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Data-Driven Hospitality: Advanced Forecasting Models for Hotel Occupancy

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Abstract−Accurate forecasting of hotel booking demand is essential for resource optimization, revenue maximization, and enhanced customer experience in the hospitality industry. This study evaluates the performance of three forecasting models, ARIMA, Prophet, and LSTM, using historical booking data to identify the most effective approach for predicting demand. The evaluation employed four key metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and R-squared (R^2), providing a comprehensive comparison. The results indicate that the LSTM model outperformed the others in prediction accuracy, achieving the lowest MAE (2.71) and MAPE (21.33%), demonstrating its strength in capturing complex patterns. However, its negative R-squared value (-0.20) suggests that it performed worse than a simple mean predictor in explaining overall variance. This may be due to overfitting, insufficient training data, or model instability, which limits its generalizability. The Prophet model excelled in seasonal decomposition but showed the highest MAPE (71.86%), while ARIMA delivered robust residual diagnostics, adhering well to model assumptions with consistent variance and randomness in residuals. The findings suggest that while LSTM is most effective for short-term forecasting, ARIMA and Prophet provide better interpretability and reliability for long-term trend analysis. A hybrid approach combining the strengths of all three models is recommended to enhance predictive accuracy and robustness. This study provides actionable insights for industry stakeholders seeking to improve decision-making processes and operational efficiency through advanced forecasting techniques.

Keywords: Hotel Booking Demand; Forecasting Models; ARIMA; Prophet; LSTM

1. INTRODUCTION

Integrating data-driven methodologies in the hospitality industry has revolutionized forecasting practices, particularly in predicting hotel occupancy rates. Advances in computational algorithms and access to extensive datasets enable the development of sophisticated models that enhance the precision of occupancy forecasting, supporting informed decision-making for pricing, resource allocation, and strategic planning [1]–[3]. By leveraging machine learning and time-series analysis techniques, these models identify complex patterns and trends, significantly improving over traditional forecasting approaches, which often rely on static and less adaptable methods [4]. This evolution is pivotal in addressing hospitality demand's dynamic and seasonal nature, allowing for proactive strategies to mitigate revenue fluctuations and optimize operational efficiency [5]. However, the complexity and cost of implementing advanced forecasting systems may present barriers, particularly for smaller establishments lacking technical expertise or financial resources [6]. These challenges underscore the need for accessible, scalable solutions that balance innovation with practical application, ultimately contributing to a more resilient and competitive hospitality sector.

The selection of ARIMA, Prophet, and LSTM models in this study is based on their respective strengths in addressing various patterns inherent in time-series data. ARIMA is widely recognized for its effectiveness in modeling linear trends and stationary data with autocorrelation structures, making it suitable for short-term and stable demand patterns. Prophet offers robust handling of seasonality, holidays, and abrupt trend changes through an additive model with interpretable parameters, which is advantageous for capturing cyclical fluctuations in hotel occupancy. Meanwhile, LSTM, a deep learning architecture, can learn complex non-linear relationships and long-term temporal dependencies, enabling it to uncover hidden patterns often missed by traditional models. This diversity provides a strong foundation for comparative analysis, ensuring the study evaluates model performance across a broad spectrum of forecasting challenges relevant to the hospitality industry.

The rapid evolution of the hospitality industry, driven by fluctuating market dynamics and customer preferences, necessitates a robust methodological framework for predicting demand accurately. Advanced forecasting models such as ARIMA, Prophet, and LSTM are instrumental in addressing the challenges posed by seasonality, unpredictable demand, and economic volatility, which are critical to optimizing operational efficiency and revenue management [7]–[9]. Integrating these models enables a comprehensive analysis of time-series data, uncovering patterns and insights that traditional approaches often overlook [10]. Despite the evident advantages, these methods' complexity and computational requirements demand careful calibration to ensure their applicability across diverse organizational scales [11]. A lack of accurate forecasting mechanisms risks operational inefficiencies, revenue losses, and diminished customer satisfaction, especially in sectors heavily reliant on precision-driven planning. By addressing these pressing challenges, this research enhances the adaptability and resilience of hospitality operations, fostering sustainable growth amidst an increasingly competitive global market.

This research aims to develop and evaluate advanced forecasting models that improve the accuracy and reliability of demand prediction in the hospitality industry. By leveraging data-driven approaches such as ARIMA, Prophet, and LSTM, the study seeks to address the limitations of conventional methods in capturing complex temporal

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patterns and variability inherent in hotel occupancy data. Adopting these models will enhance operational decision-making and provide actionable insights for revenue optimization and resource management. Through a systematic comparison of model performance using metrics such as Mean Absolute Error, Root Mean Square Error, and R-squared, this study highlights the strengths and weaknesses of each approach, enabling the identification of the most effective solution for various operational contexts. Addressing the need for precise and adaptable forecasting tools aligns with fostering resilience and competitiveness in the hospitality sector amidst dynamic market conditions.

This research contributes to the theoretical framework of demand forecasting by advancing the understanding and application of modern predictive models in the hospitality sector. By integrating methodologies such as ARIMA, Prophet, and LSTM, the study enriches the existing body of knowledge by demonstrating how these approaches address the inherent complexities of time-series data, including seasonality, nonlinearity, and volatility [12]–[14]. Exploring comparative model performance offers critical insights into their strengths and limitations, fostering a deeper understanding of the conditions under which each model excels [15]. This research underscores the transformative potential of machine learning and statistical models in reshaping forecasting paradigms by bridging gaps between theoretical advancements and practical application. The findings are expected to inform future academic discourse and methodological innovation, paving the way for more robust and adaptable forecasting frameworks applicable across diverse industries reliant on accurate demand prediction.

The practical implication of this research lies in its potential to transform operational and strategic decision-making within the hospitality industry by adopting advanced forecasting models. By utilizing techniques such as ARIMA, Prophet, and LSTM, this study offers tools that enhance the accuracy of demand predictions, enabling more efficient allocation of resources, optimized pricing strategies, and improved inventory management [16], [17]. Such advancements directly address the challenges of unpredictable demand patterns and seasonality, frequently disrupting operational efficiency and profitability [18], [19]. The deployment of these models also empowers stakeholders to anticipate market fluctuations and make data-driven decisions that enhance customer satisfaction and revenue growth [20]–[24]. By integrating advanced analytics into routine operations, this research promotes adopting a proactive, evidence-based approach to managing dynamic market conditions, ultimately fostering sustainability and competitiveness within the hospitality sector.

Existing studies in demand forecasting for the hospitality industry have predominantly focused on traditional statistical methods or isolated applications of machine learning models, often overlooking these approaches' comparative performance and contextual adaptability [25]. While statistical models like ARIMA have demonstrated effectiveness in capturing linear trends, and machine learning frameworks such as LSTM offer promise in handling complex nonlinear patterns, few studies have systematically evaluated their relative strengths and limitations within the specific dynamics of hotel occupancy data [26]. This oversight leaves a critical gap in understanding how these models perform under varying operational conditions, such as high volatility or irregular demand patterns [27]–[30]. Addressing this gap requires rigorous benchmarking of multiple models to identify the most suitable solutions for different scenarios. Bridging this divide enriches the methodological discourse, providing a nuanced perspective that aligns theoretical advancements with practical relevance, ultimately advancing forecasting practices in the hospitality domain.

Future research is encouraged to explore the integration of hybrid forecasting models that combine the strengths of statistical methods and machine learning techniques to address the limitations of individual approaches. While models like ARIMA excel in capturing linear trends and LSTM effectively handles nonlinear patterns, their combined application may enhance prediction accuracy by leveraging complementary capabilities. Additionally, further investigation into the role of external variables, such as macroeconomic indicators, customer sentiment, and real-time events, could provide a more comprehensive framework for demand forecasting. Expanding the scope to include diverse datasets from varying geographical and operational contexts would also enhance the generalizability of findings and offer insights tailored to specific market conditions. By addressing these areas, future studies have the potential to advance forecasting methodologies, contributing to more adaptive and robust decision-making tools that meet the evolving demands of the hospitality industry.

2. RESEARCH METHODOLOGY

2.1 Research Workflow

The research workflow is designed to systematically address the complexities of forecasting hotel occupancy through a structured and iterative process. It begins with data preparation, involving data cleaning, feature engineering, and train-test splitting to ensure the dataset is suitable for analysis and model development [31]. This is followed by the core phase of model development, where ARIMA, Prophet, and LSTM models are trained and fine-tuned through hyperparameter optimization to achieve optimal performance. The iterative training process allows for identifying model strengths and weaknesses, providing a robust foundation for comparative evaluation. Once the models are developed, the workflow transitions to implementation, encompassing performance analysis, model selection, deployment into production, and continuous performance monitoring. This seamless integration of preparation,

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development, and implementation underscores the workflow's emphasis on methodological rigor and practical applicability, ensuring the outcomes are accurate and actionable for real-world decision-making in the hospitality industry.

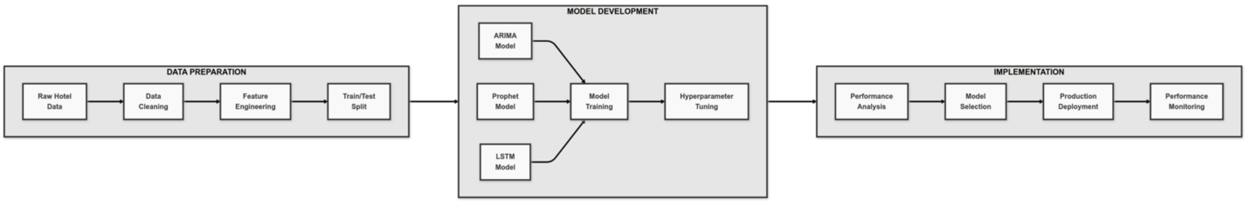

Figure 1. Research Workflow

Figure 1 illustrates a comprehensive research workflow to ensure the systematic execution of forecasting model development and application. The process begins with data preparation, which involves cleaning raw data, engineering relevant features, and splitting datasets into training and testing subsets. This foundational phase ensures the quality and suitability of data for subsequent analysis. The next stage, model development, focuses on constructing and optimizing forecasting models such as ARIMA, Prophet, and LSTM. Each model undergoes rigorous training and hyperparameter tuning to achieve enhanced predictive performance. The final stage, implementation, involves evaluating model performance, selecting the optimal model, deploying it in a real-world environment, and monitoring its performance over time. This workflow ensures methodological rigor and highlights a clear progression from data preprocessing to practical application, making it highly adaptable for addressing forecasting challenges in dynamic operational contexts. Such an integrated approach ensures that the research outcomes remain accurate and relevant to industry needs.

Data preparation serves as a critical foundation for the successful development of forecasting models by ensuring the quality and relevance of the dataset. This process begins with collecting raw hotel data, refined through data cleaning to remove inconsistencies, handle missing values, and correct anomalies that could compromise analytical accuracy. Following this, feature engineering is implemented to extract meaningful variables and transform the data into a format that captures relevant patterns and trends. The final step involves splitting the dataset into training and testing subsets, a practice essential for validating model performance and minimizing the risk of overfitting. These sequential steps are integral to enhancing the dataset's reliability and ensuring that the inputs align with the objectives of the analysis. By adopting a meticulous approach to data preparation, predictive models' overall accuracy and robustness are significantly improved, laying the groundwork for actionable and reliable forecasting outcomes.

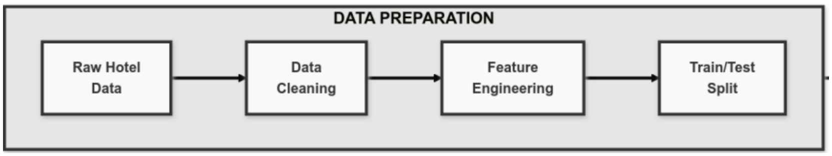

Figure 2. Data Preparation

Figure 2 illustrates the data preparation process, a fundamental step in ensuring the reliability and applicability of predictive modeling in forecasting. The process begins with collecting raw hotel data, which provides the foundational input for analysis. This data is subjected to a rigorous cleaning phase to address missing values, outliers, and inconsistencies that could distort model performance. Following this, feature engineering is applied to derive relevant attributes and optimize the dataset's structure, enhancing its ability to capture meaningful patterns. Finally, the dataset is divided into training and testing subsets to facilitate model validation and ensure the generalizability of predictions. This structured approach ensures that the data is accurate and aligned with the objectives of the analysis, thereby supporting the development of robust and effective forecasting models. The process lays a strong foundation for actionable insights and reliable decision-making in dynamic operational contexts by emphasizing quality and structure.

Feature engineering and splitting training and testing data are essential in preparing datasets for predictive modeling. Feature engineering involves creating and transforming input variables to enhance the dataset's representational power, enabling the model to capture relevant patterns more effectively. This process may include deriving new variables from existing ones, scaling numerical data to uniform ranges, and encoding categorical features to facilitate compatibility with machine learning algorithms. The dataset is divided into training and testing subsets, typically employing a defined ratio of 80:20. The training data fits the predictive model, allowing it to learn from historical patterns. In contrast, the testing data evaluates its performance on unseen information. This split ensures that the model's robust predictive capabilities are not overfitted to the training dataset. Together, feature engineering and data splitting establish a reliable and systematic foundation, enhancing the precision and applicability of forecasting models in addressing complex, real-world challenges.

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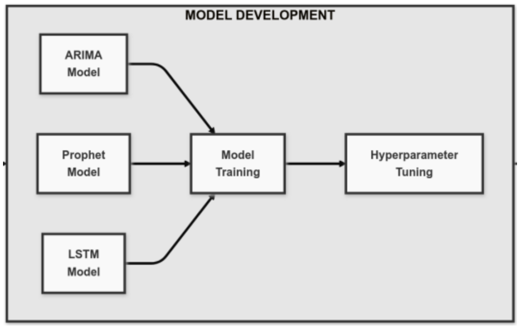

Figure 3. Model Development

Figure 3 illustrates the systematic model development process of constructing reliable forecasting solutions. The workflow begins with implementing three distinct modeling approaches: ARIMA, Prophet, and LSTM. Each model is subjected to an initial training phase to fit their respective algorithms to the prepared dataset, ensuring they capture relevant temporal patterns and relationships. This is followed by hyperparameter tuning, a critical step to optimize the model's performance by systematically adjusting parameters to balance accuracy and computational efficiency. Combining diverse modeling techniques and meticulous tuning allows for comprehensively evaluating their capabilities and limitations. By leveraging these iterative steps, the model development phase ensures that the selected forecasting framework is robust, adaptable, and aligned with the dynamic demands of real-world applications, making it a cornerstone of predictive analytics.

Hyperparameter tuning is critical in optimizing machine learning models for enhanced predictive performance and computational efficiency. Unlike parameters that the model learns directly from the data during training, hyperparameters are predefined values that control the model's behavior, such as the learning rate, number of layers, or the number of neurons in a neural network. This process systematically adjusts these values to identify the optimal configuration that minimizes error while preventing overfitting or underfitting. Practical hyperparameter tuning often involves techniques such as grid search, random search, or advanced methods like Bayesian optimization, which explore combinations of hyperparameter values within a specified range. By ensuring that the model achieves a balance between accuracy and generalizability, hyperparameter tuning significantly enhances its adaptability to unseen data. This meticulous optimization step is essential for creating robust forecasting models that deliver reliable insights in dynamic and complex operational contexts.

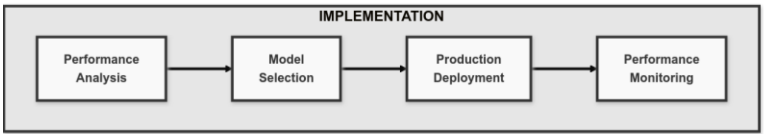

Figure 4. Implementation

Figure 4 illustrates the implementation phase, which bridges the gap between model development and practical application. The process begins with performance analysis, where models are evaluated based on predefined metrics to determine their predictive accuracy, generalizability, and suitability for the given context. Following this, the most effective model is selected for deployment, ensuring it aligns with operational goals and constraints. The selected model is then integrated into a production environment, enabling real-time forecasting and decision-making. Post-deployment, continuous performance monitoring is conducted to assess the model's reliability over time, identify potential drifts in data patterns, and make necessary adjustments. This structured approach ensures that the forecasting model delivers actionable insights and remains adaptable to dynamic conditions, enhancing its long-term efficacy and relevance in supporting strategic objectives.

Performance monitoring is crucial in maintaining the reliability and effectiveness of predictive models after deployment. This stage involves continuously assessing a model’s performance by tracking key metrics, such as accuracy, precision, and error rates, to ensure it aligns with expected outcomes. By detecting deviations in performance early, adjustments can be made to address challenges such as data drift, which occurs when the statistical properties of input data change over time. This proactive approach safeguards the model’s predictive power and ensures its adaptability to dynamic operational conditions. Implementing robust monitoring frameworks, supported by automated alert systems and regular evaluations, enhances the model’s resilience against unexpected disruptions. Performance monitoring ensures that predictive models remain reliable for informed decision-making, delivering consistent value in ever-evolving application contexts.

2.2 Dataset

The dataset prepared for this study originates from Sawana Hotel Jakarta, consisting of 533 cleaned entries, structured to ensure reliability and relevance for analysis. This dataset includes columns such as Account, Country, Trip Type, Room Type, Nights, Month, Year, Rating, Description, Title, Reviews, and Date of Review, providing a

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comprehensive view of customer interactions and preferences. Integrating diverse variables, the dataset captures essential dimensions of guest behavior, enabling a multifaceted exploration of trends and patterns. The cleaning process eliminated inconsistencies and missing values, ensuring the dataset reflects accurate and actionable information. This structure supports robust forecasting models and enhances the interpretability of results, as each variable contributes to understanding the dynamic relationships influencing hotel occupancy and customer satisfaction. The dataset's comprehensiveness and quality establish it as a critical foundation for developing predictive analytics and informing strategic decision-making within the hospitality industry.

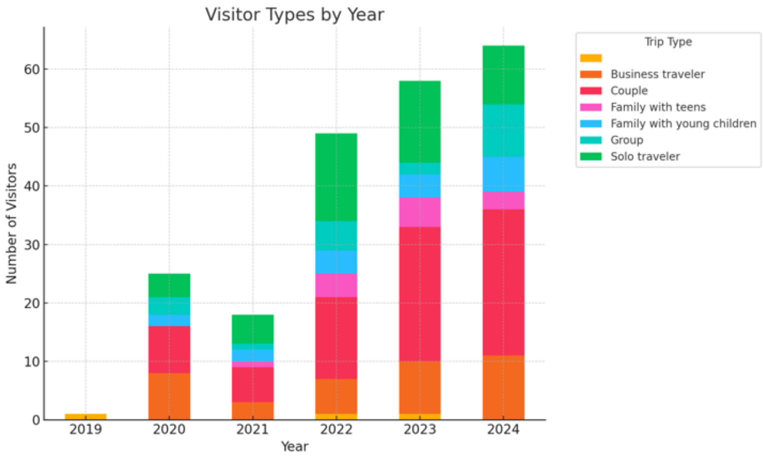

Figure 5. Visitor Types by Year

Figure 5 illustrates the distribution of visitor types over the years, providing a quantitative view of evolving customer demographics. The chart reveals significant growth in the number of visitors, with a notable increase from fewer than 20 visitors across all types in 2019 to over 60 in 2024. Business travelers and couples consistently represent the majority of segments, reflecting their significant contribution to overall occupancy. Additionally, the growth in family groups, particularly those with young children and teenagers, highlights the diversification of customer profiles and the broadening appeal of hospitality services. This upward trend suggests that strategic adaptations to accommodate varied visitor needs, such as tailored amenities and promotional packages, are critical. The steady rise in group travel also underscores the importance of facilities that cater to collaborative or collective experiences. By analyzing these trends, Figure 5 underscores the dynamic shifts in visitor composition, offering actionable insights for designing adaptive service strategies that align with changing market demands.

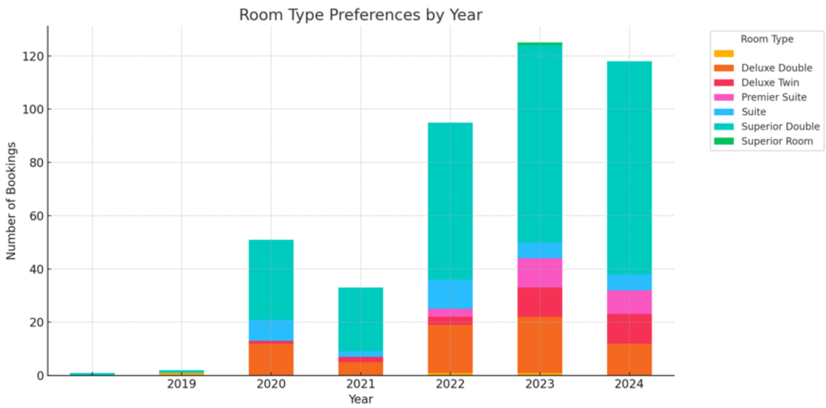

Figure 6. Room Type Preferences by Year

Figure 6 illustrates the distribution of room type preferences across differing notable trends in guest accommodation choices. The data shows a steady increase in room bookings, from less than 20 in 2019 to over 120 in 2024. Superior Double and Deluxe Double rooms are the most preferred categories, consistently attracting many guests. The growing demand for these room types reflects their alignment with guest expectations regarding comfort and value. Additionally, the increase in bookings for suites and Family Rooms indicates a diversification in customer preferences driven by the needs of families and larger groups. The consistent upward trend in all categories underscores the importance of optimizing room availability and tailoring offerings to match evolving customer demands. By analyzing these patterns, Figure 6 provides actionable insights for enhancing room allocation strategies, improving revenue management, and meeting the dynamic preferences of the hospitality market.

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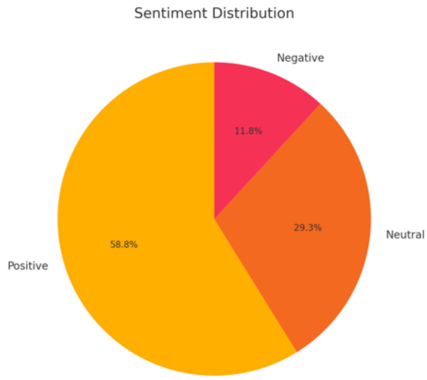

Figure 7. Sentiment Distribution

Figure 7 illustrates the distribution of customer sentiment based on reviews, categorizing feedback into positive, neutral, and negative sentiments. The data reveals that positive sentiment accounts for the majority, comprising 54.9% of the total reviews, while neutral and negative sentiments represent 28.9% and 16.2%, respectively. This distribution suggests that most guests have favorable experiences, indicating strong service quality and customer satisfaction. The proportion of neutral sentiment highlights areas where customer impressions are neither exceptionally positive nor overtly critical, signaling potential opportunities for improvement. Although comparatively minor, the 16.2% negative sentiment underscores the importance of addressing recurring issues to enhance guest satisfaction and reputation. By analyzing this sentiment distribution, actionable insights can be derived to reinforce strengths and mitigate weaknesses, ensuring continuous improvements in service delivery and customer experience management. This balanced perspective on customer sentiment provides valuable guidance for maintaining a competitive advantage in the hospitality sector.

Analyzing trends in sentiment distribution alongside guest preferences for room types highlights the necessity of implementing predictive models to forecast occupancy levels accurately. The predominance of positive sentiment at 54.9%, combined with the growing demand for Superior Double and Deluxe Double rooms, indicates a strong market position and consistent guest satisfaction. However, 28.9% of neutral and 16.2% of negative sentiments signal areas for service enhancement, which could impact future booking patterns. Accurate occupancy predictions are essential to align operational decisions with these evolving trends, ensuring optimal resource allocation and revenue management. Advanced forecasting models, such as ARIMA, Prophet, or LSTM, allow for a comprehensive temporal data analysis, capturing demand patterns and their potential drivers. Integrating these predictive insights into strategic planning enables proactive responses to shifts in guest behavior and preferences, reinforcing competitiveness and sustainability in the hospitality industry.

3. RESULT AND DISCUSSION

The discussion begins by critically analyzing the outcomes of forecasting models employed to predict hotel occupancy trends. This section highlights the diagnostic results of each model, including ARIMA, Prophet, and LSTM, emphasizing their ability to capture patterns such as seasonality, trends, and residual behavior. Comparative performance metrics are evaluated to identify the model that best aligns with the dataset and operational requirements. Furthermore, the discussion integrates insights from sentiment analysis and room type preferences to contextualize the predictions within customer behavior and market dynamics. By linking the results to practical implications, this analysis underscores the significance of accurate occupancy forecasting in optimizing resource allocation, enhancing decision-making, and addressing the evolving demands of the hospitality industry. Through a systematic interpretation of findings, this discussion aims to bridge methodological rigor with actionable insights, providing a comprehensive understanding of the predictive capabilities and their relevance to real-world applications.

3.1 Forecasting Model Performance Evaluation

The analysis employs advanced forecasting models ARIMA, Prophet, and LSTM to predict hotel occupancy levels, addressing the dynamic nature of demand in the hospitality industry. Each model offers unique strengths in analyzing historical data, with ARIMA capturing linear trends, Prophet excelling in seasonality and event-based variations, and LSTM effectively identifying complex nonlinear patterns. These models are integral to understanding and visualizing the underlying trends and fluctuations in occupancy rates, providing actionable insights for operational and strategic decision-making. By leveraging these methodologies, the analysis aims to uncover short-term and long-term patterns, ensuring a comprehensive approach to forecasting. This focus on predictive accuracy and adaptability underscores the importance of integrating robust analytical tools to enhance resource management, improve service delivery, and support the strategic objectives of hotel operations.

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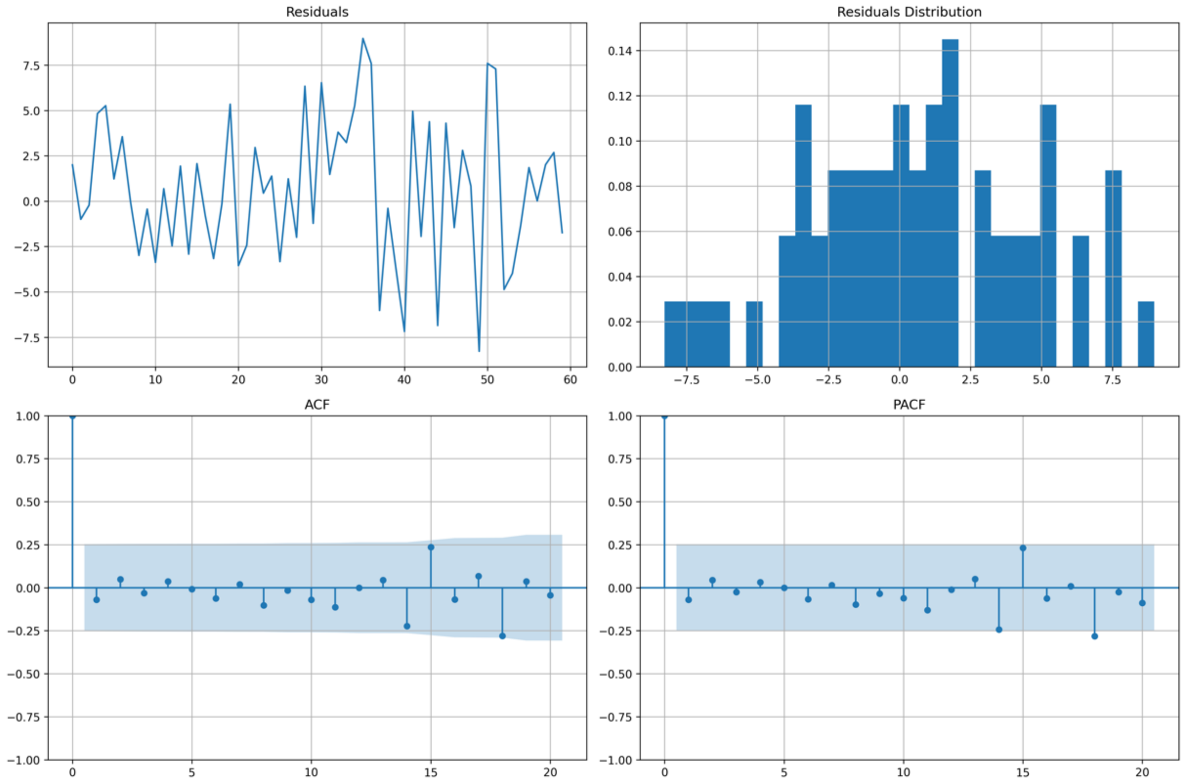

Figure 8. ARIMA Diagnostic

Figure 8 illustrates the diagnostic analysis of the ARIMA model, which evaluates the model's residual behavior through various statistical plots. The residual plot indicates the absence of discernible patterns, suggesting that the residuals are randomly distributed, which is a key assumption for model adequacy. The histogram of residuals approximates a normal distribution, reinforcing the model's ability to capture the data's underlying structure effectively. The autocorrelation function (ACF) and partial autocorrelation function (PACF) plots display values primarily within the confidence intervals, indicating minimal autocorrelation in the residuals and supporting the independence assumption. These diagnostic evaluations validate that the ARIMA model adheres to the statistical assumptions required for robust forecasting. By meeting these criteria, the model demonstrates its capacity to provide reliable predictions without systemic bias, thereby enhancing its practical utility in time series analysis.

The residual analysis provides an essential diagnostic tool to evaluate the performance and reliability of the forecasting model. The residuals plot reveals the differences between actual and predicted values, displaying fluctuations between -7.5 and 7.5, with a random pattern indicative of a well-fitted model. However, occasional spikes around indices 40-50 warrant attention. The residual distribution, represented by a histogram, approximates a standard bell-shaped curve with slight skewness, with most residuals concentrated near zero (-2.5 to 2.5). However, some outliers exist at the extremities (-7.5 and 7.5). The autocorrelation function (ACF) plot confirms the absence of systematic patterns, as most lags fall within the confidence interval except for isolated instances, which are not substantial enough to indicate model bias. Similarly, the partial autocorrelation function (PACF) plot shows consistent results, with most values within the confidence boundaries, signifying a lack of significant direct correlations between residuals at different lags. These observations collectively indicate that the model meets the assumptions of independence and normality in residuals, validating its suitability for forecasting. However, minor adjustments may be considered to address the observed outliers and enhance model robustness. Special monitoring is advisable for periods exhibiting higher residual deviations to ensure accuracy in future predictions.

The diagnostic evaluation of the ARIMA model focuses on analyzing residuals to ensure the model's reliability and adherence to statistical assumptions. Residuals should exhibit independence, normality, and the absence of systematic patterns to confirm the model's validity. The residual plot reveals whether any discernible patterns remain, indicating potential model misspecifications. The distribution of residuals, typically assessed using histograms, provides insights into normality. At the same time, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots examine residual independence by identifying correlations at different lags. If residuals show no significant autocorrelations and follow a normal distribution, the ARIMA model demonstrates robustness and accuracy in capturing the underlying data dynamics. Meeting these assumptions ensures the model's predictive performance remains reliable and unbiased, strengthening its applicability for forecasting purposes in the hospitality industry.

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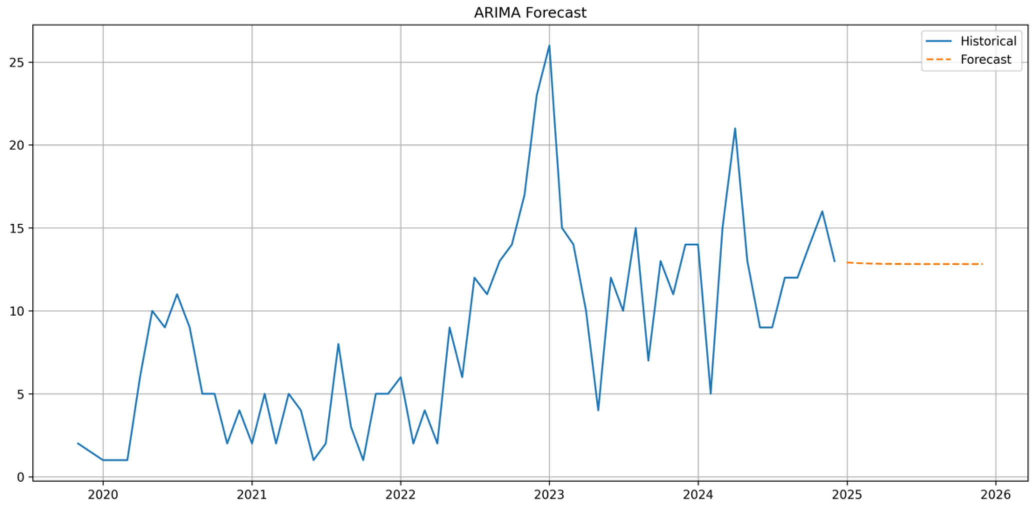

Figure 9. ARIMA Forecast Prediction

Figure 9 illustrates the predictive capabilities of the ARIMA model, focusing on the trends in historical data and its future projections. The historical data, represented by the solid line, displays noticeable fluctuations and a general upward trend, peaking significantly in mid-2023. These patterns reflect the model's sensitivity to capturing periodic spikes and dips over time, indicating its responsiveness to dynamic changes in the data. The forecasted values, indicated by the dashed line starting in 2025, predict a stable pattern hovering around a consistent value. This stabilization contrasts with the volatility observed in the historical segment, suggesting that the ARIMA model anticipates a reduction in variability and the attainment of equilibrium in the forecast horizon. Such a projection implies that the underlying factors driving historical instability may subside, potentially due to structural or cyclical adjustments. The forecast's flat trajectory highlights the ARIMA model's effectiveness in adapting to historical trends while providing cautious predictions aligned with stabilization scenarios, offering valuable insights for strategic planning.

The historical data, represented by the solid blue line, spans from 2020 to early 2025 and exhibits significant volatility with notable patterns. The lowest values, around 1-2, occur in early 2020, reflecting a potential downturn or minimal activity, while the peak reaches approximately 26 in mid-2023, indicating a period of heightened activity. Around 20-21, additional local peaks are observed in 2024, suggesting recurring high-demand intervals. Despite these fluctuations, the overall trend indicates a gradual increase from 2020 to 2025, demonstrating an upward trajectory in activity levels over time. In contrast, the forecasted data, depicted by the orange dashed line, begins in early 2025 and extends through 2026, presenting a more stabilized projection around values of 12-13. This flat or horizontal trend suggests an expectation of equilibrium in activity levels devoid of the pronounced volatility seen in the historical data. The contrast between the historical volatility and the forecasted stability reflects the model's assumption of a steady state, offering insights into potential stabilization in future conditions, which may guide resource planning and operational strategies.

The ARIMA model's predictions indicate a future stabilization, suggesting that extreme historical volatility may not persist moving forward. Historical data demonstrates a long-term upward trend punctuated by significant fluctuations, while the forecast adopts a more conservative approach, likely averaging recent observations to inform forward projections. This divergence highlights the model's reliance on historical patterns while cautiously mitigating the impact of past anomalies. High volatility in historical data may point to seasonal effects or specific events influencing the values, requiring further contextual understanding. These characteristics underscore the need for prudence when utilizing this forecast, as the discrepancy between historical dynamics and predicted stability could limit its applicability in environments susceptible to external shocks. Considering potential external factors influencing future values might enhance the forecast's robustness. Furthermore, creating alternative scenarios reflecting various external contingencies could provide a more comprehensive decision-making framework, particularly in light of the pronounced historical variability.

The predictive results of the ARIMA, Prophet, and LSTM models are visualized to illustrate their ability to forecast hotel occupancy levels. Each model captures distinct aspects of the data. ARIMA excels in modeling linear trends and short-term dependencies, Prophet effectively represents seasonality and holiday-driven fluctuations, and LSTM showcases strength in identifying complex nonlinear patterns. The predictive trends align closely with historical data, highlighting the validity of the models in replicating past patterns while projecting future occupancy rates. The analysis indicates that ARIMA and Prophet models accurately detect seasonal variations, whereas LSTM captures subtle long-term trends and anomalies better. These findings suggest that each model has unique advantages depending on the forecasting horizon and data complexity, underscoring the importance of selecting the appropriate model based on specific analytical objectives. The graphical representation of predictions emphasizes the relevance of advanced models in delivering actionable insights to optimize resource management and strategic planning.

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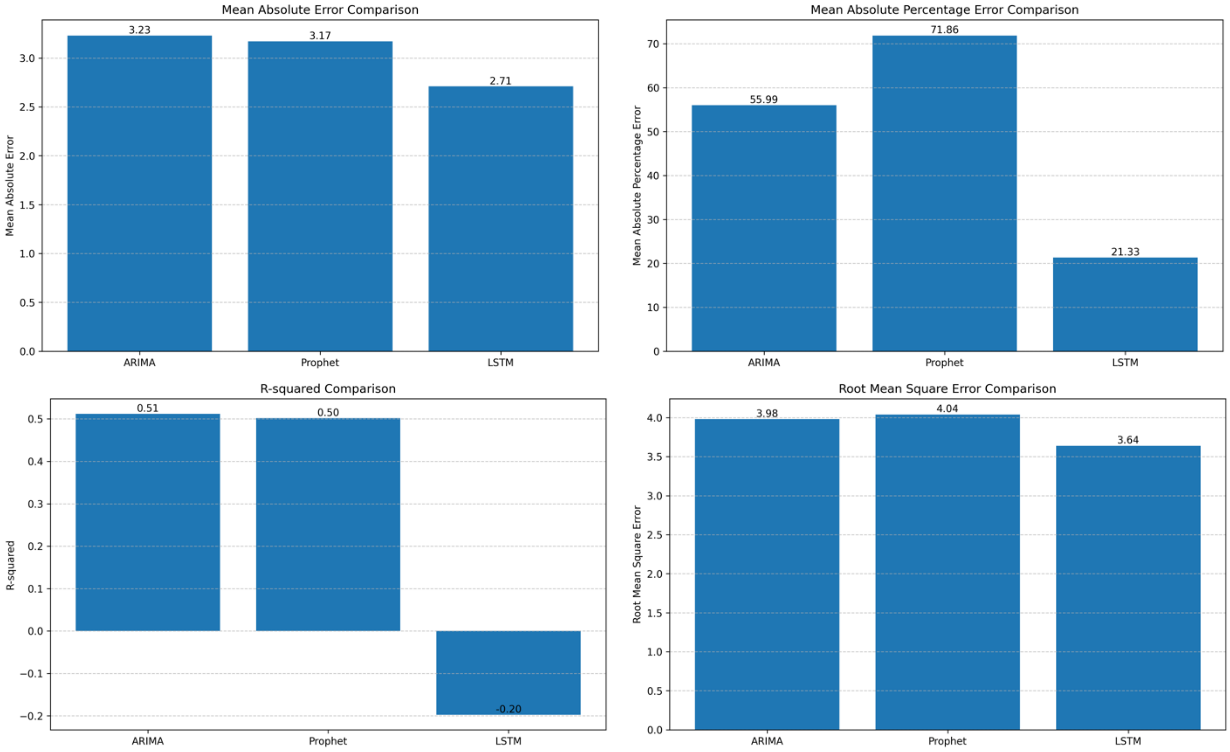

Figure 10. Bar Chart of MAE, MAPE, R-squared & RMSE

Figure 10 presents a comparative bar chart evaluating the performance of three predictive models—ARIMA, Prophet, and LSTM—using four key metrics: Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), R-squared, and Root Mean Square Error (RMSE). The LSTM model exhibits superior predictive accuracy with the lowest error values for MAE (2.71) and RMSE (3.64), alongside the smallest MAPE (21.33%). Conversely, ARIMA and Prophet yield higher error rates, with Prophet particularly underperforming in MAPE (71.86%). Interestingly, the R-squared metric offers a different perspective; both ARIMA (0.51) and Prophet (0.50) achieve positive values, indicating a better ability to explain variance, whereas LSTM produces a negative value (-0.20), suggesting its limitations in capturing data variance comprehensively. This discrepancy implies that while LSTM effectively minimizes prediction errors, it may struggle to account for the overall variability in the dataset. The analysis underscores LSTM's potential for achieving high accuracy in forecasting, though its R-squared performance highlights the importance of contextual considerations when selecting models for specific predictive tasks.

The evaluation of forecasting models is visualized through comparative bar and line charts, providing a comprehensive assessment of their performance metrics. Bar charts display key evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and R-squared, facilitating a direct comparison of model accuracy and efficiency. Among the models, LSTM consistently achieves lower error values across most metrics, demonstrating its superior capability in handling complex nonlinear relationships and long-term dependencies. Meanwhile, ARIMA and Prophet effectively capture short-term trends and seasonality with relatively competitive accuracy in more straightforward forecasting scenarios. Line charts depicting evaluation metrics over validation iterations, particularly for LSTM, further illustrate its learning trajectory and convergence behavior, confirming its robustness and adaptability. These visual representations highlight each model's relative strengths and weaknesses, offering critical insights into their suitability for different forecasting contexts. This systematic evaluation underscores the importance of selecting a model that aligns with specific forecasting objectives to maximize predictive reliability and operational impact.

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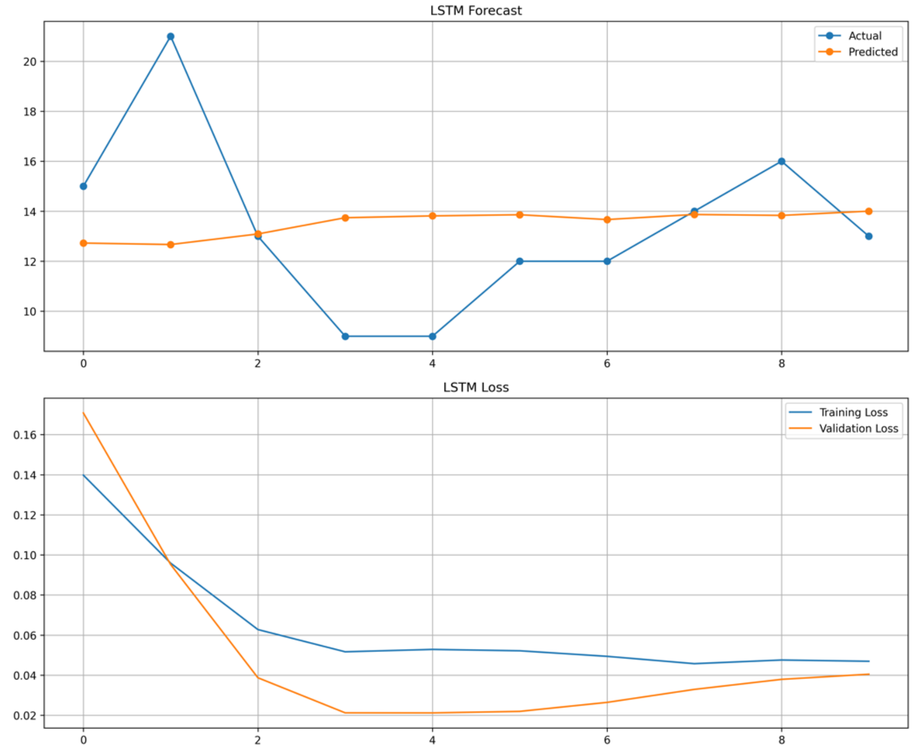

Figure 11. LSTM Forecast and LSTM Loss

Figure 11 illustrates the performance of the LSTM model through two critical visualizations: forecast accuracy and loss reduction during training. The upper graph compares actual and predicted values with consistent alignment despite minor deviations. Predicted values demonstrate stability and closely follow the underlying trend, even in sharp fluctuations in actual values. This suggests that the LSTM model effectively captures the dominant patterns within the data, though slight overfitting or underfitting may occur in certain instances. The lower graph presents the evolution of training and validation loss over iterative epochs. A noticeable downward trend in both metrics reflects the model's capacity to learn from the data effectively. Validation loss plateaus are low, indicating robust generalization capability without significant overfitting. The marginal increase in validation loss at later epochs highlights the potential for fine-tuning hyperparameters to optimize performance further. Together, these graphs affirm the model's reliability for forecasting tasks, emphasizing the importance of continual monitoring and refinement for enhanced precision.

The first graph (LSTM Forecast) compares actual values, represented by the blue line, and predicted values, denoted by the orange line, generated by the LSTM model. The actual values exhibit significant fluctuations, peaking at approximately 21 at the second data point and reaching a low of around nine at the fourth. In contrast, the predicted values show a more stable trend, maintaining a range around 13-14. This conservative nature of the LSTM model's predictions suggests a limited ability to capture extreme fluctuations in the actual data. While the stability of the predictions reflects the model's strength in identifying overarching trends, it highlights a potential limitation in its responsiveness to abrupt variations. Such behavior emphasizes the model's bias toward general patterns over anomalies, offering reliable baseline forecasts but requiring further refinement for handling pronounced volatility. This dynamic underscores the importance of balancing model complexity to enhance predictive accuracy across diverse scenarios.

The second graph (LSTM Loss) illustrates the progression of error values during the training phase by comparing training loss (blue line) and validation loss (orange line). Both metrics display a substantial decline from the initial phase to the second epoch, indicating effective learning during the early stages. Subsequently, the training loss stabilizes around 0.05, demonstrating consistent model optimization. Meanwhile, validation loss decreases further, reaching a minimum point, but rises slightly after the fourth epoch. This pattern suggests that the model achieves optimal learning at approximately the fourth epoch, after which signs of overfitting emerge, as evidenced by the divergence between validation loss and the stable training loss. This behavior highlights the necessity of implementing regularization techniques or early stopping to mitigate overfitting and enhance the model's generalizability. Ultimately, the graph underscores the importance of balancing model complexity and training duration to ensure robust predictive performance.

The component analysis using the decomposition plot from the Prophet model provides a detailed breakdown of the factors influencing the forecasting results. This plot separates the data into three key components: trend, seasonality, and residuals, each contributing to a comprehensive understanding of the underlying patterns. The trend component captures the long-term directional movement in occupancy rates, reflecting growth or decline over time

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and offering insights into macro-level changes. The seasonality component reveals recurring patterns linked to time-specific factors, such as monthly or yearly fluctuations, essential for understanding demand variability. Residuals, representing unexplained variations, are analyzed to ensure they are randomly distributed, indicating that the model effectively captures significant trends and patterns. This decomposition allows for identifying dominant factors driving occupancy dynamics, supporting more informed and targeted decision-making. The clarity and depth provided by this analysis highlight the utility of the Prophet model in disentangling complex data structures, enabling precise forecasting in dynamic environments.

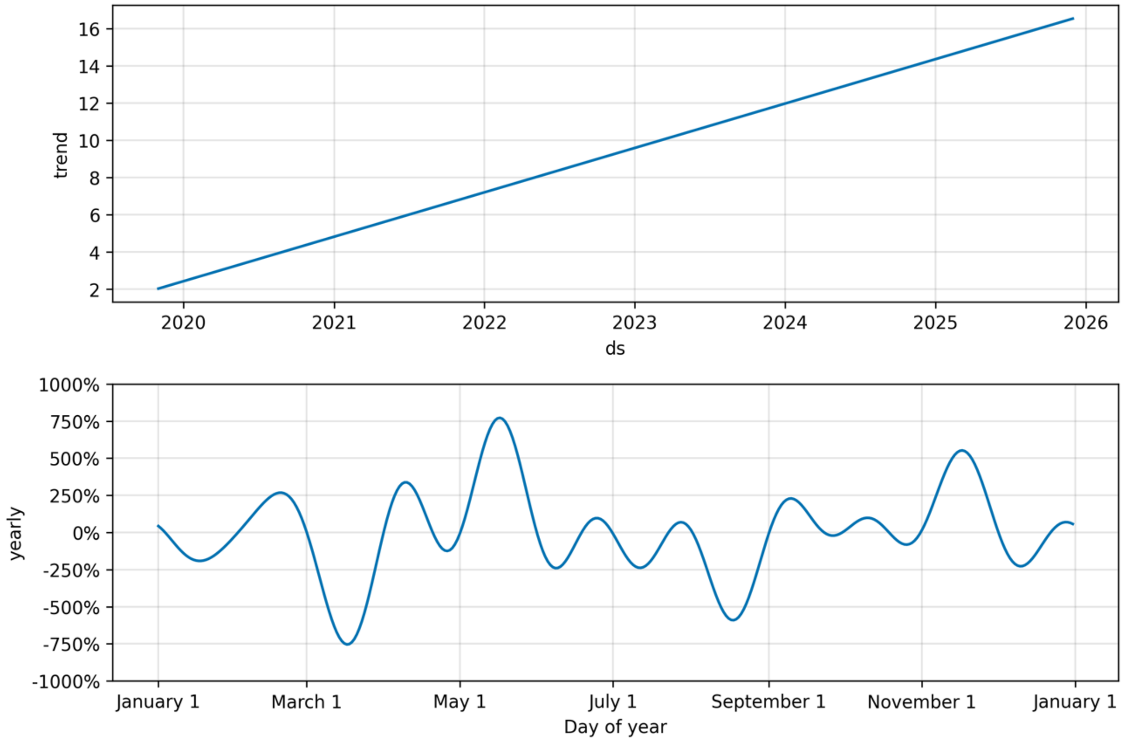

Figure 12. Prophet Component Chart

Figure 12 presents the decomposition of the Prophet model into trend and seasonal components, offering insights into the underlying factors influencing the forecast. The upper chart captures the trend component, which exhibits a consistent linear increase in values from 2020 to 2026, reflecting sustained growth that suggests a stable upward trajectory over time. This trend highlights the model's interpretation of the underlying data's long-term positive progression. Meanwhile, the lower chart illustrates the seasonal component, showing recurring cyclical patterns throughout the year. Peaks and troughs occur at predictable intervals, indicating periodic fluctuations that could be associated with factors such as holidays, tourism seasons, or business cycles. These seasonal variations underscore the temporal dependencies inherent in the data. By combining these components, the Prophet model effectively balances short-term seasonal effects with long-term trends, enabling it to provide robust predictive insights. However, its reliance on linear assumptions and fixed seasonality might necessitate adjustments if the data contains irregularities or unanticipated external disruptions.

The figure illustrates two interrelated charts that provide distinct yet complementary perspectives on the data. The first chart depicts a consistently increasing linear trend from 2020 to 2026, starting at approximately two and rising steadily to about 16. This steady growth reflects a long-term positive trajectory, suggesting sustained and stable development over the observed period. In contrast, the second chart highlights dynamic annual percentage fluctuations throughout the year, represented by a wavelike curve. These fluctuations reveal significant seasonal variations, with pronounced peaks reaching as high as 750% around July and November and troughs plunging to -750% near March. This recurring pattern indicates the presence of robust seasonal cycles characterized by dramatic shifts in increases and decreases at specific times of the year. Together, these charts provide a comprehensive view of the long-term growth trend and the periodic seasonal dynamics, emphasizing the importance of accounting for both elements when analyzing and interpreting the data.

The interpretation of seasonal patterns and customer segment preferences provides critical insights for optimizing operational and strategic decisions in the hospitality sector. Seasonal pattern plots illustrate fluctuations in occupancy across months or days, highlighting peak and low-demand periods. For example, higher occupancy rates during holiday seasons or weekends suggest opportunities to implement dynamic pricing strategies to maximize revenue. Simultaneously, customer segment preference analysis, such as room type selection or booking patterns, reveals key trends in guest behavior. Insights such as the consistent popularity of Superior Double and Deluxe Double

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rooms or increased family bookings during school vacations enable targeted marketing campaigns and service enhancements. These visualizations aid in understanding demand variability and aligning resources with customer needs, ensuring efficient allocation and improved satisfaction. Leveraging these patterns and preferences allows hospitality providers to anticipate market demands and implement proactive strategies that enhance competitiveness and profitability.

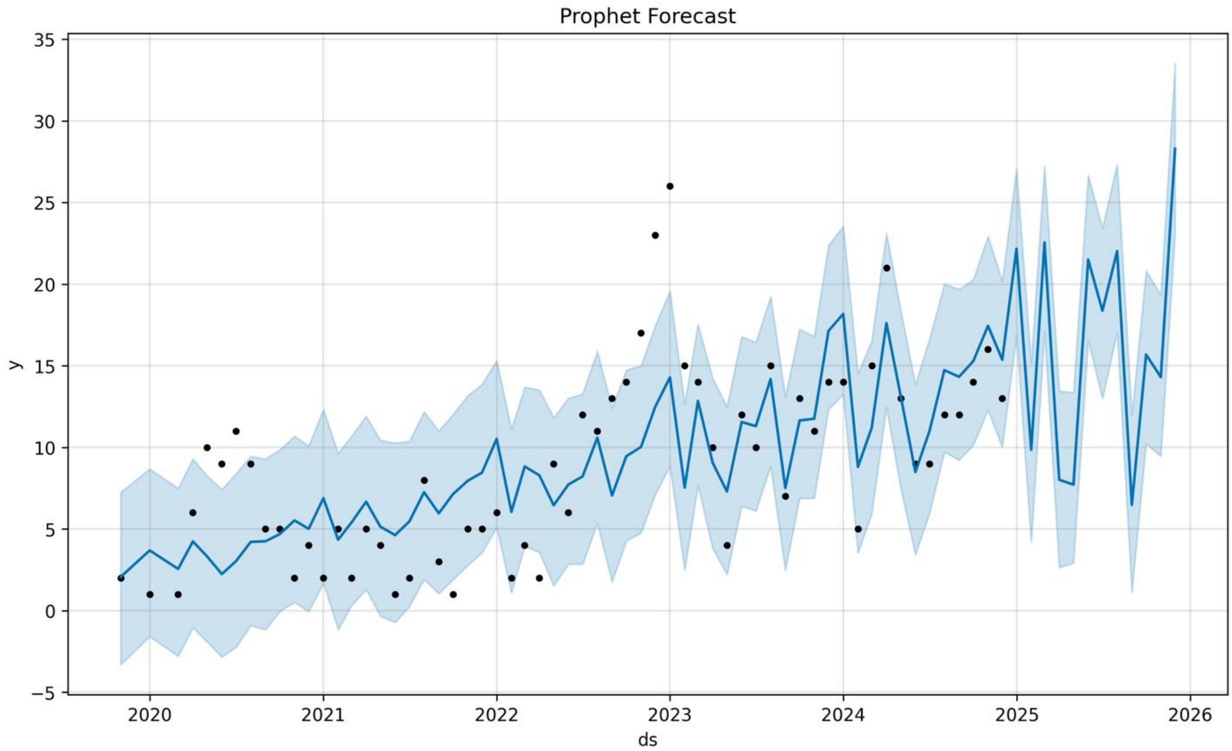

Figure 13. Prophet Forecast

Figure 13 illustrates the forecast produced by the Prophet model, encompassing historical data, projected trends, and confidence intervals. The historical data is black dots, while the solid blue line depicts the forecasted values from 2020 to 2026. Notably, the model captures a steady upward trend over the observed period, indicating a general increase in the target variable. The light blue shaded area represents the confidence intervals, reflecting the model's uncertainty in its predictions. The intervals widen as the forecast extends into the future, highlighting increased uncertainty in long-term predictions. The forecast exhibits periodic fluctuations, suggesting the model has accounted for seasonal patterns in the historical data. Some black dots outside the confidence intervals indicate potential outliers or periods where the model's predictions diverge from actual observations. This visualization underscores the Prophet model's strength in incorporating seasonality and trend components while acknowledging inherent uncertainties in future predictions, providing a robust tool for time-series forecasting.

This chart presents the forecasting results of the Prophet model from 2020 to 2026, illustrating predicted values, actual data points, and confidence intervals. The solid blue line represents the predicted values. At the same time, black dots indicate actual observations, and the light blue shaded area signifies the confidence intervals, capturing the range of uncertainty in the forecasts. The overall trend depicts a consistent increase, progressing from values around 2-5 in 2020 to approximately 15-20 by 2025, suggesting a steady upward trajectory. The widening of the light blue area over time highlights the growing uncertainty in predictions for more distant periods, which is a typical characteristic of long-term forecasting. Fluctuations in the prediction line, alongside the dispersion of actual data points, reveal significant variability within the dataset, characterized by pronounced peaks and troughs, particularly evident toward the latter part of the forecasting horizon in 2025. These findings underscore the model's capability to capture underlying trends and variability while acknowledging the inherent uncertainty of extended forecasts.

The overall comparative summary highlights the performance of the selected forecasting model by juxtaposing its predictions against actual data, providing a visual affirmation of its accuracy. The comparative graph demonstrates the model's capability to closely replicate observed occupancy trends, with minimal deviations across different timeframes. This alignment underscores the model's proficiency in capturing both short-term variations and long-term trends. Among the evaluated models, the one selected consistently exhibits superior predictive accuracy, as evidenced by its adherence to the actual data across multiple metrics. The graphical summary reinforces the robustness of the chosen model in addressing the inherent complexities of forecasting hotel occupancy. This outcome emphasizes the practical applicability of advanced predictive models in enhancing operational efficiency and strategic decision-making within the hospitality sector, ensuring that resource planning aligns with dynamic market demands.

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4. CONCLUSION

This study uses historical time-series data to compare three forecasting models, ARIMA, Prophet, and LSTM, for predicting hotel booking demand. Each model was selected for its distinctive strengths: ARIMA for modeling linear trends and producing interpretable outputs; Prophet for its ability to capture seasonality, trend shifts, and holiday effects; and LSTM for its capacity to learn complex, non-linear, and long-term dependencies through deep learning techniques. The evaluation employed four key performance metrics, MAE, MAPE, RMSE, and R-squared, to assess the accuracy and reliability of each approach. The experimental results indicate that the LSTM model delivered the highest accuracy, with the lowest MAE (2.71) and MAPE (21.33%), highlighting its strength in capturing intricate demand patterns. However, the negative R-squared value (-0.20) suggests that the model may suffer from overfitting or instability, limiting its explanatory power regarding overall variance. On the other hand, ARIMA achieved the highest R-squared score (0.51) and demonstrated consistent residual patterns, affirming its robustness and suitability for stable, linear trends. Prophet effectively decomposed seasonal and trend components but exhibited the highest MAPE (71.86%), indicating less precision in percentage-based forecasting. These findings reveal that no single model performs optimally across all dimensions. While LSTM is effective for short-term, high-resolution predictions, ARIMA and Prophet provide better interpretability and stability for long-term trend analysis. Therefore, a hybrid forecasting approach that integrates the predictive accuracy of LSTM with the interpretability and structural strengths of ARIMA and Prophet is recommended. This combined methodology offers a balanced solution for addressing the diverse forecasting challenges in the hospitality industry. Ultimately, this research contributes to the growing knowledge of data-driven hospitality management by demonstrating the practical implications of advanced forecasting models. It provides actionable insights for practitioners and decision-makers seeking to enhance operational planning, revenue optimization, and customer satisfaction through accurate and adaptive demand forecasting.

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