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Forecasting Airline Passenger Growth: Comparative Study LSTM VS Prophet VS Neural Prophet

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Abstract: To conduct an exhaustive examination of airline passenger growth prediction methods, this study compares the performance of three distinct strategies: LSTM, Prophet, and Neural Prophet. To forecast passenger volumes accurately, the aviation industry needs robust prediction models due to rising demand. This research evaluates the performance of LSTM, Prophet, and Neural Prophet models in passenger growth forecasting by utilizing historical airline passenger data. A comprehensive examination of these methodologies is conducted via a rigorous comparative analysis, encompassing prediction accuracy, computational efficiency, and adaptability to ever-changing passenger traffic trends. The research methodology consists of various approaches for preprocessing time series data, engineering features, and training models. The findings elucidate the merits and drawbacks of each method, furnishing knowledge regarding their capacity to capture intricate patterns, fluctuations in passenger behavior across seasons, and abrupt shifts. The results of this study enhance comprehension regarding the relative efficacy of LSTM, Prophet, and Neural Prophet in prognosticating the expansion of airline passenger numbers. As a result, professionals and scholars can gain valuable guidance in determining which methodologies are most suitable for precise predictions of forthcoming passenger demand. This comparative study serves as a significant point of reference for enhancing aviation prediction models to optimize the industry's resource allocation, operational planning, and strategic decision-making.

Keywords: Airline Passenger; LSTM; Prophet; Neural Prophet; Prediction Accuracy

INTRODUCTION

The aviation sector has undergone (Gunerhan et al., 2023) an exceptionally rapid rate of change over the past several decades. The remarkable expansion is evident not only in the growing fleet of airlines and the extended list of destinations but also in the substantial upsurge in passenger utilization of aviation services. In tandem with economic expansion and the phenomenon of globalization, air travel demand has increased dramatically. Nonetheless, because of this industry's exponential expansion, it is confronted with formidable management and planning obstacles. Predicting the trajectory of future passenger growth with precision is an urgent requirement. Effectively managing this exponential and intricate growth necessitates a comprehensive comprehension of historical patterns, the determinants that impact these transformations, and the capacity to accurately predict passenger influxes. Given the current circumstances, precise and dependable forecasts of passenger volume expansion assume heightened significance. In addition to aiding in the planning of flight capacity, accurate forecasts facilitate resource allocation, schedule modifications, and additional strategic decision-making. Hence, the establishment of sophisticated and efficient prediction models is imperative to ensure operational continuity in the aviation sector, which is expanding at an accelerated rate.

Forecasting passenger growth in the airline industry is becoming progressively (Redpath et al., 2017) crucial due to its susceptibility to a multitude of intricate factors. Passenger requirements can be influenced by external factors such as economic fluctuations, travel regulations, geopolitical occurrences, as well as internal variations within the aviation industry. The lack of ability to predict this growth with precision can result in significant consequences. Inaccuracies in predicting future outcomes can disrupt the efficient distribution of resources,

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escalate operational expenses, or potentially result in an inability to satisfy passenger needs, thereby negatively impacting a company's reputation. In rapidly changing market conditions, predictive accuracy is crucial for maintaining the equilibrium between supply and demand in the aviation industry. Airlines can enhance their long-term planning, optimize aircraft fleet utilization, and adjust flight schedules more effectively by accurately predicting passenger growth. Hence, it is imperative to create predictive models that can effectively encompass the intricacy and fluctuation in passenger demand to guarantee seamless operations and sustained prosperity for airlines.

This study introduces an advancement by suggesting a comparative methodology that incorporates three distinct prediction techniques for forecasting the growth of airline passengers: Long Short-Term Memory (LSTM) (Lu et al., 2023), (Bashir et al., 2022), Prophet(Lu et al., 2023), and Neural Prophet. Each of these three methods possesses distinct approaches, theoretical foundations, and computational capacities for managing intricate time series data. This research aims to compare the merits and drawbacks of each of these techniques to achieve more precise predictions regarding passenger growth. The LSTM model, due to its capacity to comprehend extended patterns in temporal data, is anticipated to surmount the intricacy of trends and fluctuations in passenger numbers. Prophet is renowned for its capability to capture both seasonal patterns and well-defined trends in time series data that exhibit seasonal characteristics.

Conversely, Neural Prophet (Hindarto et al., 2023), an enhanced version of Prophet that utilizes a more advanced neural network structure, is anticipated to offer superior accuracy in predicting intricate and erratic patterns. This research seeks to provide a comprehensive assessment of the performance and adaptability of each model in predicting passenger growth by comparing these three methods. This research aims to make a significant contribution by thoroughly analyzing the strengths and weaknesses of each approach. The goal is to identify the most suitable and effective prediction techniques for forecasting future airline passenger growth.

The objective of this study is to investigate the efficacy of three primary prediction techniques, specifically Long Short-Term Memory , Prophet, and Neural Prophet, in forecasting the growth of airline passenger numbers. The primary objective of this research is to ascertain the benefits and drawbacks of each approach in capturing trends, seasonal patterns, and reactions to abrupt fluctuations in passenger numbers. This research aims to assess the accuracy and reliability of three methods in predicting fluctuations in passenger traffic within the aviation industry. This research seeks to offer more straightforward guidance in selecting the most suitable prediction approach for overcoming the complexity of forecasting passenger growth for airlines. By gaining a more profound comprehension of the benefits and constraints of each method, this study seeks to provide valuable insights. Here are the research inquiries for this investigation. How well do LSTM, Prophet, and Neural Prophet predict airline passenger growth? What are the pros and cons of each method for capturing trends, seasonal patterns, and sudden passenger numbers? How accurate and reliable are the three methods of predicting passenger traffic fluctuations? The objective of this study is to enhance comprehension regarding the efficacy and appropriateness of the LSTM, Prophet, and Neural Prophet techniques in forecasting the growth of airline passengers. This research aims to provide practitioners and researchers with guidance in selecting the most suitable prediction technique for accurately predicting future passenger growth.

LITERATURE REVIEW

The article uses Wuhan's daily pollutant concentration data from 2014 to 2021 to make predictions. Prophet decomposition divides data into trend, periodic, and error items. K-nearest neighbor fuses spatial and temporal information, while the Long Short-Term Memory model predicts error terms. Four groups of comparative experiments compared the model to Prophet, LSTM, and Prophet-LSTM. The results showed significant periodic variation in O3 concentration, better prediction accuracy, and better prediction effect than the single model (Zhang et al., 2022). Blockchain bitcoin mining uses much energy and creates waste. Energy consumption and waste generation are predicted by two Facebook Prophet algorithms and deep neural network models. The models use daily energy consumption and electronic waste data, with block size driving them. The findings estimate energy discharge and waste accumulation (Jana et al., 2022). This paper introduces a hybrid Prophet model, ICEEMDAN, and multi-model optimization error correction to predict metal prices. The system indicates zinc, aluminum, copper, and gold prices. The model decomposes residual sequences using ICEEMDAN, ARIMA, ELMAN, BPNN, LSTM, and NAR. Experiments and performance tests verify model performance and reliability. Evaluation index and performance tests demonstrate the model's metal price prediction accuracy (Huang et al., 2022). This paper predicts India's monthly energy demand using four time-series models. The CEA model predicts total energy demand accurately but not peak demand. For both, Facebook Prophet beats CEA and LSTM RNN. According to the study, FB Prophet is the best energy forecaster for 2019–2024, with 3.9% and 4.5% annual growth (Chaturvedi et al., 2022). This paper proposes a machine learning-based time series forecasting method for unconventional reservoir oil production. The technique predicts values using historical data. ARIMA, LSTM, and Prophet were compared to overcome traditional forecasting limitations. Due to seasonal effects, ARIMA and LSTM outperformed Prophet. ARIMA accurately predicted DJ Basin oil production rates, demonstrating machine

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learning's potential (Ning et al., 2022). Banking accounts for 83% of Türkiye's financial markets by asset size. In this study, the Borsa Istanbul Banks Index, representing the domestic banking system, was analyzed for price forecasting from December 27, 1996, to August 31, 2023, using the traditional Autoregressive Integrated Moving Average (ARIMA) Model and two AI-based deep learning models: the Facebook Prophet Model (FPM) and Convolutional Neural Networks Model (CNNM). CNNM outperforms other models. The findings benefit researchers selecting time-series data methods and investment firms and managers predicting stock price movements—discussion of policy implications of the findings (Armagan, 2023). The study uses 2017–2019 data to develop time series forecasting models for Rajasthan solar power production. It compares auto-SARIMA, Facebook Prophet, and Neural Prophet GHI prediction models. The auto-SARIMA model reduces root mean squared error (RMSE) and mean absolute error (MAE) better than other models, showing the importance of accurate predictions for solar power production. Environmental issues require precise predictions, according to the study (Gupta et al., 2023).

Time series prediction studies show applications in air pollution, energy, metal prices, finance, and renewable energy production. Prophet, LSTM, ARIMA, and other model selection methods focus on different aspects of time series data. ARIMA and LSTM's seasonal prediction accuracy and Prophet's long-term trend modeling are highlighted in some studies. The comparison of these models shows model suitability and performance in specific domains, emphasizing the importance of choosing the suitable model for accurate and reliable predictions. The diversity of time series prediction models and approaches contributes to understanding and application in various fields, but each model has advantages and limitations that must be considered.

METHOD

The proposed methodology proposes to predict the annual growth in air travel passenger volume. Three primary methods employed in this endeavor include Long Short-Term Memory (LSTM), Prophet, and Neural Prophet techniques. LSTM, short for Long Short-Term Memory, is a type of neural network model that excels at capturing intricate temporal relationships in time series data. It achieves this by considering long-term dependencies and can make predictions based on previous data sequences. Prophet is a specialized statistical model that is specifically designed to analyze time series data that exhibit prominent seasonal patterns. It is capable of effectively handling trends, holiday effects, and events that have an impact on the data's behavior. Neural Prophet is an enhanced version of Prophet that employs a more advanced machine learning technique, allowing for more accurate adaptations to intricate data patterns.

Through a comparative analysis of these three approaches, our objective is to determine the most effective and precise method for forecasting the annual growth in airplane passengers. The LSTM model, known for its capacity to capture long-term dependencies, is valuable when there are specific factors that exert influence over an extended duration. Prophet and Neural Prophet, with their emphasis on seasonal patterns and enhanced machine learning capabilities, can offer more accurate predictions by considering seasonal fluctuations and swift shifts in trends. By combining and comparing these three methods, we anticipate gaining a more profound understanding of forecasting the future growth of aircraft passenger traffic.

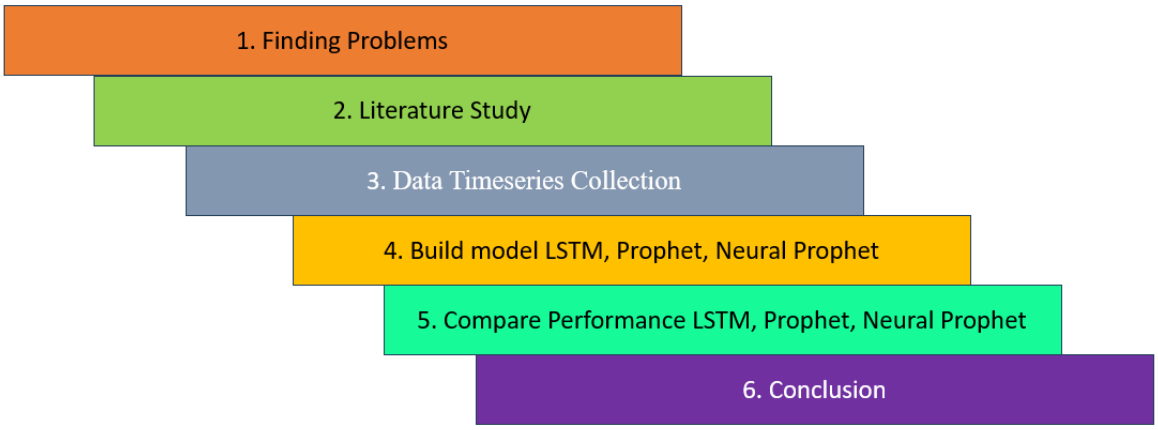

Figure 1. Proposed Methodology
Source: Researcher Property

Figure1, this study describes how to predict annual airline passenger traffic growth. Researchers identified the biggest challenge in predicting passenger numbers in the first stage. The next step is a comprehensive literature study of prediction methods used in similar contexts. In the third stage, precise time series data on airplane passengers was collected. The fourth stage's Long Short-Term Memory (LSTM), Prophet, and Neural Prophet

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prediction models use this data. LSTM is used to capture complex temporal relationships, while Prophet and Neural Prophet focus on seasonal patterns and use more advanced machine learning. After model building, the fifth stage compares the performance of the three models. This analysis compares each model's ability to predict aircraft passenger traffic growth. This comparison is used to determine each model's strengths and weaknesses for the forecast. The final stage of this research evaluates the three models' ability to predict airline passenger numbers. These findings reveal which models are best for predicting annual aircraft passenger traffic growth and future improvements.

Long Short-Term Memory

Long Short-Term Memory (LSTM) (Hasan, 2023) is a precious technique for forecasting the ongoing rise in the number of airline passengers, particularly in the presence of a consistent daily growth trend. Given the circumstances, LSTM is the optimal selection due to its capacity to capture enduring patterns from time series data effectively. When utilized for forecasting the growth in the number of airline passengers, LSTM can identify and consider intricate temporal patterns, illustrating a consistent upward trajectory. The primary benefit of LSTM lies in its ability to effectively process time series data characterized by robust temporal dependencies, such as the constant year-to-year increase in the number of airline passengers. This is attributed to its capacity to retrieve information over time in a more efficient manner compared to other neural network models. The LSTM model employs gates to control the information flow in both long-term and short-term memory. This enables the model to effectively retain and utilize pertinent information from the past, thereby enhancing its ability to make precise predictions and increase the number of airplane passengers. With the ongoing rise in the number of airplane passengers, LSTM demonstrates the ability to adjust to progressively intricate patterns over time. LSTM can incorporate continuous growth more effectively than other models. Therefore, when faced with a scenario characterized by a consistent and uninterrupted daily rise, employing LSTM (Sabzipour et al., 2023)as a forecasting model will yield dependable and precise outcomes regarding the anticipated expansion in the number of air travelers in the forthcoming period.

Prophet

The Prophet method, a time series prediction technique, is highly effective in forecasting the ongoing growth in the number of airplane passengers, particularly in cases where there is a consistent daily growth trend. Prophet is a specialized tool that is well-suited for analyzing data that exhibits pronounced seasonal patterns and dynamic trend shifts. Therefore, it is an excellent option for predicting consistent growth in air passenger traffic. The Prophet’s key benefit lies in its capacity to incorporate and represent both seasonal patterns and long-term trends simultaneously. Prophet (Saeed et al., 2023) can detect seasonal patterns, such as a surge in airplane passengers during the holiday season or specific periods annually, within the framework of predicting passenger growth. Prophet's ability to accurately capture and model daily upward trends makes it particularly valuable. Prophet employs an instinctive and adaptable methodology to address patterns, seasonal variations, and holiday impacts, rendering it appropriate for scenarios characterized by a consistent upward trajectory in air passenger figures. Prophet utilizes a flexible technique that can adjust to intricate patterns, enabling it to offer dependable forecasts regarding the anticipated increase in the number of air travelers on a yearly basis. Hence, Prophet is a reliable and efficient option for forecasting the consistent growth in aircraft passenger traffic daily, offering valuable insights into the projected number of passengers in the future.

Neural Prophet

Neural Prophet (David, 2023), an advanced iteration of the Prophet prediction model, is a highly efficient method for forecasting the ongoing rise in the number of airplane passengers. This is particularly useful when there is a consistent daily growth trend. This model employs an advanced machine learning technique that utilizes neural networks to analyze intricate time series data effectively. As a result, it becomes a feasible choice for predicting a consistent upward pattern in passenger traffic. The primary benefit of Neural Prophet lies in its capacity to manage intricate and dynamic patterns in time series data effectively. Neural Prophet can effectively comprehend and simulate the patterns of increasing airline passenger growth daily by adapting more flexibly to changing variations. By employing an advanced machine learning methodology, this model possesses the capability to adjust to variations in the continuous upward pattern. Neural Prophet includes the ability to adapt to seasonal patterns and swiftly changing time series data, which grants it an advantage. This model can identify and precisely calculate seasonal patterns that impact passenger traffic in the context of the continuously growing forecasted number of airplane passengers. Neural Prophet is a dependable and efficient option for predicting the consistent upward trend in the number of airplane passengers daily. It offers comprehensive predictions regarding future growth in passenger traffic.

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RESULT

The Kaggle dataset on airline passengers from 1949 to 1960 is useful for air traffic trend analysis. The aviation industry's growth over 12 years can be examined in detail. This data includes monthly passenger data, helping to understand seasonal and long-term aviation industry trends. This dataset allows comparison of annual growth, identification of upward or downward trends, and observation of seasonal patterns. By examining the aviation industry's early development, this dataset allows for comparative studies of air traffic today and the development of better prediction models based on historical trends.

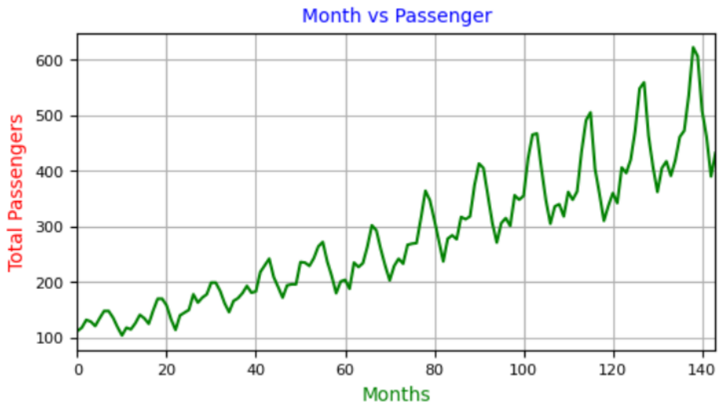

Figure 2. Dataset passenger
Source: Researcher Property

Figure 2, there is a clear upward trend in the number of passengers, as seen in the dataset graph. The offered visualization gives the impression that the annual growth rate of aircraft passengers is relatively high. A steady and continuous rising trend over the observed period characterizes this increase pattern. This aircraft passenger dataset is characterized by reasonably regular improvement, as shown by the graph, which has been consistently growing from year to year. During that time, the aviation industry saw relatively consistent growth, as demonstrated by the constantly rising trend line. Several variables, including more frequent flights, changes in people's habits, expanding economies, and more accessible air travel, can contribute to this phenomenon. As time goes on, passengers may grow used to flying, and airlines may have expanded their route networks to meet the ever-increasing demand. Assuming this trend keeps going up, the aviation industry during that time should be seeing steady growth. Additional research into this trend can shed light on the causes of its expansion and its effects on the aviation sector during that period. Finally, the dataset's upward trending trend from year to year exemplifies the robust expansion of the aviation industry throughout that time, as the number of passengers on board aircraft increased dramatically.

Table 1. Training with epoch to 500

epoch	loss	epoch	loss
1	0,05966	276	0,00112
26	0,27823	301	0,00682
51	0,17865	326	0,00000
76	0,00425	351	0,00001
101	0,00482	376	0,00030
126	0,00006	401	0,00138
151	0,00098	426	0,00002
176	0,00001	451	0,00025
201	0,00069	476	0,00207
226	0,00011	499	0,00021
251	0,00001		

Table 1 presents the data from the training model with epoch reaching 500, which contains information about loss values in every 25 epochs, including loss on the 499^{th} epoch, which gets 0,00021. This data provides an overview of changes in loss models in each epoch iteration during the training process. From this table, the loss was initially relatively high, with a value of 0.05966 in the first epoch, but gradually decreased as epoch ran. There

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is a consistent decreasing trend in the loss value throughout the training process unless there is a small spike at certain points, such as in the 26th and 2014 epochs. The surge may indicate an unexpected fluctuation or change in model learning. However, overall, the model is getting better along with the increasing number of Epochs, marked by a significant decrease in loss from the beginning of training to approaching the last epoch. The 499th epoch is a decisive point because the loss achieved is shallow, 0,00021, which shows that the model is good enough to adjust to data and can make accurate predictions or estimates. This indicates that at that point, the model is approaching or even reached the desired level of performance, where the loss decline is very minimal and not significant. Thus, the analysis of the table highlights the training process that runs well, shows continuous progress in improving the performance of the model with each epoch, and reaches a low loss level at the end of the iteration, indicating that the model has successfully learned from the data well.

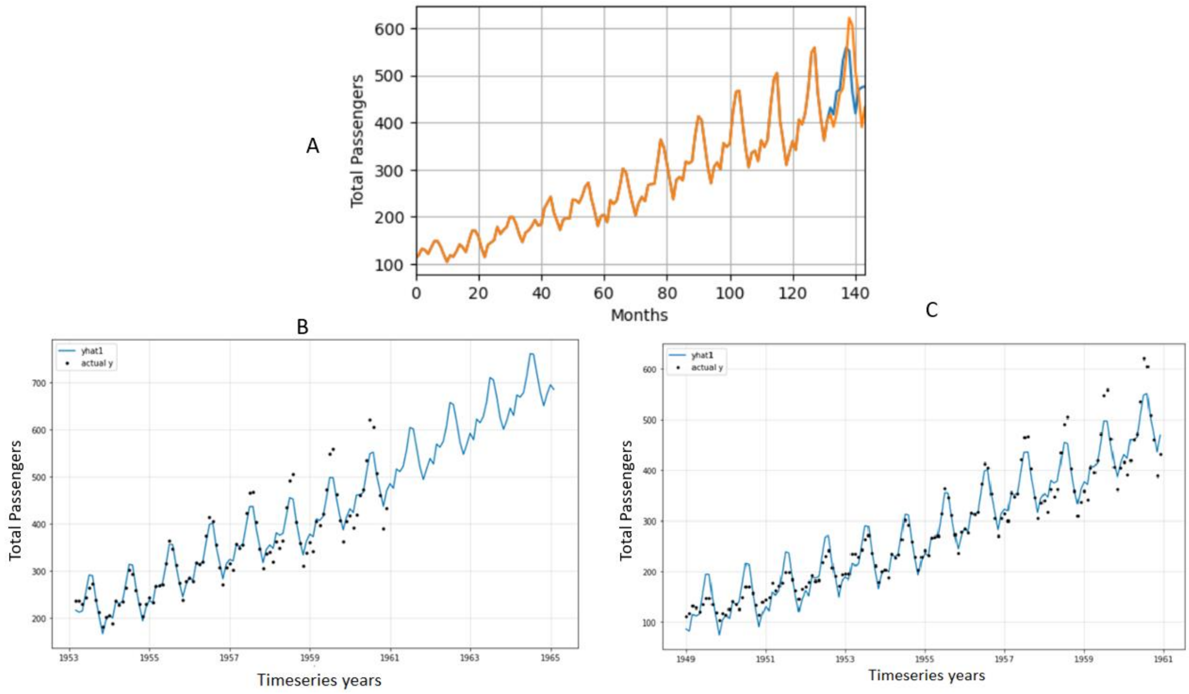

Figure 3. Result training model (A) LSTM, (B) Prophet, (C) Neural Prophet
Source: Researcher Property

Figure 3 displays the outcomes of three distinct training models, LSTM (A), Prophet (B), and Neural Prophet (C), in their predictive capabilities. Based on the graphical representation A depicting the outcomes of LSTM predictions, it is evident that this model demonstrates a tendency to deliver more concentrated predictions towards the conclusion of the given time frame. This suggests that LSTM is more likely to generate accurate forecasts for the data at the final point of the period but may not pay enough attention to the patterns of change that occur throughout the entire duration. Unlike LSTM, graph B (Prophet) and graph C (neural Prophet) demonstrate a more uniform distribution of prediction patterns over the whole period. Prophet and Neural Prophet appear to be more adept at capturing and modeling the patterns of change that take place during the observed period.

Nevertheless, based on the ratio between graphs B and C, it is evident that the Neural Prophet outperforms the Prophet in terms of prediction accuracy. The superior accuracy and capture patterns generated by Neural Prophet, as compared to Prophet, demonstrate its enhanced capability in predicting intricate patterns. The improved predictive capabilities of the neural Prophet can be ascribed to its sophisticated machine-learning approach and increased capacity to accommodate intricate patterns within time series data. This indicates that Neural Prophet potentially possesses a more advanced architecture or methodologies in comparison to Prophet, enabling it to handle and comprehend intricate patterns within data effectively. Considering the circumstances, the utilization of neural Prophet is preferable as it can offer more precise and comprehensive forecasts of the observed time series data.

DISCUSSIONS

The analysis reveals that LSTM, Prophet, and Neural Prophet exhibit varied performance when it comes to forecasting passenger growth in the aviation sector. LSTMs exhibit robust capabilities in capturing intricate patterns and enduring trends in time series data, yet they frequently show reduced responsiveness to abrupt fluctuations in passenger numbers. Prophet excels in capturing predictable patterns and organized trends but could

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be more proficient in dealing with irregular patterns or unforeseen volatility. Conversely, Neural Prophet, utilizing its sophisticated neural network structure, exhibited superior capability in adjusting to intricate patterns and unforeseeable fluctuations in passenger figures.

LSTM excels in comprehending extended-term patterns, whereas Prophet excels in capturing structured seasonal patterns. Neural Prophet demonstrates exceptional proficiency in handling intricate data patterns and unpredictable variations. However, its accuracy in forecasting abrupt shifts requires enhancement. The overall prediction accuracy generated by these three methods varies based on the intricacy and characteristics of the patterns in the data. However, each of these approaches plays a substantial role in predicting the increase in passengers. Nonetheless, they must be customized to suit the unique requirements of the aviation sector and the specific transformations it is encountering. By further refining and incorporating the favorable attributes of each approach, it is possible to create prediction models that are both dependable and flexible in adapting to the ever-changing fluctuations in passenger traffic within the aviation sector.

How well do LSTM, Prophet, and Neural Prophet predict airline passenger growth?
LSTM, Prophet, and Neural Prophet are prediction techniques that have distinct strengths and weaknesses when it comes to forecasting the growth of passenger numbers in the aviation sector. Due to its capacity to comprehend extended patterns in temporal data, LSTM frequently excels at detecting trends in passenger growth. Nevertheless, its drawback resides in its relatively slower reaction to abrupt shifts or unforeseen variations in passenger figures. The Prophet algorithm, which utilizes curve completion techniques, is highly proficient in capturing well-organized seasonal patterns within datasets. Nevertheless, the Prophet's responsiveness and accuracy in generating predictions tend to decrease when confronted with irregular patterns or abrupt changes. Conversely, Neural Prophet, an advanced version of Prophet that utilizes a more intricate neural network structure, demonstrates promise in managing more intricate data complexity. Neural Prophet can adjust to complex patterns and unforeseeable fluctuations in passenger numbers, although its accuracy in predicting abrupt changes still requires enhancement.

The strength of LSTM lies in its capacity to identify long-term trends, whereas Prophet excels in capturing seasonal patterns in a structured manner. Neural Prophet demonstrates exceptional proficiency in handling intricate data patterns and unpredictable fluctuations. However, its ability to promptly adapt to abrupt changes still necessitates additional refinement. While these three methods are valuable for predicting passenger growth, it is important to weigh their pros and cons based on the specific data and changes in passenger traffic within the airline industry. Enhancing the flexibility of each approach and incorporating the benefits of LSTM, Prophet, and Neural Prophet can facilitate the creation of prediction models that are both dependable and capable of adapting to intricate fluctuations in passenger numbers within the aviation sector.

In general, the assessment of LSTM, Prophet, and Neural Prophet in predicting the growth of airline passengers reveals that each approach possesses distinct attributes in dealing with various data patterns. LSTM exhibits the benefit of effectively capturing prolonged patterns and intricate structures in time series data, yet it tends to be less responsive to swift alterations. The Prophet model, characterized by its flexible methodology and capacity to accommodate structured seasonal patterns, yields accurate forecasts in stable scenarios but demonstrates reduced efficacy in the presence of unforeseen data fluctuations. Neural Prophet, an advancement of Prophet that utilizes more advanced neural network technology, shows advancements in managing more complex data. However, it still needs enhancements to adapt effectively to abrupt changes. It is crucial to acknowledge that the attributes and inherent qualities of the airline passenger data employed significantly impact the effectiveness of these three methods. Fluctuations influence the accuracy of each technique in making predictions about passenger numbers, seasonal variations, and unforeseen changes. Hence, the integration or simultaneous application of these three techniques has the potential to surpass their limitations and generate more dependable forecasts.
This research highlights the necessity for enhancing Neural Prophet to improve its adaptability to abrupt fluctuations in data. Optimizing prediction performance could be achieved by integrating the advantages of different methods through ensemble approaches or hybrid techniques. Hence, it is crucial to take into account the data attributes and unique requirements of the aviation sector when choosing or creating the optimal prediction technique for accurately anticipating the growth in passenger numbers.

What are the pros and cons of each method for capturing trends, seasonal patterns, and sudden passenger numbers? Every forecasting technique possesses both benefits and drawbacks when it comes to accurately capturing trends, seasonal patterns, and abrupt fluctuations in passenger volumes within the airline sector. LSTM exhibits the advantage of effectively capturing long-term patterns. The effectiveness of this system lies in its capacity to comprehend and discern intricate patterns in time series data, enabling accurate predictions of sustained passenger growth trends. Nevertheless, its drawback resides in its sluggishness in promptly adapting to abrupt shifts in passenger figures, rendering it suboptimal in capturing unforeseen fluctuations. However, Prophet demonstrated its effectiveness in capturing well-organized seasonal patterns. The curve-based approach effectively detects and represents seasonal patterns in data, enabling it to generate accurate predictions in stable conditions.

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Nevertheless, its vulnerability stems from its inability to manage abrupt alterations or unforeseen variations effectively.

Neural Prophet, an advancement of Prophet, utilizes a more advanced neural network and demonstrates promise in effectively managing more intricate data. The capacity to adjust to complex patterns and unforeseeable fluctuations provides it with an advantage in predicting more dynamic alterations. Nevertheless, the system's present drawback lies in its need for more responsiveness, necessitating further improvement to adapt to abrupt fluctuations in passenger volumes effectively. In general, LSTM is particularly adept at identifying extended patterns, whereas Prophet is highly proficient at capturing recurring patterns in a well-organized fashion. Neural Prophet demonstrates exceptional proficiency in handling intricate data patterns and unpredictable variations. However, its ability to promptly adapt to abrupt changes still necessitates additional refinement. Hence, when choosing prediction techniques, it is crucial to consider the unique characteristics of the data and the types of fluctuations observed in passenger traffic within the aviation sector. Furthermore, it is imperative to investigate the potential advantages that can be derived from integrating or employing multiple methodologies to optimize their respective merits in predicting patterns, fluctuations in passenger volumes, and seasonal changes.

How accurate and reliable are the three methods of predicting passenger traffic fluctuations?
Analyzing historical data, mathematical/statistical models and prediction techniques based on artificial intelligence are three prevalent methods used to forecast passenger traffic fluctuations. The strengths and weaknesses of each of these three approaches in measuring and predicting passenger traffic fluctuations are distinct. Historical data analysis entails the examination of previous data to discern prevailing trends and patterns. Although these methods offer valuable insights, they may need to consider external changes that have not been previously observed, such as unforeseen occurrences or shifts in societal conduct.

In contrast, mathematical and statistical models forecast fluctuations using mathematical formulas. Approximation of the model in a suitable manner can yield accurate predictions using these methods, which are typically more structured. Nevertheless, these models are susceptible to the flawed assumptions that underlie them, which may lead to imprecise prognostications. AI and artificial intelligence techniques, including machine learning algorithms and artificial neural networks, can process massive amounts of data and adapt to complex patterns. Nonetheless, a lengthy learning curve and reliance on accurate data are obstacles that must be surmounted with this approach.

The efficacy and dependability of these three approaches are substantially contingent upon the data quality employed, the choice of suitable models or techniques, and the capacity to accommodate unforeseen modifications. A composite of these three methodologies, or a combined strategy, might be the optimal selection for mitigating the drawbacks of one methodology while capitalizing on the benefits of the others. Suspicious external fluctuations necessitate situations in which adaptability and flexibility are critical for accurately predicting passenger traffic fluctuations. When implemented, a combination of these techniques is frequently the most effective strategy, as it capitalizes on the benefits of each method to enhance forecasts of passenger traffic fluctuations.

CONCLUSION

Airline passenger data from 1949 to 1960 from Kaggle is a valuable resource for air traffic trend analysis, as it offers in-depth insights into the expansion of the aviation industry over twelve years. The dataset comprises monthly passenger information, which facilitates the examination of seasonal patterns, identification of upward or downward trends, and comparison of annual growth. The data set exhibits a conspicuous progressive curve in passenger numbers, suggesting a comparatively rapid yearly expansion. Factors including increased air travel accessibility, alterations in consumer behavior, expanding economies, and more frequent flight schedules all contribute to this expansion. Loss values for the training model with an epoch of 500 exhibited a consistent downward trend during training. A shallow loss was observed in the 499th epoch, suggesting that the model showed sufficient capability to adapt to the data and generate precise predictions or estimates. The predictive capabilities of three distinct training models, LSTM (A), Prophet (B), and Neural Prophet (C), were determined through analysis of their outcomes. LSTM exhibited a propensity to generate more focused predictions towards the conclusion of the specified period, indicating that it might have needed to consider the temporal variations in patterns of change adequately. During the observed period, the Prophet and Neural Prophet demonstrated more excellent proficiency in capturing and simulating the patterns of change. In contrast to Prophet, Neural Prophet exhibited superior performance in terms of accurate predictions, thereby showcasing its heightened capacity to forecast complex patterns.

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