



**An Intelligent System for Predicting Flight Demand
and Peak Travel Periods Using Machine Learning and Deep
Learning**

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Dedications

(وآخر دعوانهم أن الحمد لله ربّ العالمين)

.Whoever says, 'I am capable of it,' shall attain it"
".And I am capable of it—even if it seemed impossible

The journey was never short, nor was it meant to be. The dream was never within easy
.reach, and the road was never paved with comfort. Yet, despite every challenge, I made it

To my ambitious self

The one who refused to give up when the road became difficult. The one who stumbled,
rose again, and kept moving despite exhaustion. The one who chose to continue when giving
up would have been easier. The one who carried ambition in her heart and turned it into an
.everlasting source of strength

To my first and greatest supporter

The man whose name I carry with honor, pride, and dignity. The light that has always
illuminated my path. The one who removed the thorns from my way and paved the road to
knowledge. The one who devoted his life to helping me achieve my dreams. The one who
.taught me that determination creates miracles and perseverance conquers the impossible

My beloved father

To the woman beneath whose feet lies Paradise

My companion through my very first steps. The one who embraced me with her heart
before her hands. The one whose prayers made every hardship easier to bear. The gentle heart
and the candle that lit my darkest nights. The source of my strength and every success I have
.achieved

My beloved mother

To my unwavering pillars

My solid ground. The ones who gave me the strength to stand tall, lightened the burden
of my journey, planted confidence within me, and walked beside me through every step of this
.struggle. The safety and comfort of my days

My dear brothers and sisters

To the silent heroes

The ones who believed in me throughout this journey despite all my moments of
uncertainty. The ones who filled my path with their love, encouragement, and prayers. To
my dearest friends and companions on this journey

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Abstract

Due to the high passenger volume during the peak seasons, severe operational bottlenecks for airport facilities and staff. This work sets out a practical framework for forecasting flight demand and identifying peak windows using historical data records from the Bureau of Transport Statistics (BTS) and Kagel. Based on recent research published between 2023 and 2026, we evaluate two main models of machine learning: Maximum Scalability Enhancement (XGBoost) and Artificial Neural Networks (ANN). The analysis focuses on how these models handle large flight datasets, how to handle unbalanced class distributions, and also extract the necessary temporal features. In addition, the paper addresses real-world practical challenges, including changing holiday patterns and hardware constraints, and provides actionable guidance for system implementation.

Table of Contents

Chapter 1 Introduction

1.1 Introduction.....	9
1.2 ProblemStatement.....	9
1.3 The Role of Predictive Analytics.....	10
1.4 Research Gap & Motivatio	10
1.5 Research Objectives.....	11
1.6 Scope and Organization.....	11

Chapter 2: Background and Related Work

2.1 Background.....	12
2.2 Extreme Gradient Boosting (XGBoost).....	12
2.3 Random Forest.....	13
2.4 Artificial Neural Networks (ANN).....	13
2.5 Temporal Preprocessing and Encoding.....	13
2.6 Feature Engineering.....	14
2.7 Feature Selection and Testing.....	14
2.8 Data Normalization and Scaling.....	14
2.9 Hyperparameter Optimization and Training Architecture.....	14
Section : Related Work	
2.2.1 Overview of Related Studies (The 16 Studies Narrative).....	15
2.2.2 Methodological Groupings (The 5 Groups).....	21
2.2.3Literature Review Summary Matrix (The Table).....	23
References.....	28

List of Abbreviations

ANN: Artificial Neural Network

BTS : Bureau of Transportation Statistics

XGBoost :Extreme Gradient Boosting

F1-Score : F1 Measure (Harmonic Mean of Precision and Recall)

SMOTE :Synthetic Minority Over-sampling Technique

ROC:Receiver Operating Characteristic

AUC:Area Under the Curve

EDA:Exploratory Data Analysis

ML:Machine Learning

DL:Deep Learning

AI:Artificial Intelligence

List of Tables

2.11 Literature Review Summary Matrix

Chapter 1 : Introduction

1.1. Introduction

Air travel has remained an essential means of global transport, connecting communities and driving economic growth. In recent years, urbanization and changes in travel behaviour have led to a steady increase in airport passenger traffic. How this flow is managed is a critical challenge for operators, as busy terminals often cause operational delays, security bottlenecks, and reduced passenger satisfaction. Fortunately, modern airports provide large amounts of daily operational data—including flight schedules and passenger records. Leveraging machine learning and predictive analytics on these groups allows management to make timely decisions to help maintain a continuous flow of passengers through the stations.

1.2. Problem Statement

The global air transport sector is a major driver of logistics, international trade and corporate traffic.

Due to the high financial costs associated with the construction and maintenance of airport facilities, the civil aviation authorities are committed to the continuous improvement of the existing infrastructure.

Managing "peak travel periods" is critical in this operational context, as these periods occur when the number of passengers rises sharply in short, compressed periods of time, causing a gap and imbalance between the incoming passenger flow and the fixed capacity of the facility.

Peak flight congestion is heavily influenced by regular consumer behaviors associated with specific time periods such as: "Weekly Patterns/School Holidays/World Tourism Seasons/Changing Public Holidays." When these peaks occur unexpectedly or are poorly managed, the immediate result is severe stress on the components of the operating room, including "check-in desks/security checkpoints/passport areas/ground service teams." This pressure, in turn, leads to "increased queue wait times/local congestion within the airport/higher labor costs/and lower overall service quality." Accordingly, analyzing air traffic trends, seasonal fluctuations and operational constraints is a key priority for fleet planners and airport managers seeking to proactively

deploy personnel, schedule ground aircraft operations, and ensure a smooth flow of passenger traffic safely and easily.

1.3. The Role of Predictive Analytics

To mitigate the increase in terminal congestion, modern airports are increasingly relying on predictive analytics. It enables the deployment of an automated forecasting framework to manage passenger traffic forecasting and identify periods of high demand before congestion occurs. The shift from an interactive operational strategy to proactive, data-driven planning allows for improved staff and facility resource allocation. Thus, this reduces delays at security checkpoints and migration while stabilizing the flow through the airport.

1.4. Research Gap & Motivation

While many studies apply machine learning and deep learning to flight demand forecasting, the majority analyze isolated datasets or evaluate algorithms separately. Few works directly compare tree-based first-generation models and neural network architecture using standardized and large-scale benchmarks such as BTS and Kaggle datasets. In addition, current studies lack a standardized summary of results from 2023 to 2026. Regarding the preference between processing speed and accuracy in real-world deployment environments. This research addresses these limitations by reviewing recent studies to determine a structured technical basis for the proposed forecast framework.

1.5. Research Objectives

The primary objectives of this study are:

1. Creating and designing a technical framework for an intelligent forecasting system to predict flight demand and classify peak travel periods.
2. Summarize the key research from 2023 to 2026 on aviation demand analytics and predictive modeling.
3. Create a structured pipeline capable of handling and processing large-scale datasets from BTS and Kaggle platforms.
4. Directly compare XGBoost and Artificial Neural Networks (ANNs) in terms of accuracy, computation speed, and imbalance management.
5. Address operational bottlenecks, including calendar changes and regulatory constraints, to improve model implementation.
6. Provide an actionable roadmap to integrate the predictive system into real-world airport operations.

1.6. Scope and Organization

This study is strictly limited to the architectural design of the flight demand forecasting system using datasets from BTS and Kaggle. The model evaluations are specifically limited to XGBoost and Artificial Neural Networks (ANNs), based on studies published between 2023 and 2026.

The rest of this paper is organized into chapters: the second chapter covers the theoretical background of both models, illustrates the relevant computing constraints, and details previous research into 16 selected papers and their methodological compilations.

Chapter 2 Background and Related Work

2.1 Background

Efficient terminal management in modern civil aviation relies heavily on careful operational planning to accommodate the fluctuation of passenger numbers. Increasing the frequency of flights often leads to terminal congestion, especially during peak seasonal traffic and holiday travel. Rather than responding to delays after they have occurred, modern forecasting models will use machine learning and deep learning techniques to analyze historical airport data and predict future demand.

Developing a strong forecasting system requires a clear understanding of the underlying algorithmic frameworks. This section outlines the theoretical concepts that form the basis of the proposed system. It starts with tree-based cluster algorithms—in particular Maximum Gradient Enhancement (XGBoost) and Random Forest—that fit structured attributive datasets. It then covers artificial neural networks (ANNs) to highlight how deep architecture models complex and nonlinear relationships in passenger traffic. Finally, the section describes the underlying data preparation pipeline, including time coding, feature engineering, class imbalance correction using SMOTE, normalization, and fine-parameter tuning to ensure execution model reliably.

2.2 Extreme Gradient Boosting (XGBoost)

XGBoost is a machine learning algorithm specifically designed for structured and tabular statements. Instead of building decision trees independently, which you train one by one, each new tree corrects the mistakes made by the previous tree. The most important key practical feature of XGBoost is that it automatically processes values lost during training, saving significant time on data preparation. In addition, it uses built-in organization techniques that prevent the model from saving only training data, helping it perform reliably and consistently on new datasets.

2.3 Random Forest

It is a group learning method that creates a large set of independent and unrelated decision trees during the training phase. Through abduction tasks, the model relies on the majority (voting) option for individual trees. The voting mechanism gives this algorithm excellent stability and immunity against the common problem of over-alignment.

2.4 Artificial Neural Networks (ANN)

Artificial neural networks process data through interconnected layers of sensory nodes, and operate in a similar way to biological neurons. In the standard setting, the structure consists of an input layer, hidden layers that discard key features, and an output layer that produces the final prediction. During training, the network relies on reverse propagation to update connection weights and reduce the error of prediction overtime. This stratified approach enables artificial neural networks to model the nonlinear seasonal patterns and unexpected increases in traffic that rigid decision trees often fail to capture.

2.5 Temporal Preprocessing and Encoding

Flight logs rely heavily on raw timestamps, which must be converted into digital features before training the model. The time processing step extracts the key time variables that precede the existing key time variables, such as departure hour, day of the week, and month. Categorical features —such as airline codes or airport IDs—are converted into binary vectors using One-Hot Encoding encoding. This transformation is necessary and critical because it prevents the algorithm from assigning the wrong numerical order to the values of the independent category.

2.6 Feature Engineering

It is the process of converting the advantages of raw data into information variables that best represents the fundamental problem of predictive models. In the field of flight ordering, it mainly involves extracting explicit chronological features such as "days of the week/month/quarters" from raw timestamps, building indicators near spooling days, and linking complex dynamic calendars (e.g., religious occasions and changing national holidays) to enable models to capture human travel behaviors over the years.

2.7 Feature Selection and Testing

Feature selection eliminates redundant or unhelpful variables to keep models computationally efficient and avoid over-compliance. Methods such as analyzing feature significance scores and calculating correlation matrices help identify attributes with true predictive value. Excluding weak LT mutations reduces training time and allows the model to be better generalized when making predictions on invisible flight data.

2.8 Data Normalization and Scaling

Data-wide technologies, such as minimum and maximum standardization, compile continuous numerical variables to fit a constant range—usually between 0 and 1. This step is necessary for training neural networks, as standardized feature ranges accelerate the convergence of The gradual descent algorithm prevents larger numerical values from dominating small inputs with equal meaning.

2.9 Hyperparameter Optimization and Training Architecture

Optimization techniques, such as network search, test combinations of superior parameter values to find the configuration that gives the highest accuracy. For neural network models, the use of the Adam Enhancer helps to dynamically adjust learning rates during training. This adaptive weighting update speeds up the model's convergence and prevents the training process from falling into the local minimum.

Section: Related Work

2.2.1 Overview of previous studies and research:

Here we review the most important recent studies related to flight order prediction and how we determine peak periods using machine learning and deep learning techniques. 16 scientific studies were analyzed from famous international journals and conferences, focusing on objectives, data used, pre-treatment methods, results, and challenges.

In a high-performance computing lab, researchers Taylor & Novak (2026) were working on building a smart, real-time system to predict moment-by-minute flight demand. The researchers' journey began with open air traffic data that flows continuously and frequently and is available for academic purposes. The researchers worked to clean it automatically and encode textual variables with Label Encoder, and then the researchers added features that link flights to seasons and days of the week.

But the biggest challenge was that setting XGBoost transactions on this big data takes a long time. The two researchers used distributed and parallel computing, so that they could implement Grid Search efficiently.

Finally, XGBoost achieved record accuracy and surpassed all traditional models, becoming the most stable model in real-time prediction

In this research Kumar & Sharma (2025) , the two researchers wanted to compare simple models such as Decision Tree with neural networks. They used public data from the Kaggle platform that includes passenger data and daily aircraft movements for several international airports.

Preprocessing began here by dealing with lost values by compensating for the average, then applying the Encoding Label to airlines, and applying Scaling digital data reconciliation.

Then, after the researchers conducted several experiments, they discovered that Decision Tree was not sufficient as a reference model, and that ANN and Random Forest had raised the accuracy by 15% compared to a normal tree.

The challenge for the researchers was the overlap of peak periods with the weather, they solved this problem by adding weather variables as additional inputs.

In Europe, the two researchers Silva & Santos (2025) collected data for 10 years of flights at European airports. The data was full of outliers, so they removed it, and then applied feature engineering to extract weekly travel patterns and balance the data by using input sizing technology.

The two researchers then made a comparison between Random Forest and ANN, and found that the random forest is faster in training, while ANN captures very fine seasonal details.

The challenge for the researchers was that the consumption of deep networks of resources was very high, so they solved this problem by reducing the size of the neural network by adjusting supercoefficients without a loss of accuracy.

At a global conference, the researchers Fernandez & Davis (2025) compared ANN and XGBoost by using data from Kaggle to predict atmospheric demand levels. They then started processing by intelligently deleting missing values, and then applied Target Encoding to large text variables and made data reconciliation for neural networks.

The results were very similar, but XGBoost outperformed ANN in speed and efficiency with tabular data.

The challenge for the researchers was the very high consumption of resources, so they solved this problem by improving and adjusting Hyperparameters.

In this research, the two researchers Liu & Gupta (2025) focused on managing aviation resources by predicting future demand. The two researchers used comprehensive historical data for a number of global airlines across open data platforms, cleaned them, coded category variables, and then applied StandardScaler to configure inputs for the neural network.

ANN for Operating Systems has demonstrated its ability to anticipate sudden demand jumps with high accuracy and standard in seasons of travel, reducing operating costs.

The challenge for the researchers was to converge the weights, which caused a slowness in ANN training, and in order to solve this problem, advanced optimizers such as Adam Optimizer were used.

The researchers Zhang & AlSuwaidan (2024) have used official data from BTS for five years. They then filtered duplicate records, applied Normalization, and extracted time features that linked holiday and holiday seasons to flight density, so the researchers thought of building an intelligent system to predict peak periods, classify passenger density, pressure on major airports, and help operational management.

ANN was built and compared with tree algorithms, and ANN proved its strong ability to achieve 94% accuracy in capturing seasonal patterns.

The challenge for the researchers was the huge volume of data, which caused a slowness in training, so they solved it by reducing the dimensions and choosing influential features.

In this research, Rodriguez & Kim (2024) the two researchers combined international flight data with global vacation indicators. They converted dates into digital features, and applied One-Hot Encoding for destinations and cleaned data from ineffective variables, in order to design an intelligent work that classifies future trips to (low / medium / high) to manage counters at airports before congestion.

XGBoost has achieved tremendous speed in processing tabular data and very high accuracy F1 91%, and the end recommends its adoption in real-time systems.

The challenge faced by the researchers was the difficulty of predicting the changing seasons annually, and in order to overcome this problem, the two researchers linked the data to the astronomical calendar in the processing.

The researchers Ahmed & Garcia (2024) used multi-class air transport data to classify passenger demand and compare machine and traditional learning algorithms. They removed outliers, applied the Encoding Label to categorical variables, and applied Min-Max Scaling to settle digital data.

They found that tree models such as Random Forest are very fast and stable, but ANN has surpassed the peak rating with an accuracy of 91.8%.

The challenge faced by the researchers was the difficulty of dealing with high-dimensional features, and to overcome this problem, they used Feature Selection to choose features.

The researchers Muller & Fischer (2024) collected three-year data from daily trips and schedules. They addressed the missing values, turned dates into scattered features such as weekdays, vacation seasons, and the Standardization application for digital inputs.

The researchers found that ANN excelled in capturing busy periods with very high accuracy compared to traditional linear models, which helps in making decisions for airport management.

The two researchers faced the problem of a sudden change in the schedules for flights, so the researchers solved this problem by adding the historical delay rate feature as an auxiliary variable.

Through this research AlSultan Taylor & Francis(2024), the two researchers focused on several regional airports, using open and general historical data to cover the details of flights, seasons and dates. The researchers removed duplicate records, coded airports, and also extracted features that linked flights to changing religious and national seasons.

The two researchers noted that XGBoost outperformed 93% between the speed of training and the characterization accuracy of congestion levels.

The challenge faced by the researchers was the different dates of the annual seasons, and in order to overcome this problem, they linked it to the variable dynamics calendars.

The researchersChoi & Lee (2024) have used real data for a number of years, to build a hybrid business that classifies aviation demand into three levels (low / medium / high) to manage the operational capacity of airports and airlines. They addressed category imbalance, coded textual variables, and applied Normalization to expand digital data.

The two researchers noted that ANN succeeded in predicting the three levels of demand, especially at the high level.

The challenge for the researchers was to overlap between categories, so they overcame this problem by setting the classification thresholds.

Researchers Chen et al. (2024) have used large data for flight bookings taken from open academic data platforms. They removed anomalous values, applied One-Hot Encoding for destinations and airports, and then the researchers extracted features that linked time periods to long vacation seasons, so that they could predict significant fluctuations in flight demand during travel seasons using gradually enhanced tree algorithms.

They noticed that the XGBoost clearly outperformed the rest of the algorithms, achieving the highest balance accuracy in the F1-Score for high-density flights.

The researchers faced the problem that the sheer size of the data group requires a large memory, so it was solved by applying partial data flow processing

The researchers Wang & Li (2023) used more than 500,000 Kaggle records. They cleaned the data, according to One-Hot Encoding, and extracted features that link dates to holidays, so that they could predict flight levels and determine peak times based on time and seasonal variables.

They noticed that XGBoost achieved a resolution of 92.4% superior to Decision Tree Random Forest & Determining Congestion Periods.

The challenge faced by the two researchers was the imbalance of data between normal days and peak days, so they solved this problem using Class Weighting techniques.

The researchers Patel & Jones (2023) in this research focused on the impact of exploratory analysis and feature engineering on raising the accuracy of machine learning algorithms in predicting overcrowding times and the demand for flight. The researchers used the huge BTS data, which includes flight schedules, extracted complex time features from it, and applied Log Transformation to modify the torsional distribution of digital data.

The researchers noted that the time features raised the accuracy of Random Forest and Decision Tree by 18% in the classification of peak periods.

The challenge for the researchers was the presence of noise, so this problem was solved using advanced statistical filtering.

The two researchers Brown & Green (2023) combined the trip data with the public holiday calendar. They extracted from this merger the features of the days before and after the holidays (Buffer Days), with the aim of studying the two researchers the impact of official and weekly holidays on flight planning and forecasting congestion periods.

They noticed that XGBoost excelled in linking holidays to high demand levels, which leads to accurate decision-making at peak periods.

The biggest problem the researchers have faced is the difference in holiday dates between countries, and they were able to solve this problem by including geographical indications for each trip.

The researchers AlQahtani & Wilson (2023) used historical BTS data to develop machine learning to classify congestion at airports, based on time and seasonal times. They cleaned up lost values, extracted accurate time features, and coded text variables.

They noticed that the Random Forest algorithm excelled in interpreting decisions and classifying congestion levels.

The challenge faced by the two researchers was the sensitivity of the lost data in some months, so this problem was solved using smart data compensation.

2.2.2 Methodological Groupings

To systematically analyze the literature on flight demand forecasting and peak travel prediction, the sixteen reviewed studies were categorized into five distinct methodological cohorts based on their core computational frameworks, shared algorithmic structures and feature engineering approaches:

Class Imbalance

The Class Imbalance Problem Simply Means That The Data Is Unequal Between The Expected Categories

In our project, for example, most of the days of the year are normal days (up to 90%), while peak and pressure days constitute a definitive and very small percentage (about 10% only). This disparity makes the model make it easier for itself to walk and biases with normal days in order to achieve high accuracy outwardly, but in fact it fails in the main goal of discovering peak times.

Temporal Features

The problem is in the travel data and time series. They are not normal numbers. Time in it is everyone. I mean, today's request depends directly on what happened yesterday and last week, and so there are seasons such as summer and holidays. The demand is in it. The challenge here. How can we understand the model? This time sequence is correct and at the same time we pay attention and do not let him see the future data while he is training for the past so that there is no data leakage error.

High-Dimensional Data

When you have many columns and features in the data, such as dates, days, holidays and previous traffic indicators, here we are in front of high-dimensional data, the many details are sweet and feed the model, but if it exceeds its limit, you can distract it and make it scrutinize unnecessary details and save them instead of understanding the general pattern, and this is not the great time it takes for the training.

Hyperparameter Optimization

These are simply the settings that we adjust as engineers before we press the start training button such as the depth of the tree or the speed of learning. Instead of sitting, we try the numbers manually by mistake and right and waste a lot of time and effort. We use smart software tools that automatically show us the best number combination that achieve the model the highest accuracy and balance.

Neural Network Convergence

Convergence is the moment when the model reaches the best stability, I mean, when the error rate goes down to the lowest possible limit and the weights are adjusted correctly, and so that the model reaches this point smoothly and without length or oscillating and commenting, we need to be equipped with the data correctly (normalization) and determining a balanced learning speed.

2.2.3 Literature Review Summary Matrix

The table below summarizes the key aspects of all sixteen reviewed studies, detailing their goals, datasets, preprocessing pipelines, model outcomes, and technical challenges:

(References)	(Goal)	(Dataset)	(Preprocessing)	Results	(Challenges)
Taylor, S., & Novak, J. (2026).	is to improve the supercoefficients of tree algorithms to design an intelligent flight demand prediction system.	The researchers collected continuously updated air navigation traffic data available for academic purposes.	The two researchers have automatically cleaned the data, encoded the text variables with the Encoder Label, and engineering that links trips and seasons or between trips and Days of the week.	After applying Search Grid techniques to adjust transactions, the researchers explained how the XGBoost algorithm achieved a standard and stable accuracy that surpassed the rest of the traditional classification models.	One of the most important challenges faced by the researchers is the time taken in the Tuning process on big and large data, and the researchers were able to solve this problem by relying on distributed and parallel computing.
(from the Kumar, A., & Sharma, P. (2025).	is to make a comparison between simple reference models such as "Decision Tree" with advanced models for forecasting traffic demand and improving operational resources at airports.	he two researchers studied a set of general data through the Kaggle passenger data platform and also the daily movement of aircraft for several international airports.	The researchers dealt with the missing values by compensating with the average Imputation, applying the Encoding Label to the names of the airlines, and making an adjustment for digital data Scaling.	The two researchers used Decision Tree as a "Baseline" reference model, and proved it by benchmarking that ANN and Forest Random raise accuracy by 15% compared to the normal tree.	The two researchers faced the problem that sudden peak periods overlap with weather conditions, and they were able to solve this problem by adding weather variables as additional inputs to the model.

(References)	(Goal)	(Dataset)	(Preprocessing)	Results	(Challenges)
Silva, F., & Santos, T. (2025).	is to conduct a fair benchmark comparison (built tree-based models) and deep learning to classify the expected demand for air transport.	The two researchers studied 10-year historical data of air traffic found in the European roll that is available to researchers.	The results of the research studied by the two researchers showed a very large convergence between the random forest and ANN, because the random forest is characterized by low time consumption by training, while the neural network is able to monitor the finest seasonal details.	The results showed a great convergence between Random Forest and ANN, as the random forest was characterized by lack of time consumption in training, while the neural network was distinguished in capturing very fine seasonal details.	The researchers faced the problem of consuming deep models of very high computing resources, and they were able to solve this problem by adjusting supercoefficients in order to reduce the size of the neural network without affecting its accuracy.
Fernandez, C., & Davis, R. (2025).	is to conduct a benchmark assessment and comparison (Benchmarking) of the performance of deep neural networks versus the XGBoost algorithm to predict the levels of atmospheric demand.	The researchers studied a general flight data set extracted from the Kaggle platform containing details of major flights from global airlines.	The researchers processed the missing values by intelligent deletion, and applied the Encoding Target for large text variables, and reconciled the data for neural networks.	Through a study of the two researchers, comparing the results showed them a significant convergence in accuracy between XGBoost and ANN, but XGBoost was characterized by higher efficiency and super speed in dealing with Data Tabular data.	The researchers faced the problem of the consumption of ANN's high computing resources, and were able to solve this problem by adjusting supercoefficients .Hyperparameter Tuning

(References)	(Goal)	(Dataset)	(Preprocessing)	Results	(Challenges)
Liu, Y., & Gupta, A. (2025).	Use data-based forecasting to manage aviation resources such as “employees, aircraft” by predicting future demand through deep learning.	The researchers have compiled and studied the data of general and comprehensive historical flights for a number of global airlines from open data platforms.	The researchers cleaned the data, coded the category variables, and applied the StandardScaler to initialize the input for neural network layers.	The researchers proved that the use of ANN allowed operational systems to predict sudden demand jumps during travel seasons with a standard accuracy that contributed to reducing operating costs.	The researchers faced the problem of slow weight convergence during neural network training, and were able to solve this problem by using advanced enhancers such as . Adam Optimizer
Zhang, Y., & Al-Suwaidan, M. (2024).	The researchers wanted to build a smart system to classify passenger density, predict peak times and pressure large airports to help operational management.	The researchers found that historical air transport data was taken from the US Bureau of Transportation Statistics BTS over a period of 5 years.	The researchers reconciled and balanced the data (Normalization), and also filtered the duplicate records, and extracted important features (Temporal Features) that link the summer holiday seasons and holidays with the congestion and intensity of trips.	The two researchers built and compared the artificial neural network ANN with tree algorithms, and proved that ANN has a superior ability to extract complex nonlinear patterns in seasons with an accuracy of more than 94%.	The researchers faced the problem of the huge volume of data, which causes slowness in training, and they were able to solve this problem using dimensions reduction techniques and choosing the most impactful features (Feature Selection).

(References)	(Goal)	(Dataset)	(Preprocessing)	Results	(Challenges)
Rodriguez, J., & Kim, S. (2024).	The two researchers designed a smart framework that classifies future trips into 3 sections "Low / medium / high" so that the airport counters are controlled before congestion occurs.	The two researchers developed integrated data from international flight schedules with global vacation indicators.	The researchers converted the dates into digital features such as "day / month / quarter year Etc." and applied the One-Hot Encoding algorithm for destinations, and they also cleaned the data from ineffective variables.	The XGBoost model achieved a very high speed in processing tabular data and with high accuracy (F1 scale up to 91%), and the conclusion was recommended by adopting it in real-time systems.	The researchers faced the problem of the difficulty of predicting the changing seasons annually, such as: "Hijri holidays / Ramadan / Hajj The two researchers were able to solve this problem by linking the data to the astronomical calendar and the moving seasons to the processing.
Ahmed, T., & Garcia, M. (2024).	The two researchers classified the demand for passengers to fly into a number of categories, and compared the machine learning algorithm and traditional learning.	The researchers studied air traffic data and historical passenger records through open aviation computing platforms.	The researchers removed the outlier values, applied Label Encoding to category variables, and also settled digital data by Min-Max Scaling.	The researchers found that tree models such as: Random Forest are characterized by speed and stability, while neural networks have strongly excelled at complex peak levels with an accuracy of 91.8%.	The researchers faced a problem in the difficulty of dealing with high-dimensional features, and this problem was solved and overcome through the use of feature selection techniques (Feature Selection).

(References)	(Goal)	(Dataset)	(Preprocessing)	Results	(Challenges)
Müller, K., & Fischer, T. (2024).	Using artificial intelligence techniques to predict passenger density and peak periods at airports to organize operating resources and employees	six general daily air traffic data and three-year schedules	Dealing with lost data and converting dates to scattered features (days, month, holiday seasons) and applying Standardization for digital input	The results proved superior to the ANN model in capturing crowded periods with extreme accuracy compared to traditional models, which helped support decision-making for airport management	A sudden change in flight schedules, solved using the "historical delay rate" feature as an auxiliary variable
Sultan, A., Al-Khaldy, M., & El-Gayar, O. (2024).	A comparative study between several artificial intelligence algorithms and the prediction of cycle periods and passenger crowds at regional port airports	Open source historical flight data covering flight details dates and seasons	Deleting recurring data and encoding the names of airports and lines using One Hot Incoding and doing feature engineering to link the trips of the moving religious and national seasons	It was found that the XG Post algorithm excelled and achieved the highest balance between the speed of training and the accuracy of the classification of congestion levels with an accuracy of more than 93%	The movement of the annual seasons and the change of their dates, solved by linking the features of time to changing dynamic calendars.

(References)	(Goal)	(Dataset)	(Preprocessing)	Results	(Challenges)
Choi, J., & Lee, H. (2024).	To build a business that classifies the level of demand for aviation low, medium, high to manage the operational capacity of airports and airlines	Real Data from Years of Open Air Traffic Platforms	Addressing Class Imbalance, Applying Text Coding, Normalizing And Expanding Digital Data.	The Conclusion indicated that the designed system succeeded in predicting the three levels with high accuracy, as the ANN was the best at capturing very high periods (High Demand)	Overlap between medium and low levels of demand and solved by setting the classification thresholds (Classification Thresholds)
Chen, H., Liu, Y., & Zhang, Q. (2024).	Predict very large flies in ordering flights during travel and peak seasons using gradually enhanced tree algorithm	Huge public data for historical flight bookings and movements from open academic data platforms	Deleting anomal values and doing on hot ending for destinations and airport names and generating derivative features that link time periods to long vacation seasons	The study reached the superiority of the performance of the XG Post model clearly over the rest of the algorithms, achieving the highest balance accuracy (F1Score) in the classification of high-intensity trips	The very large size of a data set that requires a large memory, solved by the application of partial data flow processing

(References)	(Goal)	(Dataset)	(Preprocessing)	Results	(Challenges)
Wang, J., & Li, X. (2023).	To classify the forecasting of demand levels for flights and determining peak periods based on temporal and seasonal variables	Open source historical data for flight reservations from the Kagel platform containing more than 50,000 records of flights including dates, destinations and take-off times	Cleaning data from lost values and applying one hot ending for text variables such as airport and destination names and feature engineering work to link dates to official holidays and weekends	The conclusion showed that the XGBoost algorithm excelled with an accuracy of 92.4% superior to Random Forest and Decision Tree in determining congestion periods.	Not balancing data between normal days and peak days, solved using data balancing techniques
Patel, R., & Jones, L. (2023).	To study the impact of exploratory data analysis (EDA) and feature engineering on raising the accuracy of machine learning algorithms in predicting overcession and flight demand	Large data from the US Bureau of Transportation Statistics (BTS) including flight schedules and occupancy rates	High focus on feature engineering to extract complex time features and apply Log Transformation to modify the distribution of digital data	The research summarized that the inclusion of carefully designed time features raised the accuracy of the Random Forest and Decision Tree algorithm by 18% in the peak period classification.	The presence of noise (Noise) and large distracted data in open data sets, solved through statistical filting

(References)	(Goal)	(Dataset)	(Preprocessing)	Results	(Challenges)
Brown, T., & Green, P. (2023).	To study the impact of public holidays and weekly patterns on flight planning and predicting periods of major congestion	A general dataset that combines historical flight schedules and the annual holiday calendar	Integrating holiday data with flight data, encoding airports, and extracting the features of the days immediately before and following the holidays (Buffer Days)	The result shows that the XG Post algorithm excelled in linking holiday features to high demand levels, which enhanced the accuracy of decision-making during peak periods	The difference in holiday dates between countries and destinations, solved by including geographical indicators for each trip
Al-Qahtani, S., & Wilson, B. (2023)	Developing a framework for mechanized education to classify congestion and congestion in airports based on time patterns and seasons	Historical Air Transport Data from the U.S. Bureau of Transportation Statistics (BTS)	Cleaning lost values, engineering accurate time features, and converting text variables into encoding using Hot Encoding	The Random Forest algorithm achieved a distinguished and stable performance in classifying congestion levels based on temporal variables and recommended the study as a first option for systems that need an explanation of decisions	The algorithm's sensitivity of lost data in some months, solved by processing through smart data compensation techniques

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