A Machine Learning Approach for Prediction of On-time Performance of Flights

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***Abstract*—One of the major business problems that airlines face is the significant costs that are associated with flights being delayed due to natural occurrences and operational shortcomings, which is an expensive affair for the airlines, creating problems in scheduling and operations for the end-users thus causing bad reputation and customer dissatisfaction. In our paper, a two-stage predictive model was developed employing supervised machine learning algorithms for the prediction of flight on-time performance. The first stage of the model performs binary classification to predict the occurrence of flight delays and the second stage does regression to predict the value of the delay in minutes. The dataset used for evaluating the model was obtained from historical data which contains flight schedules and weather data for 5 years. It was observed that, in the classification stage, Gradient Boosting Classifier performed the best and in the regression stage, Extra-Trees Regressor performed the best. The performance of the other algorithms is also extensively documented in the paper. Furthermore, a real-time Decision Support Tool was built using the model which utilizes features that are readily available before the departure of an airplane and can inform passengers and airlines about flight delays in advance, helping them reduce possible monetary losses.**

***Keywords*—Flight Delay Prediction, Classification, Regression, Machine Learning, Deep Learning, Decision Support Tool**

I. Introduction

In January 2017, air carriers in the United States of America reported an average on-time arrival rate of 76.0%, down from 81.0% in 2016 and 82.5% in the last quarter of 2016, according to the U.S. Department of Transportation′s Air Travel Consumer Report [1]. The carriers filing on-time performance data reported that 24.01% of their flights were delayed, of which 7.19% of their flights were delayed by aviation system delays, 7.86% by late-arriving aircraft, 5.90% by factors under an airlines control, such as maintenance or crew problems, 0.72% by extreme weather and 0.04% for security reasons. Weather is considered a factor in both the extreme-weather category and the aviation-system category as well as a factor in delays attributed to late-arriving aircraft, although airlines do not report specific causes in that category. According to the Bureau of Transportation Statistics (BTS), around 20% of all scheduled commercial flights are delayed and delays have five major causes, which are due to air carrier, extreme weather, National Aviation System, late-arriving aircraft and security [2]. BTS uses the data collected from airlines to determine the percentage of late flights delayed by weather, which includes those reported in the categories of extreme weather, late-arriving aircraft, and National Aviation System delays. In January 2017, 34.33% of late flights were delayed by weather, up from 29.76% in January 2016. Flight delays cost airlines millions of dollars per year, while causing a great inconvenience to the passengers. Thus, predicting delays beforehand can prevent unnecessary expenditure as well as improve customer satisfaction.

In our paper, a two-stage predictive model was built for predicting the departure and arrival delays of flights. The dataset for training and validating our model consists of US Domestic Airline On-time Performance data and weather data from the year 2012 to 2016 which were extracted from BTS and World Weather Online API respectively. It contains on-time arrival performance data for non-stop domestic flights served by major air carriers in 15 major interconnected airports. Following convention laid down by BTS, flights that arrive at the gate within 15 minutes of the scheduled time are considered as being on-time and rest of the flights including cancelled and diverted flights are deemed as delayed. The model comprises two states, the training state and the prediction state. The training dataset after pre-processing contains information about approximately 3.2 million flights and is used to train the predictive model. In the prediction state, the trained model labels each data point by performing a binary classification to predict whether a scheduled flight will be delayed or on time and then predicts the value of delay in minutes. The supervised learning algorithms implemented were Extra-Trees, Random Forests, AdaBoost, Gradient Boosting, Artificial Neural Networks and Deep Neural Networks. A Decision Support Tool (DST) was built using the model which can be used for predicting real-time flight delays.

The rest of the paper is organized as follows: Section 2 presents the related work in flight delay prediction, Section 3 discusses the problem statement, Section 4 enumerates the dataset and pre-processing used in building the model, Section 5 describes the model, Section 6 discusses the results of the model, Section 7 describes the Decision Support Tool and Section 8 provides conclusions and directions for future work.

II. Related Work

A good quantum of research attention has been devoted to the study of flight delays; predicting and analyzing the delays and their causes have long been active subjects of research because of their vital importance in air traffic control, airline decision making and ground delay program. Different researchers have studied this problem from various perspectives.

A statistical method has been deployed by Mueller and Chatterji [3] to analyse the departure, arrival data and characterize the delay data. Tu et al. [4] have also used statistical methods to develop a model for estimating flight departure delay distributions with long-term trend and short-term pattern. Statistical methods rely on estimates and approximations, thus their results might lead to fallacious conclusions.

Xu et al. [5] in their paper have developed a stochastic Bayesian Network model and have demonstrated the methodology on a case study analysis of two routes in the National Airspace System. Zonglei et al. [6] have built a classification model using the flight data in 2006 from a hub-airport in China. Khanmohammadi et al. [7] and Demir & Demir [8] have utilized artificial neural networks for predicting flight delays in JFK airport and Esenboga International Airport respectively. The existing models have been developed for either one particular airport or a set of few airports, whereas the proposed model considers fifteen major airports in the USA and thus can be generalized well.

Rebollo and Balakrishnan [9] proposed a new class of models, which considered both temporal and spatial delay states as explanatory variables, and used Random Forest algorithms to predict departure delays. Hugo Alonso and Antonio Loureiro [10] in their paper have developed a unimodal model for predicting flight departure delay. Liu et al. [11] and Belcastro et al. [12] have developed a model for arrival delay prediction of a scheduled flight. Choi et al. [13] have proposed a model to predict airline arrival delays caused by inclement weather conditions using data mining and supervised machine learning algorithms.

In the existing literature, researchers have worked extensively on the problem of classification of flight delays and comparatively little research exists on prediction of departure as well as arrival flight delays using machine learning methods. In this paper, a two-stage predictive model is developed employing supervised machine learning algorithms, where binary classification is performed to predict the occurrence of a delay and then the value of the delay in minutes is predicted. The model is applied to predict both departure as well as arrival delays and it is used in building a DST.

III. Problem Statement

The delays in flights create huge losses for the air carriers and also have a great impact on the daily lives of people. Hence, there is a need to predict the flight delays in advance so that the air carriers and their passengers can be pre-informed about the delays and they can act accordingly. This paper details the implementation of machine learning techniques for prediction of flight delays which is used in developing a DST that broadly addresses the above mentioned need.

IV. Data and Pre-Processing

On-time performance data was sourced from a data repository provided by the Bureau of Transportation Statistics. This dataset contains 12 features describing the on-time arrival and departure performance of domestic flights in the USA. Weather data for 5 years (2012-2016) was extracted from the World Weather Online API consisting of weather attributes for origin and destination airports. On-time performance and weather data were collected for 15 major airports throughout USA and the extracted features were combined to form the final dataset. The feature set of the proposed model is described in Table I. Filtering of null values was performed as a precursor to feature selection. Feature selection is the process of selecting a set of relevant features for the model from a set of existing features. Various techniques such as Univariate and Tree-based feature selection were implemented, however the Recursive Feature Elimination algorithm produced the optimum results, with a better accuracy and lesser time taken, as shown in Table II. This algorithm eliminates the weakest feature from the feature set recursively until a sharp decrease in the predicting accuracy of the model is observed. As a result, a reduction in the total number of features in the feature set was considered. Principal Component Analysis was also performed on the feature set and tested with the model; however this did not yield favorable results. The reduced feature set is shown in Table I.

V. Predictive Model

A. Flight Delay Prediction

The model consists of two phases:

1. Departure Delay Prediction
2. Arrival Delay Prediction

According to the standards set by the BTS, a flight is said to have a class value of 0 if it departs or arrives no later than 15 minutes from the scheduled time, otherwise it is said to have a class value of 1 and is considered as a delay. If the classification stage outputs 0, then there is an absence of delay. If the classification stage outputs 1, then the regression stage predicts the value of delay in minutes.

1) Departure Delay Prediction: The feature set used in the departure delay prediction phase consists of 9 airline on-time performance data features and 12 weather features as shown in Table I. The dependency of each feature is equally distributed, hence every feature is important in predicting the outcome.

2) Arrival Delay Prediction: The feature set used in the arrival delay prediction phase consists of 12 airline on-time performance data features and 24 weather features as shown in Table I. It was observed that the departure features also played a significant role in the occurrence of arrival delays. As a result, this feature set is an extension of the features used for departure delay prediction.

TABLE I
FEATURES OF THE PREDICTIVE MODEL

Airports Considered	ATL, LAX, ORD, DFW, DEN, JFK, SFO, CLT, LAS, PHX, MIA, IAH, SEA, MCO, EWR
Flight On-time Performance data (Input)	Airline ID, Flight Number, Origin Airport ID, Destination Airport ID, Year, Quarter of Year, Month, Day of Month, Scheduled Departure Time, Scheduled Arrival Time
Weather data (Input)	Time of Observation, Temperature, Wind Speed, Wind Direction, Weather Code, Precipitation, Humidity, Visibility, Pressure, Cloud Cover, Dew Point, Wind Chill, Wind Gust
Selected Features	Airline ID, Flight Number, Origin Airport ID, Destination Airport ID, Year, Quarter of Year, Month, Day of Month, Day of Week, Scheduled Departure Time, Scheduled Arrival Time, Wind Direction, Humidity, Pressure, Temperature
Classification (Output)	1 - indicates occurrence of delay 0 - indicates absence of delay
Regression (Output)	Numerical value of the flight delay

TABLE II
FEATURE SELECTION RESULTS

	Accuracy	Time taken (s)
Without Feature Selection	91.63	66
With Feature Selection	91.85	37

B. Classification

Binary classification was performed for predicting whether a scheduled flight is on-time or delayed. The dataset was observed to be skewed; the number of on-time flights were much higher than the number of delayed flights, constituting of around 75% of the data. Taking into consideration the imbalanced nature of the dataset, sampling of the dataset was performed before classification. Sampling is a statistical technique performed to represent the desired distribution of a class using a set of samples from the population. Sampling methods handle the class-imbalance by changing the minority and majority class sizes in the training set. We initially performed a logic-based sampling wherein ten airports out of the fifteen airports were considered for training the model, the selection of which was determined by maximising the ratio of the minority class labels. By performing this logic-based sampling, the class imbalance decreased and the accuracy of the model improved considerably, but it was seen that class imbalance still existed in the dataset. In view of this, a second level of sampling was performed.

Sampling can be classified into oversampling and undersampling. Oversampling creates synthetic samples for the minority class from the existing dataset to balance the distribution of classes, whereas undersampling technique considers only a subset of the majority class to balance the class distribution. Both undersampling and oversampling were performed on the dataset, and it was observed that oversampling techniques performed better. Undersampling considers only a sample from the majority class thus neglecting potentially important information in the ignored examples albeit the fact that it significantly reduces the run time. Synthetic Minority Over-sampling Technique (SMOTE) produced the best results among the implemented oversampling techniques. Although over-sampling minority class examples can balance class distributions, the other issues usually present in data sets with skewed class distributions are not solved. Therefore, an ensemble of oversampling and undersampling techniques was performed. The results of sampling for arrival delay prediction using Random Forest Classifier is shown in Table III and it was observed that SMOTE + Tomek Links had the highest accuracy.

TABLE III
SAMPLING RESULTS

Method	Accuracy	Recall (Minority class)
Without Sampling	91.86	0.69
Random Undersampler	86.17	0.80
SMOTE	93.79	0.91
SMOTE + Tomek	94.00	0.91

The following algorithms showed the highest accuracy from those implemented.

1) Gradient Boosting Classifier
2) Random Forest Classifier
3) Extra-Trees Classifier
4) AdaBoost Classifier

C. Regression

In order to enhance the one-dimensional nature of binary classification, we attempted to extend the problem statement by not only predicting the occurrence of flight delays, but also its numerical value. It was observed that the following algorithms encompassed the lowest mean square errors from those implemented.

1) Extra-Trees Regressor
2) Random Forest Regressor
3) Gradient Boosting Regressor
4) Multilayer Perceptron (MLP)

To improve our base results, we applied the following methods:

(A) Feature Scaling: Feature scaling is a technique used in optimization problems involving datasets with varying scales of features. The need for feature scaling is demonstrated by the fact that the range of features do not share the same scales, which heavily impact algorithms such as Random Forests as shown in Table IV. Various scaling algorithms were tested to optimise the model, namely RobustScaler and StandardScaler. RobustScaler scales features which are robust to outliers whereas StandardScaler removes the mean and scales to unit variance.

(B) Hyper-Parameter Tuning: Hyper-parameters are the higher level properties of a model which cannot be implicitly learnt by a machine learning model and must be predefined. Grid Search algorithm was used to exhaustively search the hyper-parameter space for the optimum parameter values for the estimators. The final values of the hyper parameters were validated by using the metrics fit and score provided by the Grid Search algorithm.

(C) Selective Training: The initial model was established by training the model on the entirety of origin-destination airport pairs. We further attempted to optimize the model by performing selective training on the dataset with reference to origin-destination airport pairs. The model was trained on single origin airport with multiple destination airports whereby an increase in efficiency was observed. Furthermore, the most efficient model was finally obtained by training single airport-destination pairs individually. The results of selective training are described in Section VI.

TABLE IV
FEATURE SCALING RESULTS

Regressor	Mean Squared Error
Random Forest Regressor	102.18
Random Forest Regressor with Standard Scalar	90.34
Random Forest Regressor with Robust Scalar	76.31

D. Deep Learning

Deep learning is a paradigm which consists of state of the art learning algorithms in various applications like computer vision, speech recognition, natural language processing, audio recognition and bioinformatics. The application of deep learning in the problem of flight delay prediction is relatively new [14] and hence deep learning was implemented.

The deep learning architecture implemented in our paper is Deep Neural Network (DNN), which is an Artificial Neural Network (ANN) with multiple hidden layers between the input and output layers. DNNs are typically feed forward networks in which data flows from the input layer to the output layer without looping back. Similar to shallow ANNs, DNNs can model complex non-linear relationships and can generate compositional models where the object is expressed as a layered composition of primitives. The extra layers enable composition of features from lower layers, potentially modelling complex data with fewer units than a similarly performing shallow network.

The DNN was used in both the classification and the regression process. The results achieved using the DNN Classifier and DNN Regressor are discussed in Section VI.

VI. OBSERVATIONS AND RESULTS

To analyze the performance of the proposed model, accuracy, precision and recall were used for evaluating classification results and mean squared error (MSE) and R^2 score were used for evaluating regression results.

TABLE V
DEPARTURE DELAY CLASSIFICATION PERFORMANCE

Algorithm	Accuracy	Precision		Recall	
		0	1	0	1
Random Forest	86.00%	0.82	0.91	0.92	0.79
Gradient Boosting	86.48%	0.81	0.95	0.96	0.76
AdaBoost	78.35%	0.77	0.80	0.82	0.74
Extra-Trees	85.88%	0.84	0.88	0.89	0.82
LOYOCV	82.91%	0.78	0.90	0.92	0.74
K-Fold CV	82.45%	0.80	0.91	0.90	0.75

TABLE VI
ARRIVAL DELAY CLASSIFICATION PERFORMANCE

Algorithm	Accuracy	Precision		Recall	
		0	1	0	1
Random Forest	94.09%	0.92	0.97	0.97	0.91
Gradient Boosting	94.35%	0.92	0.97	0.97	0.92
AdaBoost	92.15%	0.90	0.95	0.95	0.89
Extra-Trees	93.73%	0.93	0.95	0.95	0.93
LOYOCV	94.31%	0.91	0.98	0.98	0.91
K-Fold CV	93.13%	0.92	0.95	0.94	0.92

A. Departure Delay Prediction

The dataset was split into training data and test data in the ratio 3:1 for the purpose of evaluating the model. The results of the classification stage in the model are illustrated in Table V. The Gradient Boosting Classifier performed better than the other classifiers with an accuracy of 86.48%. The Receiver Operating Characteristic (ROC) curve of the model comparing the various classifiers is shown in Figure 1. To additionally evaluate the model, K-Fold Cross Validation (K=5) and Leave-One-Year-Out Cross Validation (LOYOCV) were performed, the results of which are shown in Table V.

The results of the regression stage in the model are shown in Table VII. Extra-Trees Regressor performs better than the other regressors with an MSE value of 880.67. As discussed in Section V, a selective training process was performed in the regression stage. The results of Selective Training process are shown in Table VII. It was observed that the selective training process greatly reduced the error and the best MSE observed was 70.16 for the Extra-Trees Regressor.

TABLE VII
DEPARTURE DELAY REGRESSION RESULTS

Regressor	MSE	R^2 score
MLP	1261.75	0.012
Gradient Boosting	1218.75	0.055
Random Forests	1105.56	0.223
Extra-Trees	880.67	0.314
MLP - Selective Training	840.19	0.200
Random Forests - Selective Training	101.39	0.919
Gradient Boosting -Selective Training	172.25	0.863
Extra-Trees - Selective Training	70.16	0.944

B. Arrival Delay Prediction

Similar to the departure delay prediction phase, the dataset was split into training data and test data in the ratio of 3:1. The results of the classification stage in the model are shown in Table VI. As seen from the table, the Gradient Boosting Classifier performs the best with 94.35% accuracy, followed by Random Forest Classifier with 94.09% accuracy. The ROC curve of the model comparing the various classifiers is shown in Figure 2. To additionally evaluate the model, K-Fold Cross Validation (K=5) and LOYOCV were performed, the results of which are documented in Table VI.

The results of the regression stage in the model are shown in Table VIII. Extra-Trees Regressor performs the best with an MSE value of 68.31, signifying that this regressor can predict the delay value in minutes with an error of approximately 8 minutes. As discussed in Section V, a selective training process was performed in the regression stage, the results of which are shown in Table VIII. By considering a single airport-destination pair (ATL-CLT), the number of datapoints were significantly reduced to 20,000. It was observed that the selective training process greatly minimized the error, resulting in an MSE value of 26.36 for the Extra-Trees Regressor.

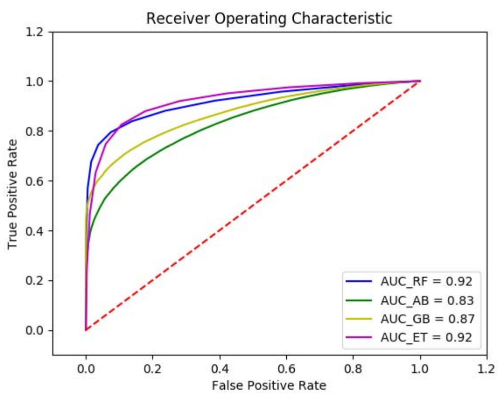

Fig. 1. ROC curve for Departure Delay Prediction

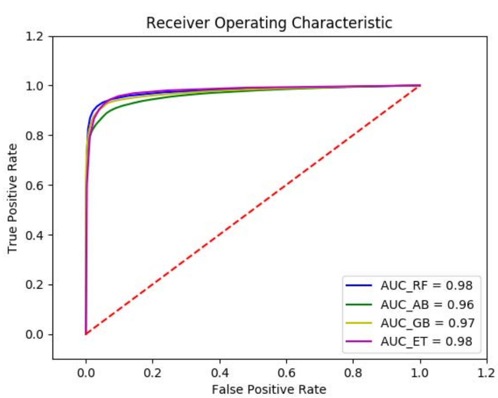

Fig. 2. ROC curve for Arrival Delay Prediction

C. Deep Learning

The classification and regression results of the deep learning algorithm are shown in Table IX. It can be inferred that the DNN performs poorly due to the fact that the training data for the network is small in size.

TABLE VIII
ARRIVAL DELAY REGRESSION RESULTS

Regressor	MSE	R^2 score
Gradient Boosting	89.26	0.929
MLP	87.83	0.931
Random Forests	75.99	0.930
Extra-Trees	68.31	0.943
MLP - Selective Training	70.41	0.933
Gradient Boosting - Selective Training	69.42	0.938
Random Forests - Selective Training	45.99	0.952
Extra-Trees - Selective Training	26.36	0.985

TABLE IX
DEEP LEARNING RESULTS

Prediction	Classification	Regression
Departure Delay Prediction	78.31%	892 MSE
Arival Delay Prediction	81.61%	110 MSE

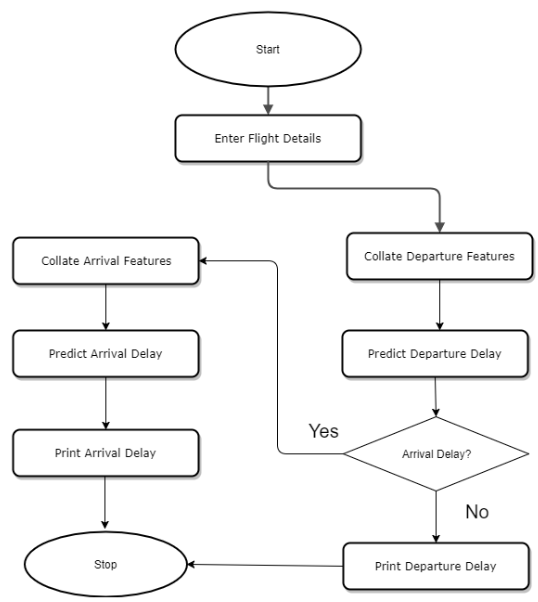

Fig. 3. Flowchart Diagram of the DST

VII. DECISION SUPPORT TOOL

One of the strengths of this predictive model is that it can easily be incorporated in applications for commercial or personal use. In order to showcase this, we developed a decision support tool (DST) which can serve the dual purpose of aiding users in arriving on time for their flights or helping airlines accurately predict when their flights would arrive at the gate in order to minimise costs and optimise fuel. This application was built using PyQt4 and thus can be easily ported to all platforms supported by Qt including Windows, OS X, Linux, iOS and Android.

TABLE X
BEST RESULTS OF PREDICTION

Prediction	Classifier	Accuracy	Regressor	MSE
Departure Delay Prediction	Gradient Boosting	86.48%	Extra-Trees	70.16
Arrival Delay Prediction	Gradient Boosting	94.35%	Extra-Trees	26.36

The interface allows the user to input their flight details and select whether they wish to view the arrival delay or departure delay. Upon selecting their desired option, the user enters the flight details in the input text fields. Then the tool extracts the necessary real-time weather forecast details, collates the departure features and performs preprocessing as discussed in Section IV. By accessing the stored trained model, the tool predicts the value of departure delay and displays the value to the user. Then if the user wishes to view the arrival delay, the tool collates the arrival delay features, predicts the value of arrival delay and displays the value to the user. The flowchart of the DST′s operation is shown in Figure 3. The interface of the DST for a sample test case is shown in Figure 4. To visually aid users, a graph is also plotted of the airline′s past history of delays. It is also possible to routinely update the model with daily flight data and retrain the model, ensuring that the application is up-to date.

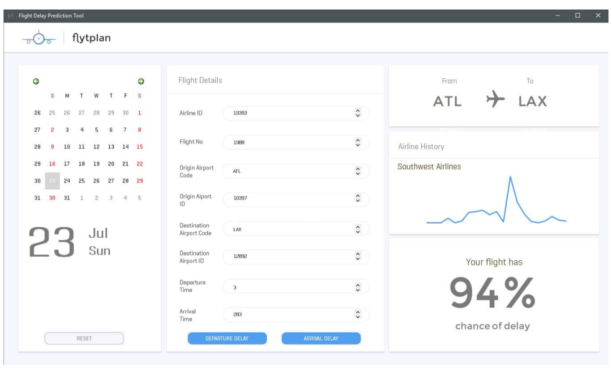

Fig. 4. Interface of the DST

VIII. CONCLUSION AND FUTURE WORK

In this paper, the authors have implemented a machine learning approach for the prediction of flight on-time performance. A two-stage predictive model was developed to efficiently predict the departure and arrival delays of flights using flight schedule and weather features. Various supervised machine learning algorithms were implemented and the best results are shown in Table X. Additionally, a deep learning approach was explored by implementing a DNN to predict the flight delays. It was found that the departure delay prediction had comparatively higher error rates due to a weak feature set. Furthermore, a Decision Support Tool was developed using the model to predict real-time flight delays.

In the future, more data can be extracted by considering a larger number of airports over a longer time frame to improve the model and other deep architectures can also be implemented. The authors are planning to improve the model using the above mentioned methods and develop an improved DST for an accurate prediction of real-time flight delays in the future. Another promising approach is to generalize the existing model for use in various domains in transportation.

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