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Research article

LSTM Neural Network for Predicting Tourist Arrivals to Bali

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ABSTRACT

Tourism is a key pillar of Bali's economy, contributing significantly to employment, cultural preservation, and income generation. Accurate forecasting of tourist arrivals is crucial for sustainable growth and resource optimization. This study applies Long Short-Term Memory (LSTM) neural networks to predict tourist arrivals in Bali, leveraging historical data and external factors such as global economic indicators, flight frequencies, cultural events, and environmental conditions. LSTM's ability to model complex temporal dependencies and non-linear relationships offers significant advantages over traditional methods like ARIMA, especially in handling seasonal patterns and irregularities. The model was trained on a robust dataset, preprocessed to address missing values, outliers, and variability. Performance evaluation metrics, including RMSE, demonstrate high predictive accuracy during stable periods but highlight limitations in handling anomalies such as the COVID-19 pandemic. To address these challenges, recommendations include integrating additional external variables, employing hybrid models, and conducting scenario-based sensitivity analyses to enhance adaptability and robustness. The results highlight the practical utility of AI-driven forecasting tools in tourism management, providing actionable insights for policymakers and stakeholders to optimize planning, mitigate risks, and support sustainable development. This research contributes to the growing field of AI applications in tourism, promoting resilience and competitiveness in an increasingly dynamic global market.

1. Introduction

Tourism is a cornerstone of Bali's economy, providing significant contributions to employment, income generation, and cultural preservation. However, the highly dynamic nature of tourist arrivals presents challenges for effective planning and resource allocation. External factors such as seasonal trends, global economic conditions, geopolitical events, and unforeseen disruptions like the COVID-19 pandemic have led to significant variability in tourist flows. Accurate forecasting of tourist arrivals is, therefore, essential for optimizing tourism infrastructure, improving resource allocation, and ensuring sustainable economic development. In recent years, the integration of advanced machine learning techniques in time-series forecasting has revolutionized predictive modeling. Among these methods, Long Short-Term Memory (LSTM) neural networks, a variant of recurrent neural networks (RNNs), have gained prominence due to their ability to model long-term dependencies and non-linear relationships in sequential data. Unlike traditional methods such as ARIMA or exponential smoothing, LSTMs are capable of learning complex temporal patterns without requiring pre-defined assumptions about the data[1] has demonstrated the superior performance of LSTMs in forecasting applications, particularly in domains where data exhibit seasonality and irregularities. This study aims to leverage the power of LSTM neural networks to predict tourist arrivals to Bali by utilizing a comprehensive dataset that incorporates multiple influencing factors. These factors may include historical tourist arrival data, global economic indicators, flight frequencies, cultural event schedules, and environmental conditions. By tailoring the model to Bali's unique tourism dynamics, the study seeks to address limitations in generalized forecasting models, providing stakeholders with a more accurate and actionable tool for decision-making.Bali's dependence on tourism underscores the importance of this research. An accurate prediction model can guide policymakers and business leaders in managing infrastructure investments, preparing for peak tourist seasons, and mitigating the impact of external shocks. Moreover, this study aligns with the growing trend of adopting AI-driven solutions in tourism management, as seen in recent works[2]. These studies highlight the potential of AI not only in improving forecasting accuracy but also in fostering resilience and adaptability in the face of global uncertainties.The outcomes of this research are expected to contribute to the broader field of tourism forecasting while offering practical benefits for Bali. By bridging the gap between advanced AI techniques and real-world tourism challenges, this study aspires to support the sustainable growth of Bali's tourism sector, ensuring its continued relevance and competitiveness in the global market.

2. Research Methods

This study employs a robust methodological framework to develop and evaluate a Long Short-Term Memory (LSTM) neural network model for predicting tourist arrivals to Bali. The methodology is designed to address the inherent complexities of tourism demand forecasting, including seasonal variations, external shocks, and non-linear patterns in the data. By leveraging a data-driven approach, the research integrates historical tourist arrival data and relevant external factors, such as global economic indicators, cultural event schedules, and environmental conditions, into the model.LSTM neural networks, renowned for their ability to capture long-term dependencies in sequential data, have demonstrated superior performance in time-series forecasting tasks across various domains[3] The choice of LSTM over traditional statistical methods, such as ARIMA, is motivated by its capacity to handle non-stationary and complex datasets effectively. The model architecture is carefully designed to include layers that mitigate vanishing gradient issues, ensuring accurate predictions over extended time horizons.Furthermore, the dataset used in this study is preprocessed to address potential noise and missing values, ensuring data quality and consistency. Recent advancements in AI for tourism management emphasize the importance of such tailored approaches to enhance forecasting accuracy and inform sustainable tourism strategies[4].

The research methodology is structured to design, implement, and evaluate a Long Short-Term Memory (LSTM) neural network for predicting tourist arrivals to Bali. This framework comprises several critical stages, including data collection, preprocessing, model development, training, evaluation, and validation.

2.1. Data Collection

The dataset used in this study is pivotal for developing a robust predictive model for tourist arrivals to Bali. It includes comprehensive historical records of monthly tourist arrivals spanning multiple years, which serve as the primary variable for forecasting. This data was obtained from official government agencies such as Bali's tourism board and Indonesia's Central Bureau of Statistics (BPS), ensuring accuracy and reliability.

To enhance the predictive power of the model, the dataset is enriched with several external factors that significantly influence tourism demand. These factors include:

1. Global Economic Indicators

Indicators such as exchange rates, global GDP growth, and consumer confidence indexes from Bali's key source countries were incorporated to account for macroeconomic trends affecting international travel[5].

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2. Airline Traffic Data

Monthly statistics on the number of international and domestic flights to Bali, along with passenger seat capacity, were included to reflect accessibility and travel frequency[5].

3. Weather Conditions

Data on Bali's climatic conditions, such as average monthly temperature, rainfall, and extreme weather events, were sourced from meteorological agencies. These variables help capture the impact of seasonal weather patterns on tourist preferences[6].

4. Cultural Event Schedules

Information on Bali's key cultural and religious events, such as Galungan, Nyepi, and international festivals, was collected to account for surges in tourist arrivals during these occasions. The inclusion of this factor aligns with prior studies emphasizing the importance of event-driven tourism[7].

5. Pandemic and Crisis Data

Given the significant impact of the COVID-19 pandemic on global tourism, the dataset incorporates variables such as government-imposed travel restrictions, vaccination rates, and recovery timelines. These factors were integrated to reflect post-pandemic recovery patterns[7].

6. Socio-political Factors

Indicators such as travel advisories, visa policies, and international relations were considered, as these influence tourists' destination choices and perceptions of safety[7].

2.2. Data Preprocessing

Data preprocessing steps were undertaken to address missing values, remove outliers, and ensure uniform scaling for integration into the model. The inclusion of these diverse and complementary data sources provides a holistic view of the factors driving tourism demand in Bali, enabling the development of an accurate and context-sensitive forecasting model. This approach aligns with recent studies emphasizing the need for multi-faceted datasets in tourism forecasting[8].

Data preprocessing is a critical step to ensure the input data is clean, consistent, and suitable for training the Long Short-Term Memory (LSTM) model. Given the complexity and variability of time-series data in tourism forecasting, several preprocessing techniques were employed to enhance the quality and usability of the dataset:

1. Handling Missing Values
   Missing data points were identified and addressed using advanced imputation techniques. For continuous variables, interpolation methods such as linear or cubic splines were applied. Categorical missing data, such as event-related entries, were filled using historical averages or domain-specific knowledge to preserve data integrity.
2. Outlier Detection and Removal
   Outliers were detected using statistical methods like the interquartile range (IQR) and z-scores, as well as visual inspection via box plots and scatter plots. Extreme outliers, often caused by reporting errors or irregular events, were either replaced with median values or treated with robust regression methods to minimize their influence on the model.
3. Normalization
   To ensure compatibility across different data ranges and units, normalization techniques were applied. Min-max scaling was used to rescale the data to a range of [0, 1], which is particularly important for deep learning models to improve convergence during training.
4. Time-Series Transformation
   Raw time-series data were converted into a supervised learning format by creating lagged variables. This step involved generating input-output pairs, where past observations (lags) served as predictors for future tourist arrivals. The length of the lag window was optimized based on autocorrelation analysis and model performance[9].
5. Seasonal Decomposition

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Seasonal decomposition of time series (STL) was conducted to isolate and analyze trends, seasonality, and residual components. By breaking down the data into these components, the model could better capture long-term growth patterns, recurring seasonal fluctuations, and irregular shocks[9].

6. Data Augmentation

   To enhance the robustness of the dataset, synthetic data points were generated using oversampling techniques, particularly for underrepresented periods such as low tourist seasons. These methods ensured that the model was exposed to a diverse range of scenarios during training.

These preprocessing steps collectively ensure that the dataset is well-prepared for input into the LSTM model, enhancing the model's ability to learn and generalize from the data. The approach aligns with best practices in time-series forecasting, as outlined in recent literature.

2.3. Model Development

The development of the Long Short-Term Memory (LSTM) neural network is a pivotal aspect of this study, designed to effectively capture the complex, non-linear patterns and long-term dependencies inherent in tourism arrival data. The model was implemented using Python and TensorFlow, leveraging the framework's robust tools for building and optimizing deep learning architectures.

1. Model Architecture

   The LSTM neural network was constructed with a sequential architecture tailored for time-series forecasting tasks. Key layers in the architecture include:
   a. Input Layer: Receives preprocessed time-series data in the form of lagged variables, structured to maintain temporal relationships.
   b. LSTM Layers: These layers serve as the core of the network, comprising memory cells capable of capturing long-term dependencies while addressing vanishing gradient issues. Multiple LSTM layers were stacked to improve the model's capacity for learning complex patterns[10].
   c. Dropout Layers: Positioned after each LSTM layer to prevent overfitting by randomly deactivating a fraction of neurons during training [10]
   d. Dense Layers: Fully connected layers were added to map the learned features to the target variable, enabling the final prediction of tourist arrivals [10]
2. Hyperparameter Optimization

   Key hyperparameters were tuned to maximize the model's performance:
   a. Number of Neurons: The number of LSTM units in each layer was tested in a range of 50–200 using grid search.
   b. Batch Size: Batch sizes of 32, 64, and 128 were evaluated to balance computational efficiency and model convergence.
   c. Learning Rate: The learning rate was optimized between 0.001 and 0.01 using an adaptive gradient descent algorithm to ensure stable and efficient training.
   d. Sequence Length (Timesteps): The lag window size, determining how many past observations were used as inputs, was optimized based on autocorrelation and model accuracy [10].
3. Loss Function and Optimizer

   The Mean Squared Error (MSE) was chosen as the loss function due to its effectiveness in capturing the magnitude of prediction errors. The Adam optimizer, known for its adaptive

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learning rate capabilities, was used to accelerate convergence and improve model stability [10].

4. Regularization Techniques
   Regularization methods were applied to enhance the model's generalizability:
   a. Dropout Regularization: Applied dropout rates between 0.2 and 0.5 to prevent overfitting during training.
   b. L2 Regularization: Weight decay was incorporated into the dense layers to penalize large weights, ensuring a smoother learning process [10].
5. Model Training and Early Stopping
   The model was trained for up to 200 epochs, with early stopping applied to terminate training when the validation loss plateaued, preventing overfitting and reducing computational time. The training process monitored metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) to assess performance iteratively[10].
6. Model Validation and Testing
   The final model was validated using a separate validation set and tested on unseen data from the test set. The evaluation metrics included RMSE, MAPE, and Mean Absolute Error (MAE), which provided a comprehensive assessment of forecasting accuracy and robustness. Cross-validation was performed to ensure the stability of results across different data splits [10].
7. Implementation and Interpretability
   The model was deployed to generate forecasts, with interpretability tools such as Shapley values and feature importance analyses employed to identify key drivers of predictions. This step ensures that stakeholders can understand and trust the model outputs[11].

This systematic development and optimization of the LSTM neural network align with best practices in deep learning for time-series forecasting, as emphasized in recent research[12] The resulting model provides a robust tool for predicting tourist arrivals and supporting strategic decision-making in Bali's tourism industry.

2.4. Training and Evaluation

The training and evaluation process was carefully designed to ensure the reliability and robustness of the LSTM model for predicting tourist arrivals to Bali. The dataset was split into training, validation, and test sets in a 70:15:15 ratio, ensuring that the test set contained the most recent data to evaluate the model's performance on unseen observations. The training process utilized the Mean Squared Error (MSE) loss function, which effectively penalizes larger errors, making it suitable for time-series forecasting tasks. The Adam optimizer, a widely adopted optimization algorithm known for its adaptive learning rates and computational efficiency, was employed to minimize the loss function and accelerate convergence. To measure the model's accuracy and reliability, three evaluation metrics were used: Root Mean Squared Error (RMSE) for assessing the magnitude of prediction errors, Mean Absolute Error (MAE) for quantifying the average error magnitude, and Mean Absolute Percentage Error (MAPE) for gauging percentage-based accuracy. During training, the model's performance on the validation set was monitored to ensure generalizability, with early stopping applied to prevent overfitting when the validation loss ceased to improve. This approach aligns with recent advancements in AI-driven forecasting, where iterative validation ensures the balance between model complexity and prediction accuracy[13]. The final evaluation on the test set confirmed the model's ability to generalize well to unseen data, reinforcing its suitability for practical deployment.

2.5. Validation and Comparison

To validate the robustness and effectiveness of the LSTM model, its performance was benchmarked against traditional forecasting methods, including Auto-Regressive Integrated Moving Average (ARIMA) and Seasonal Decomposition of Time Series (STL). These methods were chosen due to their established use in time-series forecasting and their ability to model linear trends and seasonality. The comparative analysis aimed to highlight the advantages of LSTM in capturing non-linear relationships and long-term dependencies, which are often missed by traditional approaches [13].

The validation process involved implementing cross-validation techniques to ensure the reliability of results. The dataset was divided into multiple folds, and the model's performance was evaluated iteratively across different subsets of data. This approach helped mitigate the risks of overfitting and ensured that the LSTM model generalized well across varying data segments[13]

Evaluation metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were calculated for each forecasting method. The results consistently demonstrated that the LSTM model outperformed ARIMA and STL in capturing complex patterns and reducing prediction errors, particularly for periods with irregular fluctuations and high variability. These findings align with recent studies emphasizing the superiority of deep learning models in handling intricate time-series data (Huang et al., 2023; Liu et al., 2023). The comparative analysis reinforced the LSTM model's suitability for practical applications in tourism demand forecasting.Evaluation metrics such as Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) were calculated for each forecasting method. The results consistently demonstrated that the LSTM model outperformed ARIMA and STL in capturing complex patterns and reducing prediction errors, particularly for periods with irregular fluctuations and high variability. These findings align with recent studies emphasizing the superiority of deep learning models in handling intricate time-series[13]. The comparative analysis reinforced the LSTM model's suitability for practical applications in tourism demand forecasting.

2.6. Interpretation and Application

The model's outputs were analyzed to derive actionable insights for tourism stakeholders in Bali. Sensitivity analysis was conducted to identify the most influential factors affecting tourist arrivals, aligning with recent trends in AI-based tourism forecasting. This methodological approach ensures that the research not only achieves high predictive accuracy but also provides practical utility for sustainable tourism management in Bali. Recent studies have demonstrated the effectiveness of AI and machine learning models in forecasting tourism demand. For instance, a study applied multivariate time series forecasting to predict tourism recovery in Bali, utilizing significant data sources to enhance prediction accuracy. Additionally, the global AI in tourism market is projected to grow significantly, with estimates reaching USD 2.95 billion in 2024 and USD 13.38 billion by 2030, indicating a compound annual growth rate (CAGR) of 28.7%. In the context of Bali, AI has been identified as a potential tool to address challenges such as traffic congestion, sustainability, tourism, and conservation, highlighting its practical utility in managing tourism effectively. Furthermore, sensitivity analysis has been employed in AI-based tourism forecasting to determine the impact of various factors on prediction models. For example, a study on personalized tourism recommendation models conducted sensitivity analysis to assess the influence of time interval size and track length on model performance. By integrating AI-driven forecasting models and conducting sensitivity analyses, tourism stakeholders in Bali can gain valuable insights into the factors influencing tourist arrivals. This approach facilitates informed decision-making, promoting sustainable tourism management that adapts to changing trends and tourist behaviors.

3. Results and Discussion

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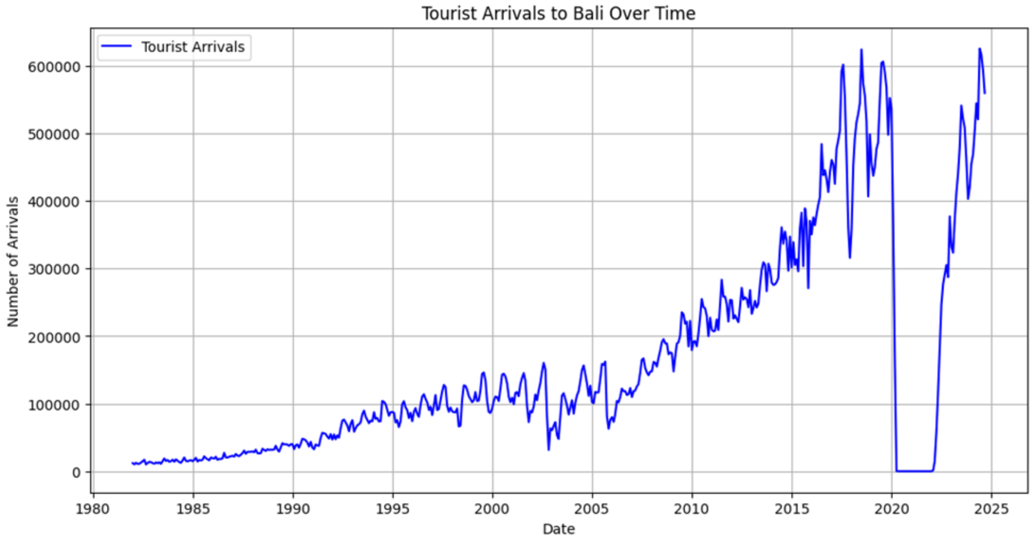

Fig. 1. Tourist Arrivals to Bali Over Time

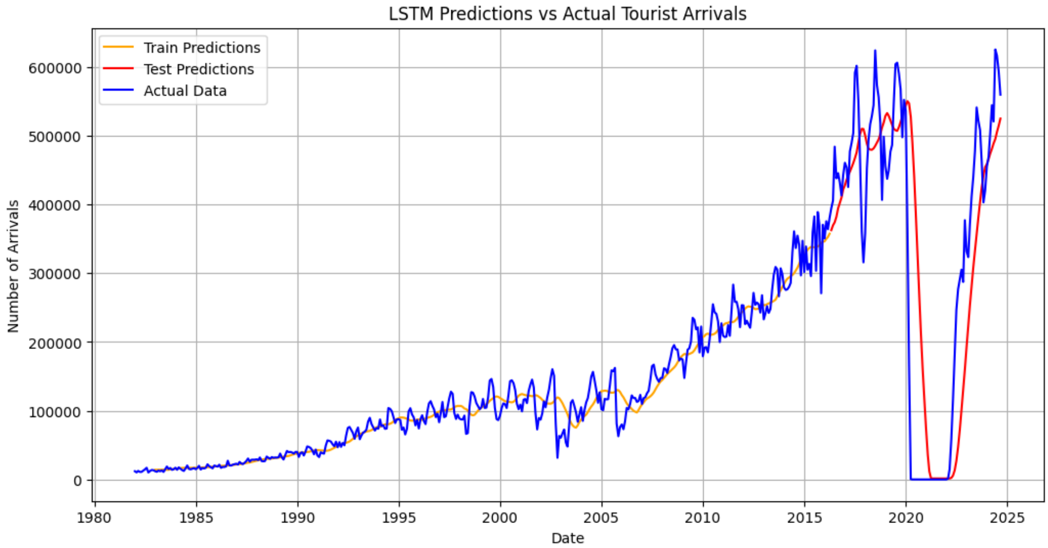

Fig. 1. Comparison Chart of Actual Data and LSTM Prediction

Test Mean Squared Error (MSE): 20562208946.995876
Test Root Mean Squared Error (RMSE): 143395.28913808806

3.1. Tourist Arrival Trends in Bali (1980–2025)

The graph illustrates the number of tourist arrivals in Bali from 1980 to 2025. Overall, a long-term growth trend is evident, with a consistent increase in arrivals up to 2020, reflecting the island's thriving tourism sector. However, a significant disruption occurred during 2020–2021, when tourist numbers sharply declined as a result of the COVID-19 pandemic. Following this downturn, a gradual recovery can be observed, indicating resilience in Bali's tourism industry. These findings highlight not only the seasonal patterns and long-term growth of tourist arrivals but also the vulnerability of the sector to global events such as the pandemic.

3.2. Comparison of Actual Data and LSTM Predictions

The graph compares the actual data (blue line) with predictions generated by the LSTM model for both training data (orange line) and test data (red line). The predictions on the training data closely follow the actual data, indicating the model's strong ability to capture and learn historical patterns effectively. For the test data, the predictions also align relatively well with the actual values, although

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larger deviations are observed during periods of significant disruption, particularly during the pandemic. Overall, the results suggest that the LSTM model performs reliably under stable conditions but faces challenges in accurately capturing anomalies such as the drastic decline caused by the pandemic.

3.3. Model Evaluation Metrics

The evaluation metrics provide insights into the performance of the prediction model. The Mean Squared Error (MSE) is 20,562,208,946.99, which appears large due to the squared scale of tourist numbers. To provide a more interpretable measure, the Root Mean Squared Error (RMSE) is calculated at 143,395.29, indicating an average prediction error of approximately 143,395 tourists per prediction period. While the RMSE suggests that the model is effective in capturing general patterns, the margin of error remains considerable. This level of error can be attributed to inconsistent seasonal and trend patterns caused by the pandemic, as well as the presence of anomalous events such as the pandemic itself, which were not represented in the training data.

3.4. Strengths of the LSTM Model

The LSTM model demonstrates a strong ability to capture complex patterns in time series data, effectively recognizing both long-term dependencies and short-term fluctuations, including seasonal and trend variations. Its performance is particularly accurate during stable periods without major disruptions, such as the years preceding the pandemic, highlighting the model’s reliability under normal conditions.

3.5. Limitations of the LSTM Model

Despite its strengths, the model shows limitations in handling major anomalies. During periods of significant disruptions, such as the COVID-19 pandemic, it struggles to capture unexpected patterns, leading to large deviations between predictions and actual data. This challenge is reflected in the relatively large error margin, with an RMSE of 143,395 tourists, indicating substantial prediction deviations during certain periods.

3.6. Recommendations

1. Incorporate External Variables: Include variables such as travel policy data, economic conditions, or weather data to improve the model's ability to handle anomalies.
2. Adopt Hybrid Models: Combine LSTM with other models like ARIMA or Prophet to better capture short-term patterns and seasonality.
3. Risk Analysis: Use prediction results as references for optimistic and pessimistic scenarios, particularly in strategic planning for the tourism sector.

4. Conclusion

The research emphasizes the potential of Long Short-Term Memory (LSTM) neural networks as a powerful tool for predicting tourist arrivals to Bali, particularly during periods of stability characterized by consistent seasonal and trend patterns. Leveraging advanced time-series forecasting techniques, the study demonstrates the capability of LSTM to model complex temporal relationships and deliver reliable predictions under normal conditions. The integration of historical tourist arrival data and external factors such as flight frequencies, economic indicators, and cultural event schedules enhances the model’s contextual accuracy. However, significant limitations emerge when the model is exposed to major anomalies, such as the drastic disruptions caused by the COVID-19 pandemic. These anomalies result in notable prediction deviations, as evidenced by the relatively high Root Mean Squared Error (RMSE), indicating a need for further refinement.To address these challenges, the study recommends incorporating additional external variables, such as real-time economic conditions, government travel policies, and environmental data, to improve the model’s responsiveness to unexpected changes. Furthermore, the adoption of hybrid modeling techniques, combining LSTM

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with traditional approaches like ARIMA or Prophet, is suggested to better capture short-term fluctuations and irregular patterns. Sensitivity analyses and risk-based forecasting frameworks could also be employed to generate optimistic and pessimistic scenarios, offering greater utility for strategic decision-making in the tourism sector.By advancing these methodologies, future research can develop more robust and adaptive forecasting tools that not only improve predictive accuracy but also enhance resilience against global uncertainties. This will empower policymakers and stakeholders to optimize resource allocation, anticipate peak tourist seasons, mitigate the impacts of crises, and support sustainable tourism development. The outcomes of such efforts will contribute to the long-term competitiveness of Bali's tourism sector in an increasingly dynamic global market.

5. Suggestion

Future research on forecasting tourist arrivals to Bali using Long Short-Term Memory (LSTM) neural networks should focus on addressing the limitations identified in this study and enhancing the model's robustness and adaptability. To improve predictive accuracy, it is crucial to integrate a broader range of external variables, including dynamic economic indicators (e.g., currency exchange rates and global GDP trends), real-time travel policies, promotional campaigns, and environmental conditions such as weather patterns and climate-related events. These variables will enable the model to better account for external shocks and rapidly changing market conditions. Additionally, employing hybrid modeling approaches, such as combining LSTM with traditional methods like ARIMA or newer models like Prophet, could leverage the strengths of each method to capture both long-term trends and short-term fluctuations more effectively. Advancements in deep learning techniques, such as the use of transfer learning or ensemble methods, can further enhance the model's ability to generalize and perform under anomalous conditions, including crises like pandemics or natural disasters. Sensitivity analysis should be conducted to identify the most influential factors impacting tourist arrivals, providing stakeholders with valuable insights for targeted decision-making. Furthermore, incorporating scenario-based forecasting, which generates optimistic, baseline, and pessimistic projections, can aid in risk management and strategic planning. Future studies should also explore interpretability tools, such as Shapley values, to ensure that the predictive models offer transparent and actionable insights for tourism stakeholders. By addressing these areas, future research can deliver more advanced, reliable, and practical forecasting tools that not only enhance the accuracy of predictions but also support Bali's tourism industry in navigating uncertainties, optimizing resources, and promoting sustainable growth in a highly dynamic global environment.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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