IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, May 2025
Impact Factor: 7.67

Forecasting Airline Ticket Prices: A Comparative Study of Time Series Models with Seasonal Trends

Ms. Akshata Asukar and Dr. Supriya Londhe
Student, MIT Arts, Commerce and Science College, Alandi, Pune, India
Assistant Professor, MIT Arts, Commerce and Science College, Alandi, Pune, India
akshatav18@gmail.com and salondhe@mitacsc.ac.in

Abstract: *Airfare pricing is a highly dynamic and complex process shaped by various factors such as changing demand, seasonal trends, airline strategies, and consumer behavior. Accurately predicting ticket prices is crucial—not just for travelers hoping to book flights at the best rates, but also for airlines aiming to maximize revenue through smart pricing. This study presents a comparative analysis of seven forecasting models: ARIMA, SARIMAX, Holt-Winters, Prophet, LSTM, XGBoost, and LightGBM, using real-world data from Indian domestic flights. Each model's performance is assessed using metrics like RMSE, MAE, MAPE, R² Score, and Accuracy. Among all, LightGBM stands out with the highest prediction accuracy, closely followed by XGBoost. In contrast, traditional time series models show limitations in capturing the complex seasonal and nonlinear patterns in airfare trends. These results highlight the effectiveness of ensemble and deep learning methods in price forecasting and support the development of smart fare prediction tools that can benefit both travelers and the airline industry..*

Keywords: airline pricing, airfare forecasting, LightGBM, LSTM, SARIMAX, ARIMA, machine learning, time series analysis, seasonality

I. INTRODUCTION

The airline industry operates in a fast-paced and unpredictable environment, where ticket prices are shaped by a wide range of interconnected factors. These include market demand, the timing of bookings, specific route characteristics, seasonal patterns, fuel costs, operational expenses, and how airlines position themselves competitively within the market [21], [20]. Over the last couple of decades, airlines have embraced dynamic pricing strategies, powered by advanced revenue management systems that continuously adjust fares in real time based on demand, seat availability, and other market signals [14], [24]. While these strategies are effective for maximizing revenue, they make it increasingly difficult for both consumers and data scientists to predict ticket prices accurately.

Traditionally, travelers were advised to book their flights early, assuming that prices would steadily climb as the departure date neared. But with the widespread use of algorithm-driven fare changes, this advice doesn't always hold true anymore. Recent research shows that airfare trends have become highly non-linear and vary significantly depending on the airline, travel route, and season [15], [6]. Additionally, pricing behavior is now influenced by broader macroeconomic conditions, global events, and disruptions such as spikes in fuel prices or political instability [16], [21], making the task of forecasting even more complex.

To tackle this challenge, researchers and industry analysts have explored a variety of forecasting methods. Traditional statistical models like ARIMA and SARIMAX have long been used in transportation forecasting due to their simplicity and interpretability [23], [25]. However, they often fall short when it comes to modeling irregular seasonality, abrupt price shifts, and the non-linear behavior that's typical in airline pricing data.

In light of these challenges, recent work has shifted toward machine learning and deep learning approaches, which can handle more complex data patterns and irregularities. Models like XGBoost, LightGBM, and deep learning architectures such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) have shown strong performance in multiple studies [8], [4], [1]. These methods can incorporate a wide range of features—like travel duration, number of stops, airline carrier, day of the week, and more—making them especially powerful for predicting airfares.

Some researchers have also explored how airline pricing varies depending on the business model—comparing low-cost carriers with full-service airlines—and how fare sensitivity differs across passenger types and booking platforms [12], [22]. These insights highlight the importance of context-aware modeling, particularly in a highly competitive and seasonal market like Indian domestic aviation.

Despite the growing body of work in this area, there is still a gap when it comes to studies that directly compare time series, machine learning, and deep learning models using the same dataset, especially in the context of seasonal airfare trends. Many existing studies focus only on short-term pricing or evaluate a limited set of models under inconsistent conditions.

To address this, our research offers a comprehensive comparison of seven forecasting models—ARIMA, SARIMAX, Holt-Winters, Prophet, LSTM, XGBoost, and LightGBM—using real-world data from Indian domestic flights between March and June 2019. These models are evaluated using common metrics such as RMSE, MAE, MAPE, R^2 Score, and a custom accuracy metric designed for this study. The goal is to identify which models are best suited for capturing seasonal airfare patterns and to provide practical insights for travelers, airlines, and pricing platforms aiming to make smarter, data-driven decisions.

II. LITERATURE REVIEW

Airfare prediction is a complex task influenced by multiple temporal, behavioral, and market-driven factors. Numerous studies have explored the application of both statistical and machine learning models to forecast airline ticket prices, with varying degrees of accuracy and interpretability.

Selvi et al. [1] presented a comparative study using classical time series models such as ARIMA and SARIMA for airline price prediction. Their work emphasized the importance of capturing seasonal effects and using well-structured time series decomposition to improve forecasting accuracy. Similarly, Sushko and Koryagin [2] developed statistical pricing models for passenger air transportation, focusing on macroeconomic influences and market segmentation.

Abdella et al. [3] provided a broad survey of both price and demand prediction in airline markets, highlighting the growing use of machine learning techniques such as decision trees, regression models, and neural networks. Their work underlined the necessity for models that can adapt to pricing volatility and consumer behavior patterns.

Boddu et al. [4] conducted a comparative analysis of time series and machine learning models, including ARIMA, LSTM, and Random Forests. Their findings demonstrated that while classical models are interpretable, machine learning approaches generally yield superior accuracy—particularly when complex patterns or non-linear relationships are present.

Wang et al. [5] introduced a novel hybrid model based on cumulative sum control charts and temporal fusion transformers for airline price prediction. Their work demonstrates the trend toward interpretable deep learning models capable of managing both short-term fluctuations and long-term trends.

Several other studies have implemented ensemble learning techniques. For example, Wang et al. [6] used a machine learning framework integrating LightGBM and feature importance methods for price prediction. Rathi et al. [7] similarly applied multiple regression and tree-based models on Indian airfare data, reinforcing the growing preference for feature-rich models over univariate approaches.

The value of deep learning in forecasting has also been explored by Degife and Lin [8], who proposed a GRU-based deep learning model. Their approach outperformed traditional models in capturing temporal dependencies, particularly where sudden shifts and nonlinear dynamics were present.

Studies by Gordiievych and Shubin [9] and Lu [10] further support the use of LSTM and other sequence-aware models in forecasting dynamic price series. Their work affirms that neural networks, when appropriately configured and trained, offer robust performance under non-stationary and noisy conditions.

In the context of real-world implementation, Lal et al. [11] focused on Indian flight fare prediction using various ML models, pointing to the practical utility of integrating airline, route, and booking time features into model design.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, May 2025
Impact Factor: 7.67

Similarly, Kayhan et al. [12] explored the relationship between airline business models and pricing strategies, offering insights into how fare trends vary by market structure.

Finally, Oliveira [13] conducted an in-depth analysis of airfare seasonality before and after the COVID-19 pandemic. Although your dataset predates the pandemic, his work provides valuable context on how demand cycles, traveler types, and route preferences contribute to seasonal fluctuations.

Together, these studies provide a solid foundation for the present research, which aims to extend comparative analysis across seven forecasting models—ARIMA, SARIMAX, Holt-Winters, Prophet, LSTM, XGBoost, and LightGBM—using Indian domestic flight data. This work builds on the strengths identified in earlier literature, while offering new insights into model performance under regular seasonal trends.

III. RESEARCH OBJECTIVES

The primary objectives of this study are:

- **To forecast airline ticket prices** using various time series models, incorporating historical data and seasonal trends.
- **To compare the performance of forecasting models** such as ARIMA, SARIMAX, LSTM, XGBoost, LightGBM, and Prophet using accuracy metrics like RMSE, MAE, MAPE, and R^2.
- **To analyze the effect of seasonal variations** (e.g., holidays, peak travel periods) on ticket prices and assess how well each model captures these patterns.
- **To identify the most accurate model** for predicting airline fares, aiding both airline pricing strategies and consumer decision-making.

IV. RESEARCH METHODOLOGY

This section describes the dataset, preprocessing steps, model selection, and evaluation metrics used in this study to forecast airline ticket prices.

4.1 Dataset Description

The dataset used in this study was obtained from **Kaggle**, a publicly available data platform. It contains information on Indian domestic flights collected between **March and June 2019**, a period considered part of the country's peak travel season. The data includes over 10,000 records and features relevant to airline fare prediction, such as:

Table 1. Summary of Key Features in the Airline Ticket Price Dataset This structure aligns with prior studies that use the **same Kaggle dataset** and similar feature representations for airline fare prediction tasks [4].

Feature Name	Description
Date_of_Journey	Scheduled travel date
Dep_Time	Flight departure time
Arrival_Time	Flight arrival time
Duration	Total duration of the flight
Airline	Name of the operating airline
Source	Origin city or airport of departure
Destination	Destination city or airport
Route	Specific path or route taken by the flight
Additional_Info	Extra information (e.g., meal, baggage, seat class)
Price	Ticket fare (target variable)

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, May 2025
Impact Factor: 7.67

4.2 Data Preprocessing

A series of preprocessing steps were applied to transform the raw dataset into a structured format suitable for forecasting and machine learning modeling. These steps ensured consistency, improved feature quality, and facilitated more accurate model training and evaluation.

Datetime Transformation:

The Date_of_Journey, Dep_Time, and Arrival_Time columns were initially in string format and were converted to appropriate datetime objects. From the Date_of_Journey field, new time-based features were derived, including month and day, to capture seasonal and daily patterns, respectively. The day of the week was encoded as integers (0 = Monday, 6 = Sunday), enabling the modeling of fare variation across the week. Additionally, a binary feature called Is_Weekend was created to indicate whether a flight occurred on a weekend. These transformations enriched the dataset with temporal context, a key factor influencing ticket pricing behavior.

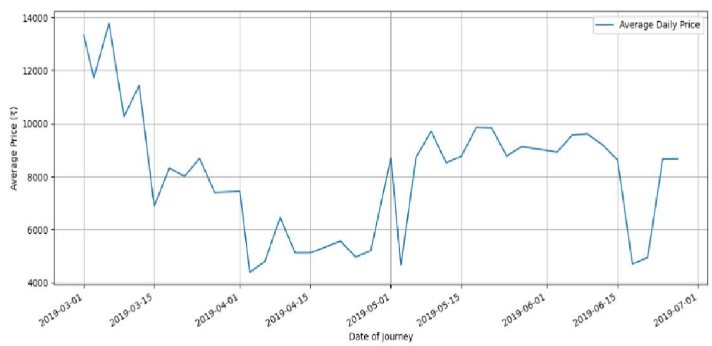

Figure 1. Daily average airline ticket prices from March to June 2019, highlighting sharp fluctuations and seasonal trends. Notable dips appear in April and mid-June, possibly linked to non-peak travel periods or promotional fare drops.

Duration Normalization:

The Duration field, originally represented as strings in formats like "2h 50m," was standardized by separating the hour and minute components and converting the total duration into a unified numerical format expressed in minutes (Duration_mins). This normalization provided consistent numerical input for machine learning algorithms and improved model interpretability.

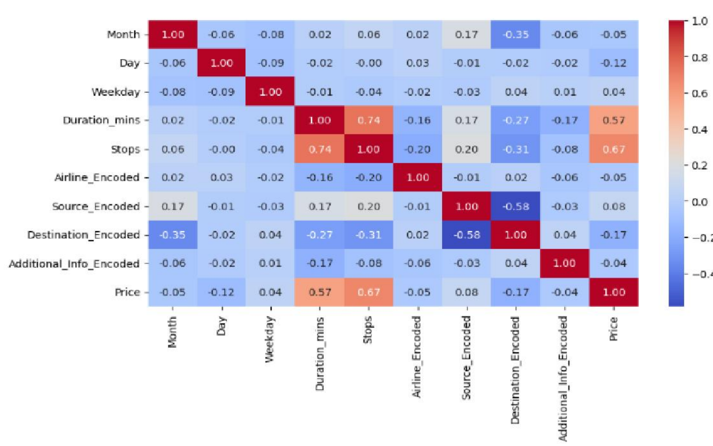

Figure 2: Correlation heatmap showing the relationship between selected features and ticket prices

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 5, Issue 1, May 2025 Impact Factor: 7.67

Categorical Encoding:
Categorical variables such as Airline, Source, Destination, Total_Stops, and Additional_Info were encoded numerically to make them suitable for computational models. Label encoding was applied to high-cardinality features like Airline, while the Total_Stops field was mapped to numerical values ranging from 0 (non-stop) to 4 (four stops). Textual inconsistencies in categorical entries, such as variations in stop descriptions, were also resolved to unify similar classes. These encoded features were particularly important for tree-based models like XGBoost and LightGBM, which rely on well-structured input data.

Data Cleaning
A meticulous data cleaning process was conducted to improve overall data quality. Null values in critical columns such as Date_of_Journey and Total_Stops were removed to prevent processing errors and ensure modeling accuracy. Duplicate entries were detected and eliminated to maintain dataset integrity. To address pricing outliers, the Interquartile Range (IQR) method was used, removing values lying beyond 1.5 times the IQR. This stabilization step mitigated the influence of extreme fare values and improved the robustness of model training. Text formatting issues in categorical fields were also corrected to ensure consistent labeling across the dataset.
This process resulted in a clean, well-structured dataset ready for modeling.

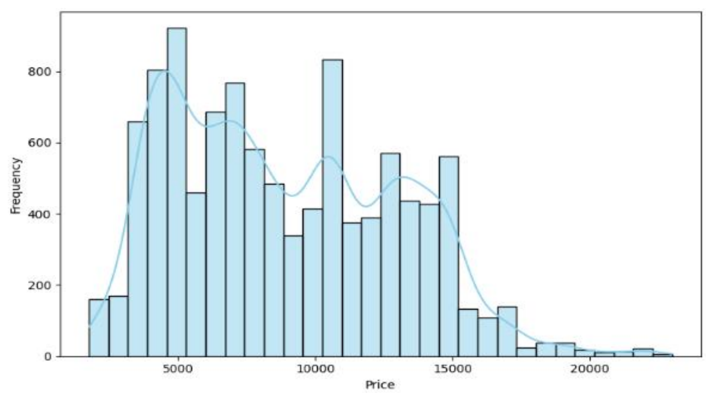

Figure 3: Distribution of ticket prices after removing outliers, showing a more normalized and symmetrical spread.

Sorting and Time Series Aggregation
To prepare the dataset for traditional time series models such as ARIMA, SARIMAX, Prophet, and Holt-Winters, the data was chronologically sorted based on Date_of_Journey to preserve temporal order. It was then aggregated at a daily level using the average Price, creating a univariate time series of daily mean fares. This transformation enabled time series models to learn from historical fare patterns and identify seasonal effects efficiently.

4.3 Model Selection
In order to provide a robust and comprehensive evaluation, seven different forecasting models were selected for this study. These models span a diverse range of methodologies, covering classical statistical models, machine learning algorithms, and deep learning techniques.
Among the traditional statistical models, ARIMA (AutoRegressive Integrated Moving Average) was chosen for its established effectiveness in univariate forecasting, especially for stationary time series data. SARIMAX (Seasonal ARIMA with eXogenous variables) was included as an enhancement over ARIMA, capable of modeling both seasonality and the effects of external explanatory variables. The Holt-Winters Exponential Smoothing method was selected for its ability to model both trend and seasonality in time series that exhibit gradual changes over time. Prophet, a model developed by Facebook, was also employed. It is a flexible, decomposable model designed to handle

various real-world complexities such as holiday effects, outliers, and irregular trends, making it especially useful in domains like airline pricing.

From the machine learning domain, two highly popular gradient boosting algorithms—XGBoost and LightGBM—were incorporated. XGBoost is known for its excellent performance on structured datasets and its capacity to balance bias and variance effectively. LightGBM, on the other hand, is a more recent and optimized gradient boosting framework that offers faster training and better memory efficiency, especially useful when dealing with large-scale data. Finally, LSTM (Long Short-Term Memory), a deep learning model based on recurrent neural networks, was included due to its superior ability to capture long-term dependencies and nonlinear temporal patterns in sequential data like time series.

By including these seven models, the study aimed to compare and contrast different modeling philosophies—linear versus nonlinear, statistical versus machine learning—under a unified experimental framework.

4.4 Evaluation Metrics

To measure and compare the predictive performance of the models, five commonly used evaluation metrics were selected. Each of these metrics offers a unique perspective on how well the models performed.

Root Mean Square Error (RMSE) is used to assess the standard deviation(SD) of prediction errors. It penalizes larger errors more heavily, making it particularly useful when large deviations are undesirable. Mean Absolute Error (MAE) calculates the average of absolute differences between predicted and actual values, offering a straightforward and interpretable measure of error. Mean Absolute Percentage Error (MAPE) goes a step further by expressing prediction errors as percentages, which is helpful for comparing performance across different price ranges. The R^2 Score, or coefficient of determination, evaluates how well the model's predictions explain the variance in the actual ticket prices. In addition to these standard metrics, a custom Accuracy metric—expressed as a percentage—was designed to quantify the average closeness between predicted and actual prices. This added an intuitive measure of performance that complements the traditional error-based metrics.

Together, these evaluation metrics provided a well-rounded framework to assess the strengths and weaknesses of each forecasting approach.

4.5 Model Training and Comparison

All models were trained and tested using a consistent 80:20 train-test split. Time series models (ARIMA, SARIMAX, Holt-Winters, Prophet) were implemented using Python's statsmodels and Prophet libraries. Machine learning models (XGBoost, LightGBM) were developed using scikit-learn, xgboost, and lightgbm. The LSTM model was built using TensorFlow and Keras.

Hyperparameter tuning was done using grid search or manual adjustment, depending on the model complexity. All models were trained using the same feature set derived from the original dataset to ensure a fair comparison.

V. RESULTS AND ANALYSIS

This section presents the performance evaluation of all models used in this study, based on key forecasting metrics. The models were trained on data from March to early June 2019 and tested on the remaining portion. The comparison evaluates each model's accuracy in predicting airline ticket prices.

5.1 Model Performance Summary

The performance of each model is summarized in Table 2, which includes key evaluation metrics such as RMSE, MAE, MAPE, R^2 Score, and Accuracy.

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429
Volume 5, Issue 1, May 2025
Impact Factor: 7.67

Model	RMSE	MAE	MAPE	R² Score	Accuracy(%)
LightGBM	1330.58	891.67	11.35%	0.8936	83.37
XGBoost	1644.32	1183.20	14.90%	0.8375	79.45
ARIMA	1772.28	1418.43	23.42%	0.1009	77.85
LSTM	1789.62	1727.46	24.63%	0.0833	77.64
Prophet	1998.06	1867.54	26.42%	-0.1427	75.03
SARIMAX	2166.38	1371.65	25.38%	-0.3434	72.93
Holt-Winters	2415.91	1662.19	29.03%	-0.6706	69.81

Table 2. Model Performance Comparison

Accuracy (%) is calculated as:
Accuracy(%) = 100 − ((RMSE/Mean Price in Test Set)×100)

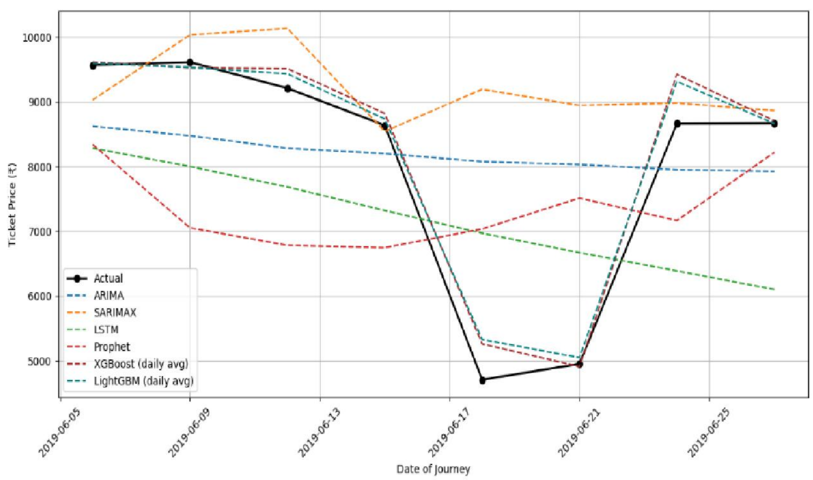

Figure 4: Comparison of actual and predicted ticket prices across all forecasting models.

5.2 Key Insights

The **LightGBM model** outperformed all others models-, achieving the lowest RMSE and highest R² score. Its ability to model complex nonlinear patterns and leverage structured features contributed to its superior performance.

XGBoost also showed competitive results, reinforcing the effectiveness of ensemble-based tree models for fare prediction tasks.

Classical models like ARIMA and SARIMAX exhibited limited predictive power. Their linear assumptions and difficulty in handling abrupt fluctuations and complex seasonality restricted their performance.

LSTM, though inherently suitable for sequence modeling, did not surpass simpler machine learning models—likely due to the limited dataset size and model tuning constraints.

Prophet and **Holt-Winters** underperformed in terms of both accuracy and R² score, indicating lower adaptability to volatile airline price patterns.

DOI: 10.48175/IJARSCT-26105

IJARSCT
International Journal of Advanced Research in Science, Communication and Technology
International Open-Access, Double-Blind, Peer-Reviewed, Refereed, Multidisciplinary Online Journal
ISSN: 2581-9429 Volume 5, Issue 1, May 2025 Impact Factor: 7.67

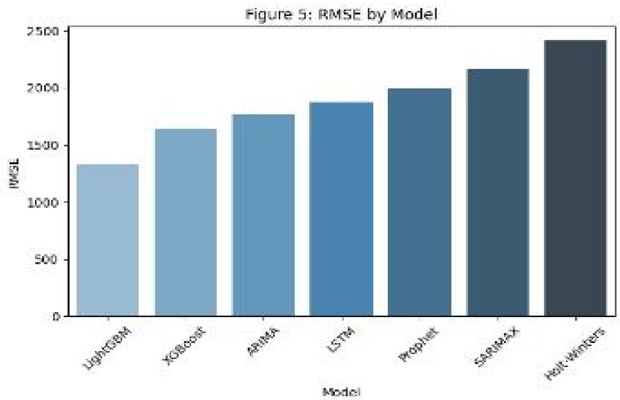

Figure 5: RMSE comparison across all forecasting models.

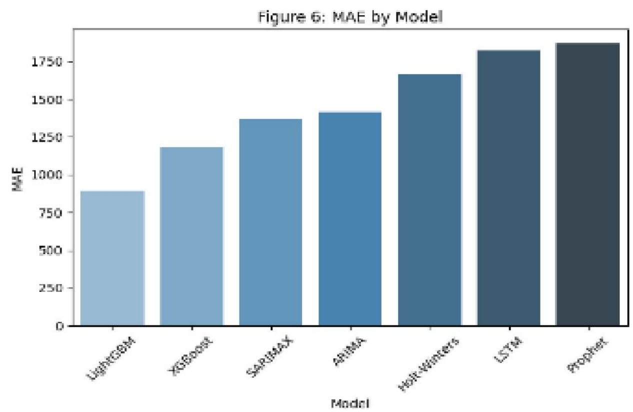

Figure 6: MAE comparison across all forecasting models.

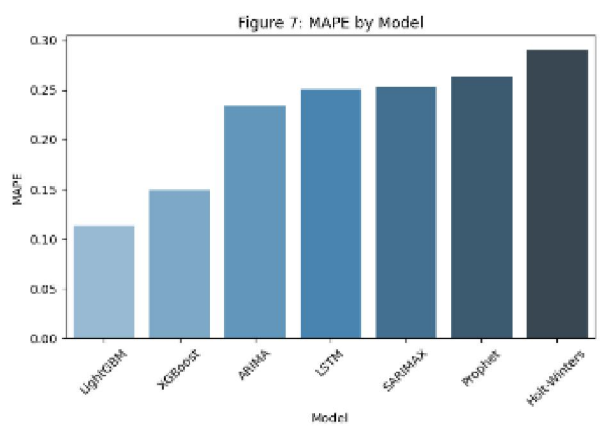

Figure 7: MAPE comparison across all forecasting models.

5.3 Practical Demonstration

To demonstrate real-world applicability, a sample input with specific flight characteristics (e.g., 1 stop, 180-minute duration, weekday travel) was passed to the trained LightGBM model. The predicted ticket price for this configuration was:

Predicted Price (LightGBM): □ 4500.76

This highlights the model's potential for assisting users in estimating airline fares based on custom travel configurations, offering valuable decision support in fare-sensitive scenarios.

VI. CONCLUSION & FUTURE SCOPE

This study compared the performance of seven forecasting models—LightGBM, XGBoost, ARIMA, LSTM, Prophet, SARIMAX, and Holt-Winters—in predicting airline ticket prices. LightGBM outperformed all models, achieving the lowest RMSE (1330.58), highest R^2 score (0.8936), and top accuracy (83.37%), highlighting its ability to capture complex, nonlinear relationships in the volatile airline industry. In contrast, classical models like ARIMA and SARIMAX were limited by their linear assumptions and inability to model sudden price fluctuations, which are common in the airline industry. The LSTM model, though capable of sequential modeling, underperformed due to hyperparameter constraints and limited data size, suggesting the need for larger datasets or better tuning. Prophet and Holt-Winters, which are typically suited for capturing seasonality, struggled to model the price volatility accurately, emphasizing the challenge of predicting airline fare prices that are influenced by dynamic external factors.

The results reinforce the importance of using more advanced machine learning techniques, such as **ensemble models** like LightGBM and XGBoost, which effectively handle the intricacies of the data and provide more accurate predictions. Given the unpredictability of airline pricing, future work could enhance model performance by incorporating additional features, such as real-time weather data, regional holidays, or special events, which are known to affect travel demand. Furthermore, exploring deep learning models like **Transformers** could help better capture long-term dependencies in price trends. Optimizing model hyperparameters using advanced techniques like grid search or Bayesian optimization could also improve predictive performance. Combining multiple models in a hybrid framework could offer further benefits, especially in accounting for the various complexities within the data. Additionally, developing a **real-time forecasting system** could be a valuable tool for airlines and travelers, enabling more accurate, on-the-spot pricing and dynamic adjustments. Extending this study to **international flight data** and considering global events, such as pandemics or political disruptions, could offer further insights into how global factors influence airline pricing strategies and provide a broader scope for future price forecasting.

VII. ACKNOWLEDGMENT

The author would like to express heartfelt gratitude to **Dr. Supriya Londhe** for her unwavering guidance, valuable insights, and continuous encouragement throughout the course of this research. Special thanks are also extended to **Dr. Vaishali Kherdekar** for her support and motivation during the study. The author is also thankful to the **Department of Design, Analytics, and Cyber Security, MIT Arts, Commerce and Science College, Alandi**, for providing the necessary resources and a supportive environment to carry out this work.

REFERENCES

[1]. Selvi, A., Sinegalatha, B., Trinaya, S., & Varshaa, K. K. (2023). Airline ticket price forecasting using time series model. In K. V. Ramana Murthy & A. Abraham (Eds.), *ICT with intelligent applications* (pp. 215–226). Springer. https://doi.org/10.1007/978-981-99-3758-5_20

[2]. Sushko, O. P., & Koryagin, N. D. (2022). Modelling of passenger air transportation prices. *World of Transport and Transportation*, *20*(5), 171–179.https://doi.org/10.30932/1992-3252-2022-20-5-7

[3]. Abdella, J. A., Zaki, N. M., Shuaib, K., & Khan, F. (2019). Airline ticket price and demand prediction: A survey. *Journal of King Saud University - Computer and Information Sciences*, *33*(4), 387–399.https://doi.org/10.1016/j.jksuci.2019.02.001

[4]. Boddu, S., Reddy, K. S., Sahitya, G. L., Afrin, S., & Sudha, K. (2024). Exploring predictive models for airfare forecasting: A comparative analysis of time series and machine learning approaches. *International Research Journal of Modernization in Engineering, Technology and Science*, *6*(3), 5276–5282.https://doi.org/10.56726/IRJMETS51520

[5]. Wang, Y., Tang, X., Zhang, S., Wang, L., & Witlox, F. (2024). Interpretable airline ticket price forecasting based on improved cumulative sum and temporal fusion transformer. SSRN. https://doi.org/10.2139/ssrn.5045119

[6]. Wang, T., Pouyanfar, S., Tian, H., Tao, Y., Alonso Jr., M., Luis, S., & Chen, S.-C. (2019). A framework for airfare price prediction: A machine learning approach. In *Proceedings of the 2019 IEEE 20th International Conference on Information Reuse and Integration for Data Science (IRI)* (pp. 200–207). IEEE.https://doi.org/10.1109/IRI.2019.00041

[7]. Rathi, K., Kumar, A., & Yadav, M. (2022). Airline fare price prediction. *International Research Journal of Engineering and Technology (IRJET)*, *9*(5), 2448–2452. Retrieved fromhttps://www.irjet.net/archives/V9/i5/IRJET-V9I5571.pdf

[8]. Degife, W. A., & Lin, B.-S. (2023). Deep-learning-powered GRU model for flight ticket fare forecasting. *Applied Sciences*, *13*(10), 6032.https://doi.org/10.3390/app13106032

[9]. Li, Y., Li, Z., & Qin, S. (2017). Ticket price forecasting based on machine learning. In *Proceedings of the 2017 7th International Workshop on Computer Science and Engineering (WCSE)* (pp. 471–475). https://doi.org/10.18178/wcse.2017.06.080

[10]. Oliveira, A. V. M. (2024). The seasonality of air ticket prices before and after the pandemic. *Communications in Airline Economics Research*, *10102E*, 1–6. https://doi.org/10.5281/zenodo.10663499

[11]. Wong, P., Thant, P., Yadav, P., Antaliya, R., & Woo, J. (2023). Using Spark machine learning models to perform predictive analysis on flight ticket pricing data. *arXiv preprint arXiv:2310.07787*.https://doi.org/10.48550/arXiv.2310.07787

[12]. Candela, R., Michiardi, P., Filippone, M., & Zuluaga, M. A. (2020). Model monitoring and dynamic model selection in travel time-series forecasting. In *Proceedings of the European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases (ECML-PKDD 2020)* (pp. 517–532). Springer.https://doi.org/10.1007/978-3-030-67667-4_31

Lu, J. (2017). Machine learning modeling for time series problem: Predicting flight ticket prices. *arXiv preprint arXiv:1705.07205*.https://doi.org/10.48550/arXiv.1705.07205

[13]. Gordiievych, A., & Shubin, I. (2015). Forecasting of airfare prices using time series. *In Information Technologies in Innovation Business (ITIB), 7-9 October, 2015, Kharkiv, Ukraine* (pp. 68-71). IEEE. https://doi.org/10.1109/ITIB.2015.23

[14]. Kayhan, S., Kiracı, K., & Yaşar, M. (2023). Relationship between airline ticket price, demand and business model: A worldwide analysis. *Aksaray Üniversitesi İktisadi ve İdari Bilimler Fakültesi Dergisi, 15*(3), 211-218.https://doi.org/10.52791/aksarayiibd.1234849

[15]. Lal, V., Stynes, P., & Muntean, C. H. (2023). An investigation into predicting flight fares in India using machine learning models. In *Lecture Notes in Networks and Systems: The 4th Joint International Conference on Deep Learning, Big Data and Blockchain (DBB 2023)* (Vol. 15, pp. 106–118). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-42317-8_9

[16]. Ricardianto, P., Suryobuwono, A. A., Endri, E., & others. (2023). The impact of service quality, ticket price policy, and passenger trust on airport train passenger loyalty. *Uncertain Supply Chain Management, 11*(1), 93-104. https://doi.org/10.5267/j.uscm.2022.9.012

[17]. Husen, K., Wiweka, K., Parantika, A., & others. (2019). A time series analysis of airline pricing behavior: Case study Jakarta (CGK)-Denpasar (DPS) market. *Journal of Economics, Management, and Trade, 22*(6), 301-315. https://doi.org/10.9734/JEMT/2019/v22i630105

[18]. Tissera, P. H. K., Perera, M. A. I., Ilwana, A. N. M. R. S. P., Nawinna, D. P., Waduge, K. T., & Kasthurirathna, D. (2020). Predictive analytics platform for airline industry. *Proceedings of the 2020 2nd*

International Conference on Advancements in Computing (ICAC), 1–6. IEEE. https://doi.org/10.1109/ICAC51239.2020.9357244

[19]. Merkert, R., & Webber, T. (2018). How to manage seasonality in service industries – The case of price and seat factor management in airlines. *Journal of Air Transport Management, 72*, 39–46. https://doi.org/10.1016/j.jairtraman.2018.08.002

[20]. Kalakou, S., & Moura, F. (2021). Analyzing passenger behavior in airport terminals based on activity preferences. *Journal of Air Transport Management, 96*, 102110. https://doi.org/10.1016/j.jairtraman.2021.102110

[21]. Abdelhady, M. R. R., & Abou-Hamad, M. M. H. (2020). Airlines' pricing strategies and O-D markets: Theoretical and practical pricing strategies. *Journal of Travel, Tourism and Recreation, 2*(3), 19–36.https://sryahwapublications.com/article/abstract/2642-908X.0203004

[22]. Gupta, R., & Ganesh, L. (2017). Dynamic pricing in airline industry. *Asian Journal of Research in Business Economics and Management, 7*(1), 15–29. https://doi.org/10.5958/2249-7307.2017.00002.0

[23]. Krembsler, J., Spiegelberg, S., Hasenfelder, R., Kämpf, N. L., Winter, T., Winter, N., & Knappe, R. (2024). Fare revenue forecast in public transport: A comparative case study. *Research in Transportation Economics, 105*, 101445. https://doi.org/10.1016/j.retrec.2024.101445

[24]. Chudy-Laskowska, K., & Pisula, T. (2017). Seasonal forecasting for air passenger traffic. *SGEM Conference on Social Sciences, 14*, 89–98. https://doi.org/10.5593/sgemsocial2017/14/S04.089

[25]. Aziza, V. N., Moh'd, F. H., Maghfiroh, F. A., Notodiputro, K. A., & Angraini, Y. (2023). Performance comparison of SARIMA intervention and Prophet models for forecasting the number of airline passengers at Soekarno-Hatta International Airport. *BAREKENG: Journal of Mathematics and Its Applications, 17*(4), 2107–2120.

[26]. https://doi.org/10.30598/barekengvol17iss4pp2107-2120
Sirish, U. M., Belavagi, M. C., & Attigeri, G. (2022). Profit prediction using ARIMA, SARIMA, and LSTM models in time series forecasting: A comparison. *IEEE Access*. https://doi.org/10.1109/ACCESS.2022.3224938

[27]. Rajankar, S., & Sakharkar, N. (2019). A survey on flight pricing prediction using machine learning. *International Journal of Engineering Research & Technology, 8*(6), Article 060672.http://www.ijert.org