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Performance Evaluation of Artificial Intelligence-Based Ticket Demand Forecasting

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***Abstract*—Complex policies are generally employed by corporations to fluctuate the price of the products. The airline industry is amongst the most advanced in the application of the revenue management in an effort to optimize their revenue. Air ticket market is not uniform in all countries and it depends on the supply volume and pattern as well as demand. The paper explores the issue of ticket demand prediction and customer support behavior along with real-life Customer Support Ticket Dataset of Kaggle (8,469 records with rich metadata). Once the exploratory analysis of the ticket priorities and word cloud visualization of the resolved and unresolved issues were completed, the text preprocessing with tokenizing, normalizing of cases, stopwords elimination, and TF-IDF features extraction was conducted to prepare the textual fields to be modeled. This was followed by the division of the data into training (80) and testing (20) set and the application of a Gradient Boosting model, which predicts the demand of tickets based on its high ensemble learning properties to transform a number of weak learners into a powerful predictor. The assessment of the performance according to R^2 RMSE MSE MAE indicated that the model has outstanding predictive power with R^2 value 95.0 percent and low error measures of RMSE 0.47, MSE 0.22, and MAE 0.30 being obtained and with the close clustering of the actual and predicted plots and also close-to-the-data residual values. It was demonstrated that Gradient Boosting was more effective than the traditional and deep learning baselines such as Linear Regression (72.3%), LSTM (70.0%), and KNN (65.0%). Findings support the validity of enhancing-based ensemble techniques in demand prediction in customer support settings, which is important in terms of resource allocation, workload, and service optimization.**

Keywords—ticket demand forecasting, revenue management, customer support ticket, machine learning, predictive modeling.

I. Introduction

The fast growth of mobility services, transport infrastructure, and event-based industries have made a considerable effort in terms of the complexity of predicting the demand of tickets. Precise demand forecasting [1] is also important in strategic and operational decision making such as resource planning, pricing optimization, capacity management, staffing and increasing overall customer satisfaction. It enables operators and service providers to predict demand variations, reduce the inefficiencies in operations, cost reduction, and service reliability. The conventional statistical and econometric methods that have been used in the past to predict the demand of tickets have included ARIMA, Exponential Smoothing and other regression-based approaches. Although these methods offer convenient base predictions, have been extensively used because of their interpretability, they can be hard to fit nonlinear interactions, combine various other contextual aspects, or respond rapidly to changing and uncertain market environments.

High amounts of past and contemporary data have become more and more available with the rapid development of computer processing capacity, storage, and extensive digitalization. Consequently, the new promising paradigm of forecasting has appeared, which is known as AI [2], [3]. ML [4] and DL [5] algorithms have shown a significant benefit in modeling multidimensional and complex and high-dimensional data structures within the wider field of AI [6]. The ML algorithms (RF, SVR, GBM, and other ensemble based methods) allow the expression of data-driven patterns, involve a wide range of exogenous variables, and even capture more complex feature interactions than the simple temporal dependencies. On a lower level of computation, architectures such as RNNs [7], LSTM [8] models, Gated Recurrent Unit (GRUs), and more elaborate hybrid [9] or attention-based networks are more effective at the representation of nonlinear temporal dynamics, seasonality, and multi-step prediction behavior without the use of extensive manual feature engineering.

With the shift of industries in the field of transportation, travel, and event management to data-centric operational models, ML-[10] and DL-based predictive models are more flexible, adaptable, and predictive than conventional statistical models. Nonetheless, with their potential contributions, there are a number of viable considerations and issues, such as model interpretability, computational cost, large data demands, system integration, model maintenance, and scalability. Moreover, the profound comparative performance analysis, where the ML [11] and DL [12] predictive algorithms are strictly compared with the traditional ones, is underrepresented in the specific field of ticket demand forecasting [13], which means the necessity of additional empirical studies.

A. Motivation and Contribution of Paper

The difficulty in predicting the demand of tickets is still difficult because of the dynamic market environment, non-linear consumer behavior, and the presence of other external factors that are difficult to predict traditionally through the use of the statistical model. This causes inaccuracies that influence the pricing, capacity planning as well as the efficiency of the services. Despite the fact that AI, particularly ML and DL provide a better predictive ability, there is a lack of literature that has relatively tested the techniques in predicting the demand of tickets in a real-life scenario. The current research is driven by the necessity to fill this gap by evaluating AI-based models in comparison with the traditional ones in order to improve the forecasting efficiency, assist in making data-driven decisions, and enhance the results in the transportation and event-driven sectors in terms of its operational and customer-centric outcomes. The main contributions are:

- Presents a real customer support ticket forecasting model based on Kaggle data which consists of text, categorical and temporal variables.
- Applies systematic text preprocessing such as lowercase conversion, non-space and non-white space character removal, tokenization and stopword removal.
- Installed TF-IDF feature extraction as a way of transforming textual messages to machine-learning ready inputs.
- The forecasting model based on Gradient Boosting is created and has a high predictive performance.
- Assesses model performance by using quantitative (R^2, RMSE, MSE, MAE) and visual (actual vs. predicted plot, residual analysis) diagnostic outcomes.

B. *Justification and Novelty*

The chosen study is justified because it is related to the increasing necessity of correct demand forecasting in the customer support setting where the competent resource allocation and timely response play a pivotal role in the quality of service. Using machine learning and real-life ticket data, the study offers data-driven information to aid organizations in predicting workloads, staffing, and enhancing customer satisfaction. The significance of the proposed research is that the authors combine actual customer support ticket data and machine learning-powered predictions to inform predictions (rather than merely describe them) as a novel approach. In contrast to the past where most previous methods rely on analyzing the text in tickets to determine the category or sentiment, the current work has exploited the attributes of the ticket and preprocessing methods to develop a forecasting model, which offers a new insight into the process of workload prediction and operational planning in customer service settings.

C. *Structure of the Paper*

The paper is organized as follows: Section II presents the pertinent literature about the prediction of ticket demand. The procedures, materials, and methodologies are explained in Section III. Section IV provides discussion, outcomes and analysis of the proposed system along with the experimental data. Section V outlines the last considerations and intentions.

II. Literature Review

In this part, Table I contains a summary of the literature review of the recent works in ticket demand forecasting on the basis of ML and DL methods. It summarizes the problem, methodology, dataset, and the main findings, which were discussed in the reviewed works.

Güzel, Akkaya and Acar (2025) proposed mGRNN integrates the relationships between customers and the temporal dimension of the sales process within a single model. While customer interactions are modeled in the GNN component of the model, the RNN part combines the CDS Index, exchange rates, sales trends, and Google Trends data to conduct a comprehensive analysis. In the final layer, regression is performed by incorporating product attributes. Experimental studies conducted on real-world data with the proposed mGRNN observed success rates of 85%, 82%, and 83% (1-MAPE) for forecast horizons of 1, 2, and 3 weeks, respectively [14].

Lu (2024) proposed traditional revenue management tools based on the assumption of independent demand cannot fit the new environment very well. Passenger demand was redivided into three components and demand forecast model was then proposed. Marginal revenue data transformation as well as expected marginal seat revenue method was used to calculate booking limits of fare classes. The forecasting and seat allocation methods were applied to branded fare families with multiple classes. The simulation results show that the new approaches increase expected revenues by 10 to 15% and maintain a relatively high load factor [15].

Ruchi et al. (2024) research utilized historical booking records, cancellations, passenger preferences, and travel patterns to develop precise predictive models to address this issue. A Machine Learning framework, specifically the Light Gradient Boosting Machine (Light GBM), is proposed in this paper to accurately forecast the likelihood of waitlisted train tickets being confirmed. This algorithm has displayed an astonishing accuracy rate of 96.67%. This research aims to address the complexities of this problem while also investigating the potential enhancements in data availability through online ticketing systems and digitization [16].

Kashef (2023) study presents a summary of contemporary ML methodologies proposed for the estimation of aircraft ticket prices. Existing methodologies demonstrate limitations in accurately forecasting flight fares across both short-term and long-term horizons. This study presents a new hybrid-based prediction model that combines CNN with recurrent neural networks (GRU-ST and CNN-LSTM-ST), with an emphasis on short-term prediction. When compared to the most advanced models, the suggested one improves accuracy by as much as 40% [17].

Aliberti et al. (2023) presented novel Bayesian neural networks, which, as far as their understanding goes, constitute the first effort to use Bayesian Inference for the purpose of predicting airfare. As a result, they use an open dataset to test how well their optimized models work. The experimental findings demonstrate that Bayesian neural networks can outperform the other ML techniques, but DL-based approaches generally outperform conventional ones. However, the RF turns out to be the best choice in this situation when prediction performance and processing time are taken into account [18].

Alapati et al. (2022) suggested airlines use many computational strategies, such as price discrimination and demand forecasting. This is for customers who purchase flight tickets by calculating the cost of the ticket. The primary challenge from the customer's perspective is determining the optimal value or the most advantageous timing for purchasing tickets, representing the most intricate aspect. The majority of these methods are based on ML, a subfield of computer science that deals with enhanced computational intelligence and prediction models. The components and steps for creating an aviation fare prediction model using ML are highlighted in this study [19].

A. Research Gaps

Recent studies suggest that there are gaps in coherent predictive model that integrates interaction with customers, age trends of sales and real-time interactions with prices. Current methods usually have simplistic demand models, are not robust over forecasting horizons and ignore detailed behavioral data of current digital booking systems. Also, little attention is paid to the balance between predictive performance and computational efficiency and user-centered understandings, and further, more holistic, scalable, and consumer-oriented prediction and revenue management systems are possible.

TABLE I. BENCHMARKING STUDIES ON TICKET DEMAND FORECASTING

Author(s) & Year	Context / Problem	Method / Model Used	Data / Inputs	Key Findings / Results
Güzel et al. (2024)	Integrating customer relationships and temporal sales dynamics	mGRNN model combining GNN + RNN + regression with product attributes	CDS Index, exchange rates, sales trends, Google Trends, customer interaction data	Achieved 85%, 82%, 83% (1-MAPE) for 1, 2, 3-week forecasts on real-world data
Lu (2024)	Revenue management limitations due to independent demand assumptions	Decomposed demand model + Expected Marginal Seat Revenue (EMSR) for seat allocation	Historical passenger demand separated into components	New methods increased expected revenue 10–15% while keeping high load factor
Ruchi et al. (2024)	Predicting waitlisted train ticket confirmation	Machine Learning using LightGBM	Historical bookings, cancellations, preferences, travel patterns	Achieved 96.67% accuracy; shows benefits of digitized booking data
Kashef (2023)	Need for short-term accurate airfare forecasting	Hybrid CNN-LSTM-ST and CNN-GRU-ST models	Flight price time series data	Accuracy improved up to 40% compared to state-of-the-art
Aliberti et al. (2023)	Bayesian inference usage in airfare prediction	Bayesian Neural Networks + comparison with ML & traditional models	Open airfare dataset	Deep learning outperforms traditional; Bayesian NNs best among ML; Random Forest best trade-off (performance + computation)
Alapati et al. (2022)	Airline fare prediction difficulty for consumers	Survey and analysis of ML-based pricing & forecasting approaches	Factors influencing airfare + ML modeling guidelines	Provides guidance on developing ML price prediction systems for consumers

III. METHODOLOGY

The research adheres to a systematic workflow that starts with Customer Support Ticket Dataset that goes through pre-processing steps such as lowercasing, character cleaning, tokenization, and elimination of stopwords. The resulting processed data is subsequently divided into training and testing data, a Gradient Boosting model is subsequently employed in predicting ticket demand. R^2, RMSE, MSE and MAE are the metrics used to determine model performance and the results are then reported. The suggested methodology's flowchart is shown in Fig. 1.

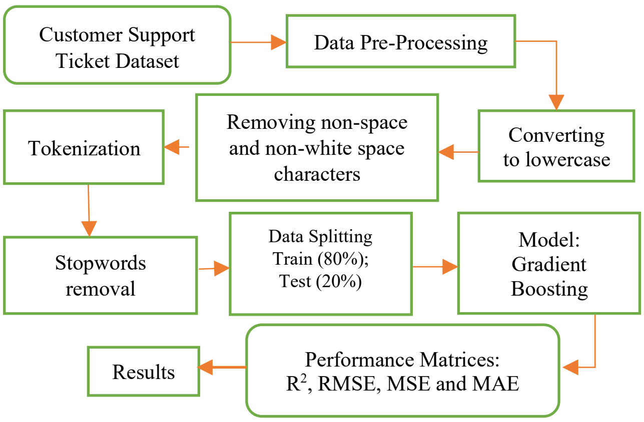

Fig. 1. Flowchart of Ticket Demand Forecasting

This section explains the following phases of the flowchart in a nutshell:

A. Data Analysis and Visualization

The Customer Support Ticket Dataset in this study is the Kaggle dataset that includes 8,469 rows and 17 columns of real-world support ticket records, including information about customers, products, categories, channels, and statuses, which can be used in such tasks as the classification of support tickets, demand predictions, performance analysis, etc.

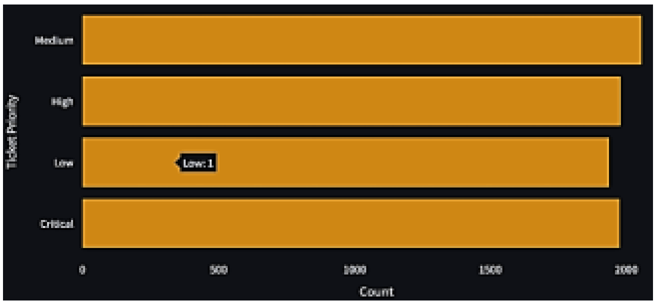

Fig. 2. Ticket priority count plot

Fig. 2 indicates the allocation of tickets based on the level of priority wherein, the four levels, namely the Medium, High, Low and Critical, have slightly equal volumes of tickets. The number of priorities is balanced in both levels and this implies that support requests are fairly distributed among the levels of urgency instead of being in one level.

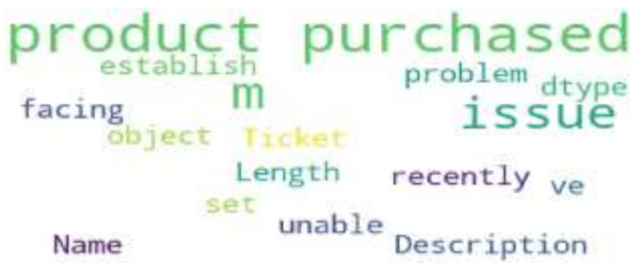

Fig. 3. Word cloud of ticket resolved

Fig. 3 presents a word cloud of description of tickets where the words such as product, purchased and issue occur most of the time as they are some of the frequent product related customer issues.

Fig. 4. Word cloud of ticket not solved

In Fig. 4, there is a word cloud of words used to describe tickets, and most of them were common words, such as, product, purchased, and issue, which recounted widespread customer issues with the product.

B. Text Preprocessing

Under this step, it will do basic procedures to clean text. The process begins with changing the case of all the text to lowercase and continues with eliminating stopwords and other characters that do not belong in words or spaces.

- **Converting to lowercase:** Python is a case-sensitive programming language. Therefore, to eliminate any problems and ensure uniformity in the text processing, it transforms all of the content to lowercase. Free and free will be regarded as a single term in this way, improving the accuracy and dependability of their data analysis.
- **Removing non-word and non-whitespace characters:** It is essential that the text collection be free of any characters, especially non-whitespace ones, that are not words. Characters that do not constitute words or spaces include symbols, punctuation marks, and other special characters that do not contribute anything meaningful to analysis.
- **Tokenization:** Tokenization is the process of breaking down large pieces of text into smaller, more manageable pieces, such as paragraphs or phrases. Word tokenization will be applied to the data in the column that will produce the Message at this stage.
- **Stopword removal:** Stopwords are most frequently used words that occur in any natural language. Eliminating stopwords might enhance the precision of their analysis by drawing attention to the most important parts of the text.

C. Feature Extraction using TF-IDF

Term frequency (TF) and inverse document frequency (IDF) are abbreviations for the word. The number of relevant terms in a list or corpus may be ascertained statistically using the TF-IDF. A word's value grows in relation to its frequency of appearance in the text, but it is normalised according to its document occurrence.

Term Frequency (TF): It is the number of times a word occurs in a document's text. A phrase is likely to occur more often in longer texts than in shorter ones due to the different page sizes. The normalization process also involves dividing the term frequency by the text length, as seen in Equation (1):

$$F(t) = \frac{\text{No.of times } t \text{ appears in a document}}{\text{Total no.of terms in the document}} \quad (1)$$

Inverse document frequency (IDF): It is a measure of how often the phrase appears in a certain text. IDF denotes the significance of a word because to its rareness. The IDF scores of the uncommon words are higher. Equation (2) shows the IDF:

$$IDF(t) = log_e \frac{Total\ no.of\ documents}{No.of\ documents\ with\ term\ t\ in\ it} \quad (2)$$

Equation (3) is used to determine TF-IDF by combining TF and IDF:

$$TF - IDF = TF_{t,d} * \log\frac{N}{D_f}, \quad (3)$$

Where the $TF_{t,d}$ is frequency of term t in document d.

D. Data Splitting

Finally, the processed data were separated into test and training sets. The model was trained using the training dataset, and its capacity for generalization was evaluated using the testing dataset. The training split is 80% whereas testing set is of 20%.

E. Classification of Gradient Boosting Model

The transformation of a group of ineffective learners into an effective and resilient classifier is the defining feature of "boosting." The phrase "weak learner" is used to describe almost any prediction model that has a high rate of misclassification error, produces dangerous conclusions, and generally has poor performance (e.g., in terms of accuracy). Combinatorial learning includes gradient boosting. Ensemble learning takes a different method than conventional learning by combining several weak learners into a single strong one. Ensemble boosting is an alternative to bagging that builds models sequentially by repeatedly minimizing the error of previously trained models, as opposed to building models individually as in bagging. The learning process involves integrating M additive tree models (*f0, f1, f2,..., fM*) to make predictions based on Equation (4):

$$f(x) = \sum_{m=0}^{M} f_m(x) \quad (4)$$

Equation (5) states that the predicted generalization error L should be minimized in order to optimize the tree ensemble model:

$$L = \sum_i^n (y_i - \hat{y}_i)^2 \quad (5)$$

L is a loss function that calculates the difference in loss among the target y_i and the prediction $\hat{y}_i$ of a datapoint.

F. Performance Evaluation

In the process of training and testing, the test dataset was utilized to evaluate each model and various error measures were determined such as R^2, RMSE, MSE, MAE.

- R^2 is used to determine the extent to which the model can account for the variation in the target variable with 1 implying a better fit.
- When compared to MSE, MAE—the mean absolute difference between the actual and anticipated values—offers a more neutral assessment of prediction accuracy that is less affected by outliers.
- MSE is the mean of the squared deviations of the predicted and actual values whereby large deviations are more penalized.
- RMSE is the other measure that is commonly used to assess prediction models. It is the objective which optimizes classic regression models.

The corresponding formulas are used in calculating each error metric as shown in Equations (6)-(9).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (6)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \quad (7)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (8)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \quad (9)$$

Where:

- n—Total number of data points;
- y_i—Actual true value;
- $\hat{y}_i$—Predicted value from the model;
- $\bar{y}$—Mean of all actual target values.

IV. Result Analysis and Discussion

The trials are run on a computer with an Intel i9-9900K CPU, graphics cards from Nvidia's GeForce RTX 2080 Ti series, 64 GB of RAM, and the software packages CUDA 10.1 and Python 3.10. The ticket demand forecasting results of the model are presented in Table II with Gradient Boosting with high accuracy, with a high R^2 of 95.0 and low error values (RMSE, 0.47, MSE, 0.22, MAE, 0.30) indicating that the demand is highly close between the predicted and actual demand.

TABLE II. Performance of the Model Ticket Demand Forecasting

Metrics	Gradient Boosting
R^2	95.0
RMSE	0.47
MSE	0.22
MAE	0.30

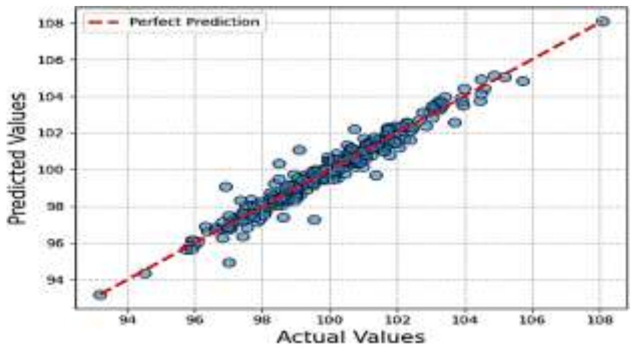

Fig. 5. Actual vs. predicted graph

A scatter plot (Fig. 5) was used to compare the values of the predictions with the actual values and most of the points are on the line of perfect prediction. This implies that the model is accurate with low deviation as the predictions are highly accurate and close to the actual values.

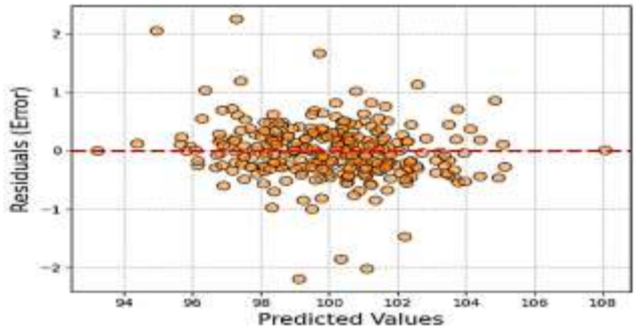

Fig. 6. Residual plot

Fig. 6 offers a residual plot showing the error values against predicted values. The errors are randomly distributed around the zero line with no obvious pattern, which means that the errors of the model are comparatively small, and they are distributed almost equally, which substantiates the good model fit and reliability.

A. Comparative Analysis and Discussion

Table III delineates the comparative analysis of various ticket demand forecasting models and reveals that Gradient Boosting is the most precise approach, achieving a R^2 value of 95.0%, surpassing traditional and DL models such as Linear Regression (72.3%), LSTM (70.0%), and KNN (65.0%).

TABLE III. Comparison of Models in Ticket Demand Forecasting

Models	R^2
Gradient Boosting	95.0
LR [20]	72.3
LSTM [21]	70.0
KNN [22]	65.0

It is evident that the suggested method outperforms the other forecasting methods, providing noticeably higher predictive and alignment accuracy between the actual and anticipated demand for tickets. It has better generalization and more faithful error behavior compared to traditional statistical models and even deep learning models, which suggests that it is more aware of nonlinear trends in the data. Generally, the findings indicate that the proposed approach is more successful and sounder to forecast the demand of tickets in comparison to other models that were experimented.

V. Conclusion and Future Direction

These days, airline ticket rates may change dramatically and dynamically for the same trip, even for seats that are next to one another in the same cabin. This paper shows that Gradient Boosting is a very effective tool to predict the demand of airline tickets in customer support settings and that it performs better than classic and deep learning models. The systematic preprocessing, feature extraction based on TF-IDF features, and strict evaluations based on various error measurements enabled the model to perform well in predicting the target variable with a high percentage of 95.0% R^2 and low error values. Integration in the form of priority distributions, word clouds, actual- vs- predicted plots and residual analysis also confirmed the reliability of the model and its consistency with actual results. Gradient Boosting had better performance in comparison with Linear Regression, LSTM, and KNN methods, which proves the benefit of ensemble learning in this scenario. The findings suggest that forecasting powered by ML might help with proactive resource allocation, workflow management, and customer service in real-life support systems.

Future research can use larger and more varied datasets, add other contextual features, and use more advanced deep learning models like transformers. Real-time predictability, customer sentiment analytics integration, and operational support system applications might can further increase predictive capabilities and facilitate smarter and automated decision-making processes within customer service.

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