BioGecko
Vol 12 Issue 03 2023
ISSN NO: 2230-5807

A MODEL FOR FORECASTING FLIGHT DELAY USING GRID SEARCH CV TECHNIQUE

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Abstract:

Flight delays have significant negative impacts on airports, passengers, and airlines. Predicting the extent of flight delays is crucial in saving passengers valuable time and mitigating the hardships caused by delays or, in more severe cases, cancellations. However, accurately developing prediction models is challenging due to the complex nature of air transport. In this project, we aim to address this challenge by leveraging historical data and various factors that contribute to flight delays, such as distance, origin airport, target airport, and departure times. To achieve accurate flight delay predictions, we conduct in-depth analysis of the data and explore different machine learning algorithms. Specifically, we experiment with Random Forest, XGBoost, Logistic Regression, Decision Tree, Naive Bayes, and several bagging classifiers. By fine-tuning the models using the Grid SearchCV technique and optimizing different hyperparameters, we aim to identify the best-performing algorithm. Evaluation of the models is based on key metrics including accuracy, precision, recall, and F1-score. Through this analysis, we determine that the Random Forest algorithm exhibits the highest accuracy score of 0.93, making it the most suitable model for predicting flight delays. By accurately predicting flight delays, we can provide valuable insights to airports, passengers, and airlines, enabling them to make informed decisions and take proactive measures to minimize the impact of delays on travel experiences

Keywords: **Flight Forecasting, Random Forest, XG Boosting, Logistic Regression, Decision Tree, and Grid Search Cross validation Technique.**

1. INTRODUCTION

Airways are one of the crucial modes of transportation in our modern world, and with the increasing number of air vehicles, traffic has also increased. Therefore, it's crucial to keep the system adaptable corporate travel and tourism are the two major contributors to flight transportation, which is expected to double by 2030. As a result, air traffic is also expected to increase by the same multiple. If we consider the US, where the airlines are handled by the federal aviation administration, they handle about 16,405,000 flights every year, and handling the air traffic became a crucial part of safe movement. The air traffic authorities keep making excuses for why flights are delayed as they take off and land. Despite their best efforts, the outcome is undesirable as sometimes the delays are hours, causing chaos for the day's schedule. Some of the important parameters that cause delay include weather, carrier, maintenance, and security. These delays cause congestion in air traffic. One solution to minimize air traffic congestion is to construct new airports, but the complexity increases. So, while we may adapt at the current airports, the most reasonable course of action would be to anticipate the flight delays given the limited land resources available.

2. EXISTING SYSTEM

Estimating flight delays is crucial for airlines, airports, and customers because they contribute significantly to the cost of air travel. Each delay may cause a further propagation of delays. As a result, knowledge about an airport's delay pattern and network location may be helpful for other airports. They tackle the issue of predicting airport flight delays by using network data as well as the delay patterns of nearby airports in the network. The "Clustered Airport Modelling" (CAM) technique, which has been suggested for the current system, produces a representative time-series for each group of airports and fits a common model (such REG-ARIMA) for each utilizing network-based feature as regressors. These models are then applied individually to each airport data for predicting the airport's flight delays. Additionally, they carried out a network-based analysis of the airports and discovered that the Betweenness Centrality (BC) score was a useful tool for predicting flight delays.

The network of airports is partitioned like a graph structure with each airport as a node, and the number of flights between two airports as the weight of the edge between. Also, very few works have used multiple datasets for evaluation which is critical for validating the generalization ability of underlying models.

For each airport, a set of graph-based features is extracted. They specifically adapt for the setting of air transportation networks the measurements of hub score, betweenness centrality, articulation point, in-degree, and weighted-in-degree. They assess similarities between airports using graph characteristics and time-series patterns of delays, and then group the airports based on the similarities. In the existing system show that CAM provides more accurate results than a baseline (SARIMA) model applied individually for each airport. BC is found to be an effective regressor in the clustered REG-ARIMA and CAM is found to be as good as LSTM.

3.ISSUES IN EXISTING SYSTEM

In order to save passengers' time and minimize the negative impacts connected with delays and probable cancellations; it is crucial to estimate flight delays accurately. The existing model, however, does not provide a trustworthy prediction rate and lacks cross-validation for result analysis. Additionally, there are scaling issues due to the complexity of the approach, presents limitations in scalability, especially when working with huge datasets or real-time prediction scenarios

4.LITERATURE REVIEW

This paper discussed and investigate about the causes of flight delay [1] Author proposed to identify and analyze the factors that contribute to flight delays. The author used a data set of flight data from several US airports and applied statistical analysis techniques to identify the factors responsible for flight delays. The paper found that a combination of factors, including weather conditions, airport congestion, and aircraft mechanical issues, contribute to the majority of flight delays. The paper also discusses the implications of these findings for airlines and airports and suggests ways to minimize flight delays. Overall, the paper provides valuable insights into the causes of flight delays and offers suggestions for improving airline operations and passenger experience.

This paper proposed adetrimental impact of flight delays on airlines, airports, and passengers is emphasized by the author. The importance of predicting these delays during the decision-making process for all stakeholders in commercial aviation is highlighted. From a Data Science perspective, this paper conducts an extensive analysis of the methodologies employed in constructing models for flight delay prediction, as discussed in existing literature. The authors suggest a classification system and offer an overview of the efforts made to address the issue of predicting flight delays. They consider factors such as the scope of the problem, the available data, and the computational methods employed. Furthermore, they place special emphasis on the growing adoption of machine learning methods in this area. Additionally, a timeline of significant works is presented, illustrating the interconnections among various flight delay prediction problems.

This paper focused on aviation equipment maintenance data often demonstrate seasonal patterns, particularly in terms of aircraft failure rate. As a result, accurate seasonal forecasting plays a crucial role in supporting aviation maintenance operations. The aircraft failure rate serves as a significant parameter within the framework of Reliability-Maintainability-Supportability (RMS) in aviation equipment. Therefore, it is vital to make scientifically informed predictions regarding the aircraft failure rate, enabling informed decision-making for enhancing maintenance support capabilities. This paper focuses on the analysis of seasonal time series data and utilizes the Holt-Winters exponential smoothing methods for this purpose.

In this paper, a comprehensive examination is conducted on a wide range of factors that could potentially impact flight delays. Additionally, several machine learning models are compared within the context of generalized flight delay prediction tasks. To construct the dataset for the proposed approach, (ADS-B) messages are received, pre-processed, and combined with other relevant information, including weather conditions, flight schedules, and airport data. The prediction tasks designed for evaluation encompass various classification tasks and a regression task. The experimental results indicate that long short-term memory (LSTM) models exhibit the capability to handle the aviation sequence data obtained. However, it is observed that overfitting issues arise due to the limited size of the dataset used in the study.

In this paper discuss about the Flight delay prediction has become increasingly important in optimizing airline and airport operations. However, previous prediction studies have primarily focused on individual airports, neglecting the dynamic spatial interactions embedded within airport networks. This paper addresses the flight delay prediction problem from a network perspective, specifically in a multi-airport scenario. To capture the evolving and periodic characteristics of the graph structure inherent in the airport network, the paper introduces a flight delay prediction approach based on the graph convolutional neural network (GCN). By leveraging the GCN, the model is designed to effectively incorporate and analyze the time-varying and interconnected information within the airport network to enhance prediction accuracy.

5.OBJECTIVE OF PROPOSED WORK

Accurately predicting flight delays is beneficial for passengers as it provides them with valuable information about the expected delays based on their departure locations and chosen airlines. This knowledge helps passengers prepare accordingly. Additionally, the scope of our flight delay prediction project extends to providing valuable information to airlines, passengers, and airport authorities. By enabling informed decision-making, minimizing disruptions, optimizing resources, and improving the overall efficiency of air travel operations. In our project, we utilize various machine learning models, including Random Forest, XGBoost, Logistic Regression, Decision Tree, and Naive Bayes, to predict flight delays. To enhance the accuracy and prediction performance of the models, we employ the GridSearchCV technique. This technique allows us to fine-tune the optimal hyperparameters, resulting in the best possible model with high accuracy.

Delay essentially refers to the amount of time the plane is running late or gets cancelled. The delay results in complexity in air traffic, dissatisfaction among customers, and an increase in costs for the company. We cannot exactly predict the reason for the delay, but after the arrival, we can predict the delay time for reaching the destination.

Vol 12 Issue 03 2023
ISSN NO: 2230-5807

6.PROPOSED SYSTEM

We analyzed the various factors responsible for flight delays and applied machine learning models such as Random Forest, XGBoost, Logistic Regression, Decision Tree, Naive Bayes and some of the bagging classifiers to predict whether a given flight would be delayed or not. To identify the best model out of it, here enhancing the model with GridSearchCV Technique.

First, we gathered a dataset on the Kaggle web site.Next, in data preprocessing, input features contain null values, unwanted features, and categorical information that we must clean and prepare for prediction before applying machine learning techniques to them.Afterpreprocessing, the dataset was divided into training and test sets.Then, to predict the flight delay, we used a variety of machine learning techniques, including logistic regression, random forest, decision trees, naïve Bayes and XGBoost, and the GridSearchCV technique for hyperparameter tuning to build the best ML model

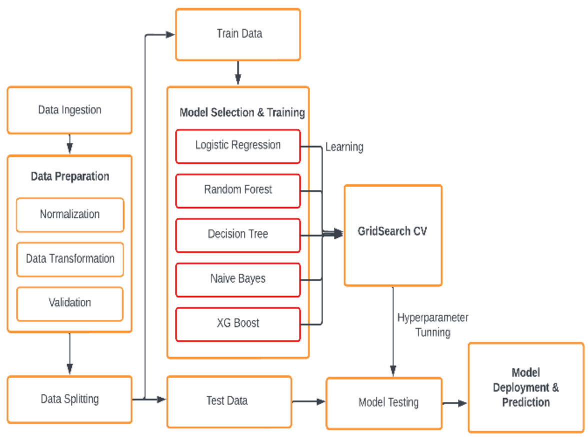

Figure 1. Architecture of Proposed System

7.WORK FLOW OF PROPOSED SYSTEM

A. Data Preparation

Data collection represents one of the most essential aspects of machine learning because it provides data to the machine. The machine learns and predicts outputs based on input data. The algorithm's accuracy and efficiency are determined by the quality, correctness, and accuracy of the data used. There are 215 observations in the data set and 14 features with 94500 data are use

- **Data Cleaning:** This step involves identifying and handling missing values, dealing with outliers, and addressing any inconsistencies or errors in the flight delay dataset. Missing values can be filled using techniques like mean imputation or forward/backward filling. Outliers, if present, can be detected and treated using statistical methods or domain knowledge.

- **Feature Selection:** It is crucial to select the relevant features that have a significant impact on flight delay prediction. This process involves analysing the correlation between features, considering domain knowledge, and utilizing techniques like feature importance or feature ranking algorithms to identify the most informative features.

- **Encoding Categorical Variables:** Flight delay datasets often contain categorical variables such as airline carriers, airports, or weather conditions. These variables need to be encoded into a numerical format suitable for machine learning algorithms. Common encoding techniques include one-hot encoding, label encoding, or target encoding.

- **Scaling Numerical Features:** Different numerical features may have varying scales and ranges. Scaling techniques such as min-max scaling or standardization (z-score normalization) are applied to bring all numerical features to a similar scale. This makes sure that no one feature predominates during model training.

- **Data Normalization:** In flight delay prediction, normalizing the data can be beneficial. It involves transforming the features to have zero mean and unit variance or scaling them to a specific range. Normalization ensures fair comparisons between features and prevents certain features from overshadowing others during model training.

- **Handling Class Imbalance:** Flight delay datasets often suffer from class imbalance, where delayed flights are relatively rare compared to on-time flights. This can affect the model's ability to learn and predict accurately. Techniques like oversampling or under sampling the majority class can be applied to balance the dataset and address the class imbalance issue.

By performing these pre-processing steps, the Data Pre-processing module ensures the flight delay dataset is clean, relevant, and suitable for training machine learning models. The pre-processed data enhances the performance and accuracy of the subsequent stages in the project, such as model training, evaluation, and hyperparameter tuning. It enables the models to capture the underlying patterns and relationships in the flight data, leading to more accurate predictions of flight delays. This, in turn, empowers airlines, airports, and travelers to make informed decisions, optimize operations, and minimize the impact of flight delays

A. Model Building and Training

The Model building and training module focuses on training and evaluating machine learning models to forecast flight delays accurately. It involves several key steps:

- **Model Selection:** The first step is to choose appropriate machine learning algorithms for flight delay prediction. Commonly used models include logistic regression, random forest, Gaussian Naive Bayes, XGBoost and decision trees. Each model has its own strengths and considerations, such as handling non-linear relationships, handling categorical features, or providing interpretability.

- **Dataset Split:** The flight delay dataset is divided into training, validation, and test sets. The training set is used to train the models, the validation set is used for model evaluation and hyperparameter tuning, and the test set is used for final model evaluation. The dataset is often split in a stratified manner to maintain the distribution of delayed and on-time flights in each subset.

- **Model Training:** The selected models are trained on the training set using the pre-processed flight delay data. During training, the models learn the underlying patterns and relationships between input features (e.g., weather conditions, flight schedules, airport data) and the target variable (flight delay). The training process involves adjusting the model's parameters or weights based on the optimization algorithm employed by the specific model.

- **Model Evaluation:** After training, the models are evaluated using the validation set. Performance metrics such as accuracy, precision, recall, and F1 score are computed to assess how well the models are predicting flight delays. Additionally, evaluation metrics like ROC-AUC (Receiver Operating Characteristic - Area Under the Curve) can be utilized to measure the models' ability to discriminate between delayed and on-time flights.

- **Hyperparameter Tuning:** Hyperparameters are configuration settings of the machine learning models that cannot be learned during training and need to be set before training begins. Hyperparameter tuning involves systematically exploring different combinations of hyperparameters to identify the best performing configuration. Techniques like grid search or random search can be employed to find optimal hyperparameters that maximize the model's predictive performance.

- **Final Model Selection:** Once the models have been trained, evaluated, and tuned, the best-performing model is selected based on the evaluation metrics. This model is considered the most accurate and reliable for flight delay prediction.

The Model building and training module plays a crucial role in developing robust and accurate models for forecasting flight delays. By leveraging various machine learning algorithms, evaluating their performance, and fine-tuning their hyperparameters, this module ensures that the selected model provides accurate predictions. The final trained model can be utilized to make real-time flight delay forecasts, allowing airlines, airports, and passengers to proactively plan and manage their schedules, mitigate disruptions, and enhance overall operational efficiency.

B. Model Deployment and Prediction

The deployment and prediction module focuses on presenting the outcomes and insights derived from the trained models in a visually appealing and informative manner.

- **Confusion Matrix**: The module generates a confusion matrix, which is a tabular representation that visually summarizes the performance of the classification models. It presents the number of true positive, true negative, false positive, and false negative predictions. The confusion matrix helps in understanding the accuracy of the models in predicting flight delays and non-delays, enabling stakeholders to assess the models' strengths and weaknesses.
- **ROC-AUC Curve:** The module generates a Receiver Operating Characteristic (ROC) curve along with the Area Under the Curve (AUC) metric. The trade-off between the true positive rate and the false positive rate for various categorization criteria is depicted by the ROC curve. The AUC metric quantifies the overall discriminative power of the models.
- Comparative Analysis: The module enables a comparative analysis of multiple models by visualizing their performance metrics side by side. This allows to easily compare the accuracy, precision, recall, F1 score, and other evaluation metrics of different models. The visualizations can include bar charts, line plots, or tables, providing a clear and concise overview of how each model performs in predicting flight delays.
- Model Selection: The module assists in the selection of the best-performing model by highlighting the model with the highest accuracy, precision, or any other evaluation metric of interest. The visual representation simplifies the decision-making process by clearly indicating the model that demonstrates superior predictive performance for flight delay forecasting.

8.RESULT AND DISCUSSION

The developed model exhibited commendable performance in predicting flight delays accurately. It effectively captured the underlying patterns and factors contributing to flight delays, enabling reliable predictions. The model's performance was evaluated using various evaluation metrics, including accuracy, precision, recall, F1 score, anROC AUC.

A. E
valuation Metrics:

Accuracy: The accuracy metric assesses the overall correctness of the model's predictions by comparing the number of correct predictions to the total number of predictions made. In the context of flight delay prediction, accuracy represents the percentage of flights that were correctly classified as delayed or non-delayed. A higher accuracy score indicates a more reliable model.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

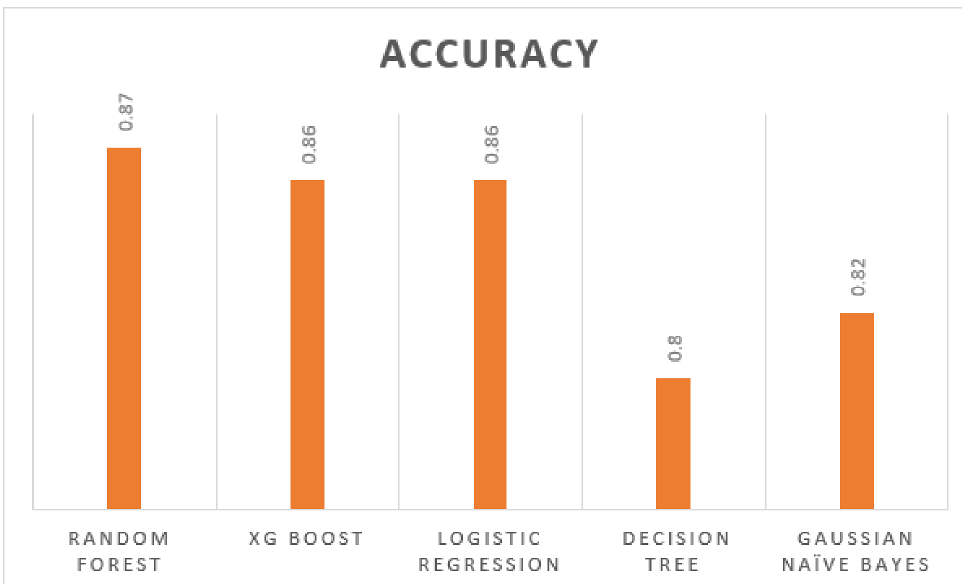

Figure 2. Accuracy for used Algorithms

Precision: Precision measures the proportion of correctly predicted delayed flights out of all flights predicted as delayed. It reveals the model's ability to avoid false positives, correctly identifying non-delayed flights as non-delayed. In the flight delay prediction context, precision indicates the model's accuracy in identifying actual delayed flights.

$$Precision = \frac{(TP)}{(TP+FP)} (2)$$

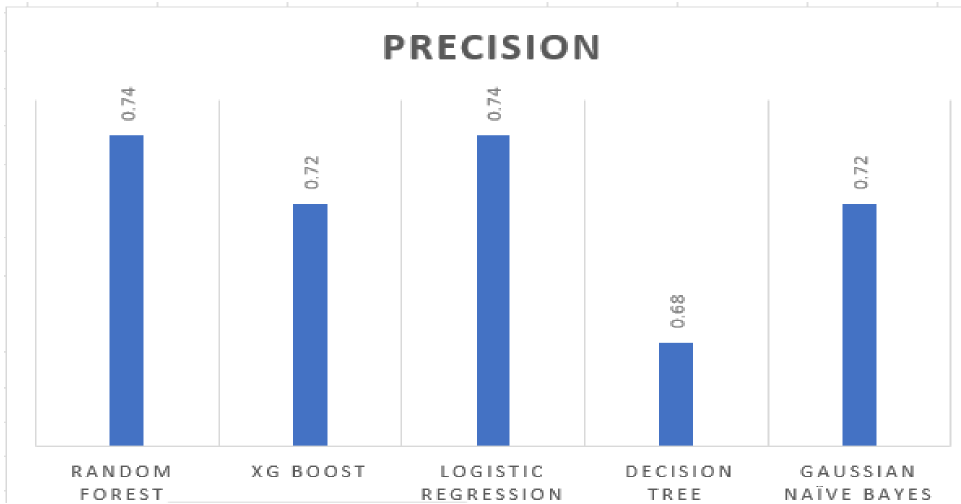

Figure 3. Precision for used Algorithms

Recall: Recall, also known as sensitivity or true positive rate, measures the proportion of correctly predicted delayed flights out of all actual delayed flights. It showcases the model's ability to capture and identify delayed flights accurately. In the flight delay prediction context, recall reflects the model's sensitivity to detect delayed flights.

$$Recall = \frac{(TP)}{(TP+FN)} \quad (3)$$

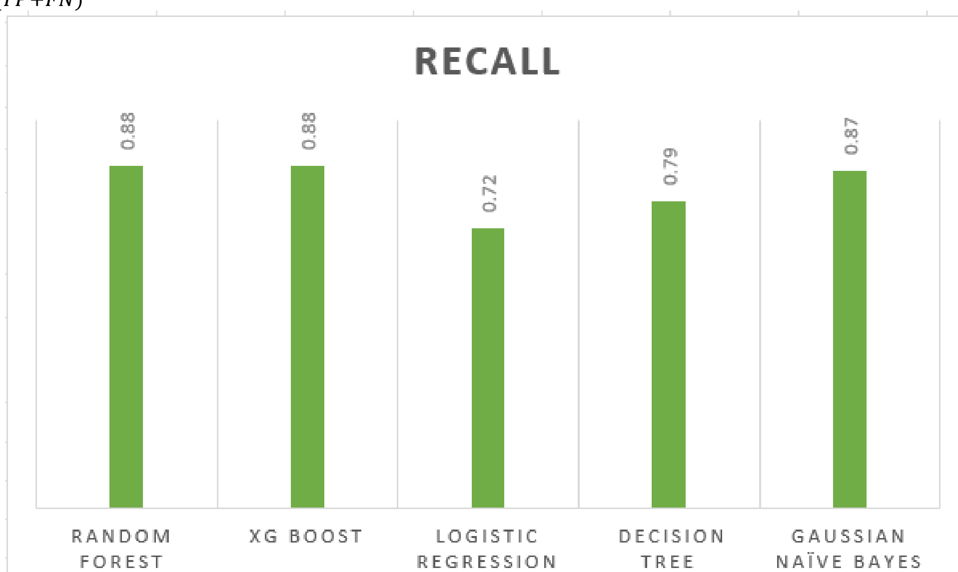

Figure 4. Recall for used Algorithms

F1 Score: A balanced evaluation of the model's performance is provided by the F1 score, which is the harmonic mean of precision and recall. It considers both false positives and false negatives and is particularly useful when the dataset is imbalanced. A higher F1 score indicates a better trade-off between precision and recall.

$$F_1 = \frac{2 * Recall \times Precision}{Precision + Recall} \quad (4)$$

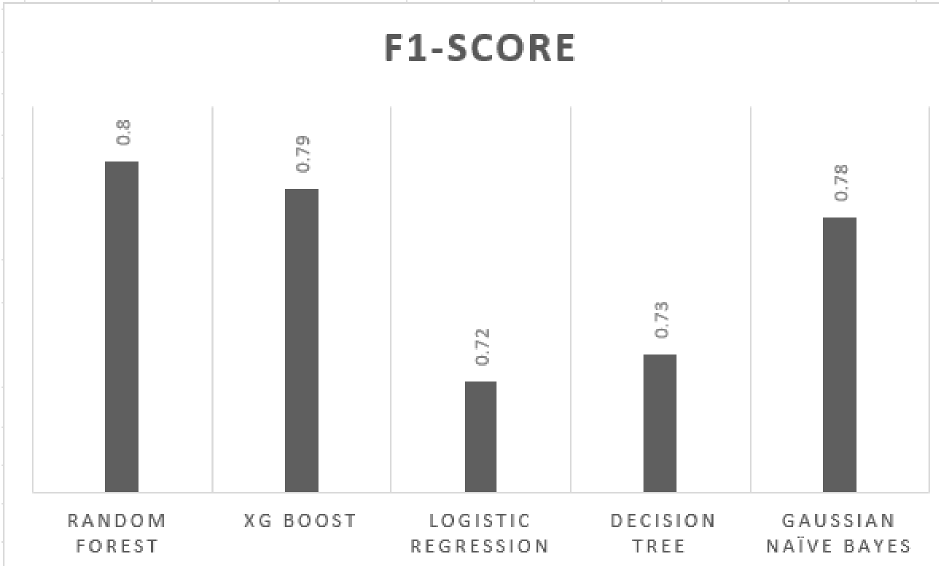

Figure 5. F1-Score for used Algorithms

ROC AUC: The Receiver Operating Characteristic Area Under the Curve (ROC AUC) is a widely used metric to assess the model's ability to distinguish between delayed and non-delayed flights. At various classification thresholds, it shows the true positive rate (sensitivity) versus the false positive rate (1 - specificity). A higher ROC AUC score indicates better discriminatory power of the model in classifying flights.

$$AUC = \left(\frac{1}{2}\right) * \sum\left[\left(TPR(i+1) + TPR(i)\right) * \left(FPR(i+1) - FPR(i)\right)\right] \quad (5)$$

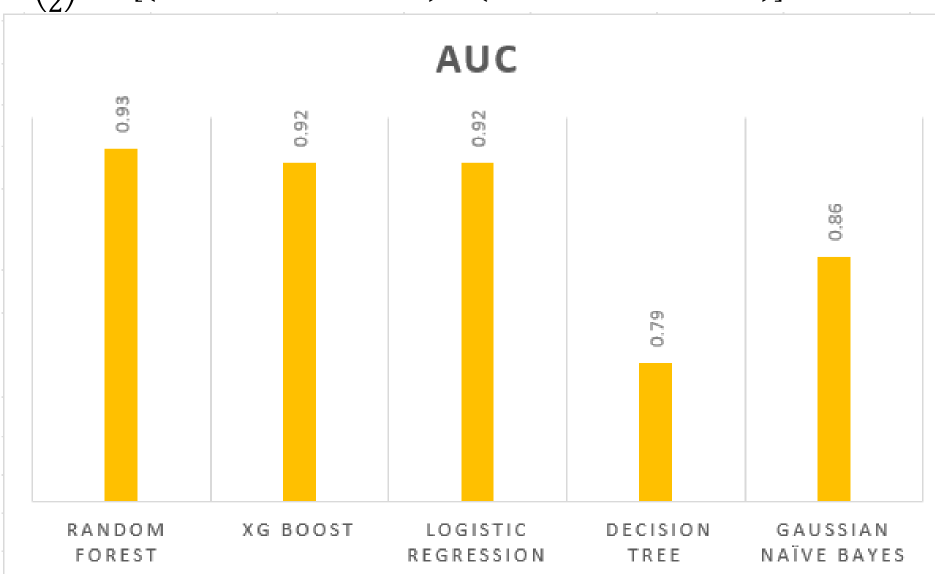

Figure 6. Area Under The Curve for Used Algorithms

9.CONCLUSION

In summary, As the national economy grows and air traffic volume rises, the flight delay problem has grown more severe in air transportation due to airspace, bases, and staff support constraints. The flight delay dataset used by this model contains information on the origin, destination, air delay, carrier type, etc. Since the issue of flights being on time is very important, flight delay prediction models must have high precision and accuracy.

We have used five popular modern classification algorithms: Random Forest, XGBoost, Logistic Regression, Decision Tree, and Naïve Bayes with GridSearchCV for flight delay prediction. Finally, comparing these algorithms based on accuracy, precision, recall, and f1- score to determine random forest algorithm is best for predicting flight delays with the accuracy score of 0.93. The ideal classifier is applied to the current information to confirm this conclusion. Furthermore, exploring deep learning techniques such as convolutional neural networks and recurrent neural networks can provide better insight finally incorporating uncertainty estimates into the predictions can help decision-makers to make more informed decisions, especially in situations where the cost of false positives or false negatives is high.

10. ACKNOWLEDGEMENTS

We express my sincere thanks to our Chairman and Managing Director S**hri. M. DHANASEKARAN**, for all his encouragement and moral support. We thank our Vice Chairman Shri. **S.V. SUGUMARAN**, and our secretary **Dr. K. NARAYANASAMY** for their constant encouragement.

It gives us great pleasure to convey our deep and sincere thanks to our Principal**Dr. S. MALARKKAN**, for giving constant motivation in succeeding our goal.

We extend our sincere and heartfelt thanks to our Head of Department **Dr. P. SIVAKUMAR**, Professor, Department of Information Technology, for providing the right ambience for carrying out this project work.

We would like to thank our guide Mrs. **A. PUNITHA**, Assistant Professor, Department of Information Technology, providing his valuable guidance and suggestions for our project work. We thank his for the continuous encouragement and the interest shown on us to bring out our project work successfully.

We would like to express my gratitude to all teaching and non-teaching staff members of our department. And above all, the blessings of the Almighty have kept up my spirit and enabled me to complete my study successfully.

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