalanced data, with MLP emerging as the best model for delay predictions. Muros Anguita and Díaz Olariaga (2023) [24] highlighted deep learning's potential for optimizing air traffic and predicting delays. Alla et al. (2021) [25] used selective-data training with MLP to enhance accuracy in arrival delay prediction. Banavar Sridhar (2019) [26] provided a comprehensive overview of machine learning applications in air traffic management, emphasizing feature selection, data quality, and techniques to prevent overfitting. Chin et al. (2024) [27] addressed no-show passenger prediction using random forest and decision trees for improved operational efficiency. Finally, Kim et al. (2023) [28] employed multilayer complex networks to analyze aircraft cancellations due to adverse weather, revealing significant impacts of rainfall and node interactions in network dynamics.

III. AI-DRIVEN WEATHER FORECASTING AND FLIGHT OPTIMIZATION

To address this issue, we implemented logistic regression techniques along with label encoder to estimate the probability of flight cancellations. It will also help to find the actual reason behind the cancellation.

A. Understanding Weather factor

To understand the reason behind flight cancellation a statistical factor[5] has been shown.The statistics summarize weather-related general aviation accidents over a 32-year period and identifies the following as some of the major hazard categories: ceiling/visibility/precipitation, temperature/humidity/pressure, wind, turbulence, and convective weather. Of all weather-related accidents, wind was the most common hazard involved in such accidents(57%),although only 7.8 percent of wind-related accidents were fatal. Ceiling, visibility, and precipitation hazards represented the highest percentage of fatalities-27.5 percent-and fatal accidents-66.9 percent-of any category. High percentages of deaths were shown within the categories of turbulence at 47. 7% and convective weather at 64. 7% fatalities in turbulence-related accidents and convective, respectively. Here we can see adverse weather played an important role visibility is the main fact behind flight cancellation in case of adverse weather.

B. Data pre-processing:

To do our research, we have collected sample data from Kaggle to do a key regression task. Then label encoder is applied to convert the non-numerical into a numeric one.

C. Label Encoder and Logistic Regression:

Logistic Regression is a statistical model used for binary classification, predicting the probability that a given input belongs to one of two classes represents the probability of the positive class. The model is trained to minimize the log loss to align predicted probabilities with actual class labels.[16] On the other hand, Label Encoding is a method for converting categorical data into numerical data by assigning a unique integer to each category. This method is particularly useful when the categories have an ordinal relationship, though it can introduce unintended ordinal relationships if applied to nominal data.[8]

D. Random forest Regression:

Random Forest is a method that builds multiple decision trees during training and merges their predictions to improve accuracy . It uses random subsets of features for each tree to enhance diversity in the model's predictions. It splits the data and takes the corresponding value to look at which feature contributes more to the output.[6]

E. SHAP (SHapley Additive exPlanations)

SHAP is a powerful framework for interpreting machine learning models by calculating the impact of each feature on the model's predictions. SHAP values provide insights into how features influence predictions on an individual level, making them valuable for model transparency. By visualizing SHAP values, practitioners can identify which features drive decisions and how they interact with each other.[10]

F. Correlation Matrix

A correlation matrix is a table that displays the correlation coefficients between multiple variables, summarizing the strength and direction of their linear relationships. Each cell in the matrix shows the correlation value, ranging from -1 (perfect negative correlation) to 1 (perfect positive correlation), with 0 indicating no correlation. This matrix is useful for identifying patterns and relationships among variables, helping researchers and analysts understand the dynamics within their dataset. It also aids in detecting multicollinearity, which can affect the performance of regression models.[12]

G. *Confusion Matrix*

A confusion matrix is a performance evaluation tool used in classification tasks that compares the actual labels of a dataset with the predicted labels of a classification model. It breaks the results into four categories: True Positive (TP), where the model correctly predicts the positive class; False Positive (FP), where the model incorrectly predicts the positive class; True Negative (TN), where the model correctly predicts the negative class; and False Negative (FN), where the model incorrectly predicts the negative class. The confusion matrix helps calculate key metrics such as accuracy, precision, recall, and F1 score, providing a detailed view of the model's performance, identifying errors, and enabling better model optimization, especially in cases of imbalanced datasets.[29]

IV. Flowchart of the entire process to control with AI

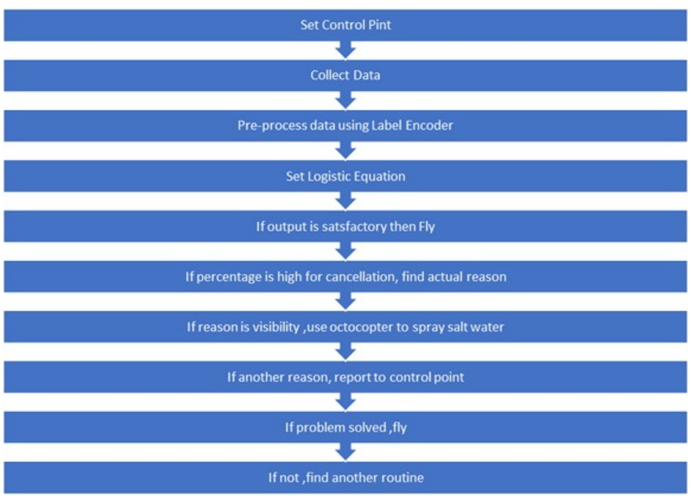

Fig. 1. Flow chart of the entire flight control process.

A. *Forecast cancellations by analyzing past performance.*

Provided by historical data, the logistic regression equation gives a better analysis of forecast flight cancellations than traditional weather prediction methods. This model takes into account a wide variety of delay features as well as airline-specific and airport activity information in order to predict the likelihood that a flight will be canceled. This will make it possible to take data-driven decisions in real-time within the flight control centers. As such, the method predictively improves inaccuracy cancellations anticipate several factors which can come from the daily operation of operations beyond just weather-related ones,which would then make it an invaluable tool for anticipating cancels. This can make it easier for airline companies to make the proper schedule and give the certainty of the flight cancellation before several days, which can be a great sign of operational system. The accuracy of the given model is 99.9 percentage which gives a great assurance of predicting the future and perfect mathematical simulation with ML .We predicted a logistic regression analyzing a Kaggle dataset given in [17]

V. Predicted Machine Learning EQUATIONS

Accuracy: 99.9% **Main feature columns in the table:** YEAR, MONTH, DAY, DAY_OF_WEEK, AIRLINE, FLIGHT_NUMBER, TAIL_NUMBER, ORIGIN_AIRPORT, DESTINATION_AIRPORT, SCHEDULED_DEPARTURE, DEPARTURE_TIME, DEPARTURE_DELAY, TAXI_OUT, WHEELS_OFF, SCHEDULED_TIME, ELAPSED_TIME, AIR_TIME, DISTANCE, WHEELS_ON, TAXI_IN, SCHEDULED_ARRIVAL, ARRIVAL_TIME, ARRIVAL_DELAY, DIVERTED, CANCELLATION_REASON, AIR_SYSTEM_DELAY, SECURITY_DELAY, AIRLINE_DELAY, LATE_AIRCRAFT_DELAY, WEATHER_DELAY.

A. *Logistic Regression:*

Coefficients of Logistic Equation

TABLE I
Logistic Regression Coefficients for Flight Cancellation Prediction

Feature Name	Coefficient
Intercept	-0.000552077
YEAR	0
MONTH	-0.0069756
DAY	-0.009185528
DAY OF WEEK	-0.001770671
AIRLINE	-0.002014157
FLIGHT NUMBER	0.000078875
TAIL NUMBER	-0.000047177
ORIGIN AIRPORT	-0.000190176
DESTINATION AIRPORT	-0.00132268
SCHEDULED DEPARTURE	0.001697
DEPARTURE TIME	-0.005643199
DEPARTURE DELAY	0.00310785
TAXI OUT	-0.007189963
WHEELS OFF	-0.013081281
SCHEDULED TIME	-0.000045041
ELAPSED TIME	-0.050743971
AIR TIME	-0.037915582
DISTANCE	-0.000679128
WHEELS ON	0.020362302
TAXI IN	-0.008667429
SCHEDULED ARRIVAL	0.001329775
ARRIVAL TIME	-0.003901765
ARRIVAL DELAY	-0.0658628
DIVERTED	-0.001147727
CANCELLATION REASON	-0.00934325
AIR SYSTEM DELAY	-0.002277167
SECURITY DELAY	-0.00001174
AIRLINE DELAY	-0.0090255
LATE AIRCRAFT DELAY	-0.010285443
WEATHER DELAY	-0.002022624

General Logistic Equation

$$P(CANCELLED = 1) = \frac{1}{1 + e^{-(Y)}}$$

Where: $Y(LinearEquation) = c + m_1x_1 + m_2x_2 + m_3x_3 + \cdots$

- C: Intercept
- M: Coefficients of individual features
- X: Feature values

Our team utilized multiple evaluation criteria to assess the efficacy of the suggested model. Accuracy = $\frac{TP+TN}{TP+TN+FP+FN}$ where:

- **TP**: True Positives
- **TN**: True Negatives
- **FP**: False Positives
- **FN**: False Negatives

B. Random forest classification:

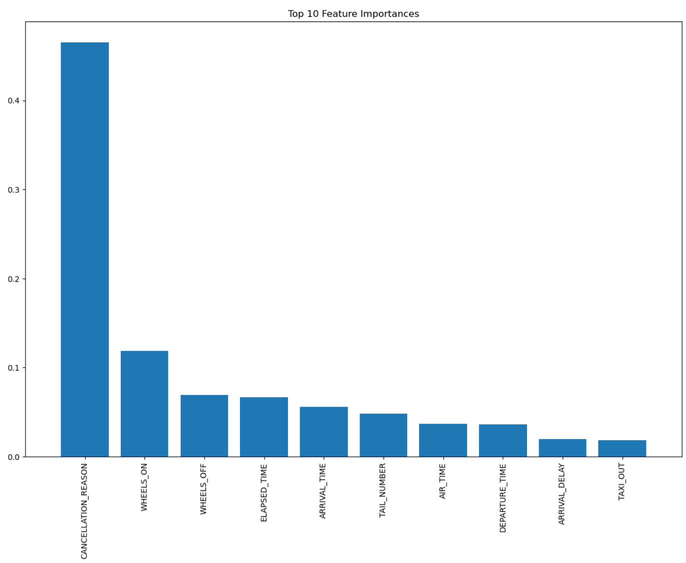

Fig. 2. Random Forest Classification

C. SHAP-INTERPRETATION:

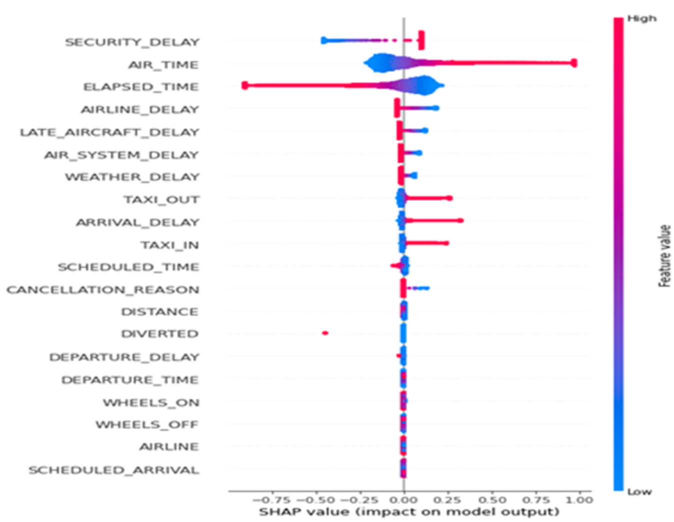

Fig. 3. Shap-Interpretation of features affecting flight cancellation

D. Correlation matrix

VI. RESULTS

The equations and correlation matrix, with their high accuracy, provide confidence in predicting the reasons behind flight cancellations and allow sufficient time to implement appropriate solutions.The Logistic equation will give a certain amount of percentage, which will give an indication of future results. The Random Forest regression also provides a view to look for future research to find the way to overcome the problems faced in regular time arrival. The given logistic regression model predicts flight cancellations with high accuracy by a rich feature set, including flight details, delays, operational timings, and environmental factors. Each feature's coefficient reflects its real-world impact, with delays like ARRIVAL_DELAY showing significant influence. The model's probabilistic approach ensures reliability when trained on balanced and representative data. But regular updates and monitoring are essential to maintain accuracy for potential changes in operational or environmental conditions. It can impact flight slots in several ways. If a flight is canceled well in advance, the allocated slot becomes vacant, providing an opportunity for another airline to request and use that slot. On the contrary, if a flight is canceled close to its scheduled time, it can lead to operational disruptions, causing delays for other flights and affecting shared resources such as gates, runways, and air traffic control. The impact on slots is influenced by specific slot allocation rules set by different airports and aviation authorities, which may include mechanisms to redistribute vacant slots among airlines or immediate reassignment procedures. Frequent cancellations can undermine the schedule's reliability and integrity, affecting passengers, connecting flights, and overall airline operational efficiency. So this model can give a hand to give warning of prior sudden flight cancellation.

As this equation helps to get the appropriate reason behind flight cancellation ,it can be used for slot allocation as well.

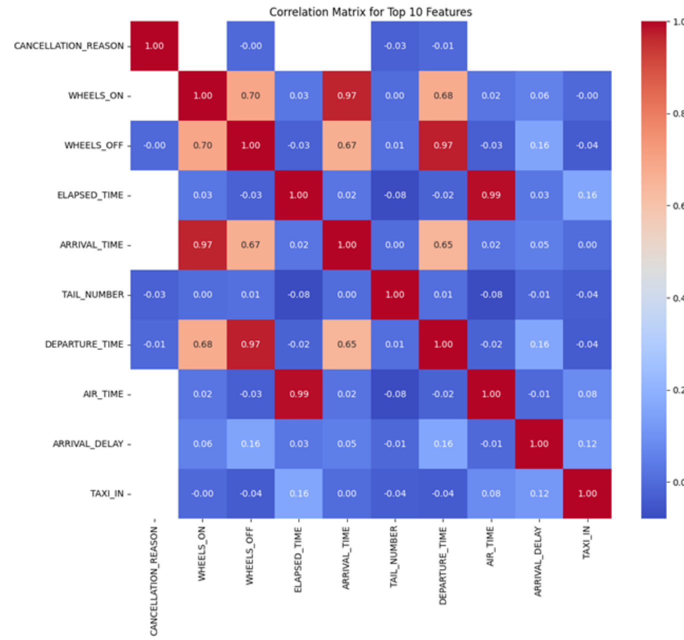

Fig. 4. Correlation Matrix of features affect flight cancellation

We used a confusion matrix of number of rows=100000, as the whole dataset crashed the environment to code.

A. *Confusion matrix:*

$$\begin{matrix} [9738 & 0] \\ [\ 0 & 262] \end{matrix}$$

The confusion matrix represents the performance of a binary classification model, showing 9738 True Negatives (instances where the actual class was 0, and the model correctly predicted 0), 0 False Positives (instances where the actual class was 0, but the model incorrectly predicted 1), 0 False Negatives (instances where the actual class was 1, but the model incorrectly predicted 0), and 262 True Positives (instances where the actual class was 1, and the model correctly predicted 1).

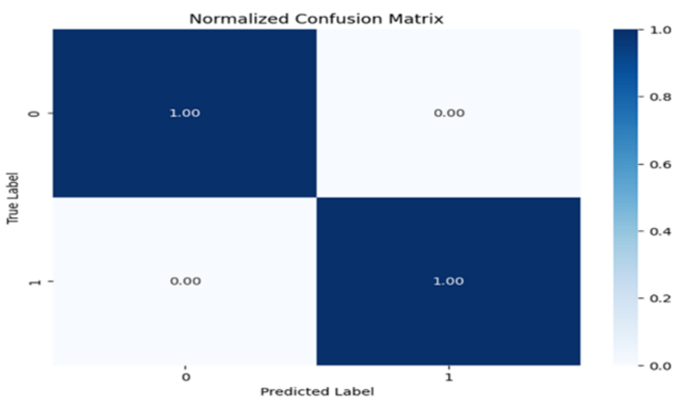

Fig. 5. Confusion Matrix

$$\text{Precision} = \frac{\text{TP}}{\text{TP}+\text{FP}} = \frac{262}{262+0} = 1.0$$

$$\text{Recall} = \frac{\text{TP}}{\text{TP}+\text{FN}} = \frac{262}{262+0} = 1.0$$

$$\text{Specificity} = \frac{\text{TN}}{\text{TN}+\text{FP}} = \frac{9738}{9738+0} = 1.0$$

B. *Additional solutions to help flight control management in terms of adverse weather*

Enhancing airport safety and efficiency through various strategies, including integrating Enhanced Vision Systems and LED lights[15] for better visibility, and using octocopters for fog removal[1]. It highlights the importance of wind safety measures, utilizing advanced sensors and real-time hazard communication to pilots[5]. Additionally, it explores market-based approaches for reallocating flight resources during adverse weather, focusing on both non-monetary and payment-based slot trading schemes[9]. The paper also addresses the complexities of slot allocation mechanisms during Ground Delay Programs (GDPs), proposing algorithms for fair and efficient slot reallocation. Lastly, it emphasizes the need for stable allocations and minimizing airline manipulation in these processes.

C. *Comparison to other model*

Logistic Regression predicts more quickly than tree diagram like Random Forest Regression[6] .Besides, in this predicted equation,it defines the exact coefficients of each feature that impact flight cancellation. In fact compared to normal tree base structure, the equations give a combination of every feature coefficient which gives a combined result of flight cancellation

TABLE II
COMPARISON OF DIFFERENT MACHINE LEARNING MODELS FOR PREDICTION ACCURACY

Study(Ref)	Methodology
Somani[19]	Cart [99.15% accuracy]
Chin et al.[27]	Random Forest [90.4% accuracy]
	Decision Tree [90.2% accuracy]
	Gradient Boosting [86.5% accuracy]
	Neural Network [67.6% accuracy]
Our study	Logistic [99.9% accuracy]

VII. CONCLUSION

Adverse weather significantly impacts flight cancellations and delays, making it a critical concern for aviation safety and operational efficiency. This study effectively demonstrates the application of machine learning techniques, particularly logistic regression, in predicting flight cancellations with high accuracy. By using historical data and integrating feature importance analysis through SHAP and correlation matrices,the findings emphasize the importance of proactive measures, such as advanced weather monitoring, improved scheduling strategies, and real-time data-driven decision-making, to mitigate disruptions caused by various challenges. Implementing such predictive models can enhance operational planning, reduce passenger inconvenience, and improve overall safety and reliability in the aviation industry.

VIII. ACKNOWLEDGMENT

While this study demonstrates the potential of machine learning in predicting flight cancellations, we acknowledge the need for further research. Future work should focus on expanding the dataset with real time experiment.

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