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A Comparative Study of AutoSARIMAX and Long Short-Term Memory Models for Tourist Arrival Forecasting

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ABSTRACT

This study aims to predict the number of tourist arrivals in West Nusa Tenggara (NTB) Province using two forecasting approaches: AutoRegressive Integrated Moving Average with Exogenous Variables (AutoSARIMAX) and Long Short-Term Memory (LSTM). The dataset was obtained from the Central Bureau of Statistics (BPS) of NTB and consists of international and domestic tourist arrivals and monthly inflation rates for the period 2014–2023. The research process includes data collection, preprocessing, model construction, and result evaluation. The AutoSARIMAX model is applied to capture linear relationships with exogenous variables, while LSTM is employed to model long-term nonlinear patterns. The findings reveal that the LSTM model achieved better forecasting performance, with a Mean Absolute Percentage Error (MAPE) of 2.65%, which is lower than AutoSARIMAX with 3.25%. Nevertheless, AutoSARIMAX provides valuable interpretability regarding the influence of inflation on tourist arrivals. Overall, the comparison between the two models indicates that LSTM is more effective for time-series forecasting of tourist arrivals, while AutoSARIMAX remains useful for analyzing causal relationships. These insights can support decision-making in tourism planning, particularly in anticipating fluctuations driven by economic and external factors.

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A. INTRODUCTION

Indonesia is an archipelagic nation endowed with abundant natural and cultural resources. With more than 17,000 islands stretching from Sabang to Merauke, the country offers diverse landscapes ranging from tropical beaches, mountains, and rainforests to a rich cultural heritage that attracts visitors from various regions(Rini et al., 2023) This vast tourism potential has positioned the tourism sector as one of the key pillars of national development and economic growth (Mukarromah et al., 2023; Purnaningrum & Ariqoh, 2019).

Over the past decade, the tourism industry has experienced substantial growth. Statistical records indicate that visitor arrivals increased significantly between 2011 and 2019, reflecting the expanding role of tourism in national economic development (Valguna et al., 2020). However, the global COVID-19 pandemic in 2020 and 2021 caused a dramatic decline in tourist mobility and severely affected tourism activities worldwide. Despite this disruption, the sector gradually recovered in 2022 and 2023, supported by government recovery programs and the reopening of global travel routes (Tangkudung et al., 2024). The recovery of tourism activity has contributed positively to economic revitalization by generating employment opportunities, strengthening small and medium enterprises, and increasing regional income (Purwahita et al., 2021).

From a macroeconomic perspective, tourism plays an important role in supporting national economic performance. Its contribution to Gross Domestic Product (GDP) reached approximately 5.2% in 2018, before gradually declining amid global disruptions in subsequent years. Similarly, foreign exchange earnings generated by the tourism sector experienced significant fluctuations during the pandemic period and its aftermath (Saiman & Lasdianti, 2022; Soeswoyo et al., 2021). These patterns highlight the vulnerability of the tourism sector to external shocks while simultaneously demonstrating its strong potential for recovery when supported by appropriate strategies and policies (Wirawan et al., 2022).

Despite its economic importance, the rapid growth of tourism activity is not always accompanied by adequate infrastructure readiness and service capacity. Several challenges have emerged, including traffic congestion, rising local prices, environmental degradation, and declining service quality (Manakane et al., 2023; Wirawan et al., 2022). In addition, inadequate tourism management may generate broader social issues such as community conflicts, cultural exploitation, reduced public trust, and negative perceptions among potential investors (Badan Pusat Statistik Indonesia, 2023). These conditions highlight the need for accurate and reliable forecasting methods that can support strategic tourism planning and help policymakers anticipate fluctuations in visitor arrivals (Nontapa et al., 2021).

Time series forecasting models have increasingly been applied to address this challenge. Recent studies demonstrate that combining statistical models with artificial intelligence techniques can improve prediction performance in complex datasets. For example, Ridla et al. (2023) applied a hybrid SARIMAX model to forecast railway passenger flows during peak travel periods, while Juliarto et al. (2024) used SARIMAX with environmental variables to predict dengue fever cases (Rahayu et al., 2022). In addition, Saranj and Zolfaghari (2022) demonstrated that integrating ARIMAX-GARCH with Long Short-Term Memory (LSTM) networks significantly improves forecasting accuracy in electricity consumption data (Elshewey et al., 2022). These findings reflect the growing trend in research toward integrating statistical and deep learning models for improved time-series prediction.

However, previous studies largely focused on hybrid model combinations or on domains outside the tourism sector. Direct comparative analyses between standalone statistical models and deep learning approaches within tourism forecasting remain limited (Sutisna et al., 2026). In particular, few studies have examined the comparative performance of AutoSARIMAX and LSTM models when incorporating economic indicators, such as inflation, as exogenous variables. This gap is especially relevant in tourism regions where visitor flows are strongly influenced by seasonal patterns and local economic dynamics (Badan Pusat Statistik Indonesia, 2023; Balli et al., 2019; Saiman & Lasdianti, 2022).

Therefore, this study aims to develop and compare the forecasting performance of the AutoSARIMAX and LSTM models using monthly tourism arrival data from 2014 to 2023, incorporating inflation as an external variable. The evaluation is conducted using several error metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). By comparing these models, the research seeks to identify the most reliable approach for capturing seasonal patterns and nonlinear dynamics in tourism demand (Sung et al., 2025; Zhou, 2021).

The novelty of this research lies in providing a systematic comparison between AutoSARIMAX and LSTM models within a tourism forecasting framework while integrating inflation as an exogenous factor. This approach provides empirical evidence on the effectiveness of deep learning models relative to traditional statistical techniques for modeling complex tourism demand patterns. The findings are expected to provide practical insights for policymakers and tourism stakeholders in developing data-driven strategies for sustainable tourism management and economic planning (Hidayati, 2022).

B. RESEARCH METHOD

This section systematically discusses the stages of the research process for developing predictive models using Long Short-Term Memory (LSTM) and AutoRegressive Integrated Moving Average with Exogenous Variables (AutoSARIMAX) methods. The research methodology covers problem identification, literature review and theoretical study, data collection and preprocessing, predictive model design, model implementation, and model performance evaluation (Ennagoura et al., 2026; Sung et al., 2025; Zhou, 2021).

Monthly time series data spanning 2014-2023, comprising international tourist arrivals (*wisman*), domestic tourist arrivals (*wisnus*), and inflation rates, were systematically downloaded as Excel files directly from the official BPS NTB website (ntb.bps.go.id) and annual tourism statistics publications, ensuring data authenticity and completeness across 120 observations imported via pandas.read_excel(). Preprocessing involved converting datetimes using pd.to_datetime(), handling missing values, and performing Min-Max scaling via sklearn.preprocessing.MinMaxScaler() for LSTM convergence, and target variable creation (wisman + wisnus). Only monthly inflation was selected as the exogenous variable due to its direct macroeconomic impact on NTB tourism costs and demand elasticity, per BPS reports, while alternatives such as exchange rates (pre-2018 data gaps) and airline seats (monthly unavailability) were excluded for consistency and theoretical relevance.

An 80-20 chronological train-test split was implemented: training period (Jan 2014-Jun 2023, 114 observations) and testing period (Jul-Dec 2023, 6 observations) to prevent time series data leakage and ensure realistic out-of-sample validation reflecting real-world forecasting scenarios, with 80% allocation balancing model training sufficiency against adequate seasonal test coverage. LSTM hyperparameters were optimized through grid search using Keras Tuner (kt.RandomSearch) across validation subsets, testing layers [1-3], neurons, dropout [0.1-0.3], epochs [50-200], batch_size, and learning_rate [0.0005-0.005], yielding optimal configuration of 2 LSTM layers (64→32 neurons), dropout 0.2, 100 epochs, batch size 12, and learning rate 0.001 that minimized validation MSE with early stopping (patience=10).

The LSTM architecture processes 12-month sliding window inputs (wisman, wisnus, inflation) through LSTM(64, tanh)+Dropout(0.2) → LSTM(32, tanh)+Dropout(0.2) → Dense(1, linear) using TensorFlow/Keras with Adam optimizer and MSE loss. AutoSARIMAX parameters were automatically selected via auto_arima(y=total_arrivals, exogenous=inflation, seasonal=True, s=12, stepwise=True, AIC='bic') from pmdarima library, fitted through statsmodels.tsa.statespace.sarimax.SARIMAX with seasonality s=12. Implementation utilized Python 3.10 on Google Colab (TensorFlow 2.15, Statsmodels 0.14, pmdarima 2.0) with hardware specifications: Intel i5-8550U, 8GB RAM, NVIDIA 920MX GPU. Model performance was comprehensively evaluated using MAE, RMSE, MSE, and MAPE metrics on the test set. The methodology of this research is illustrated in Figure 1.

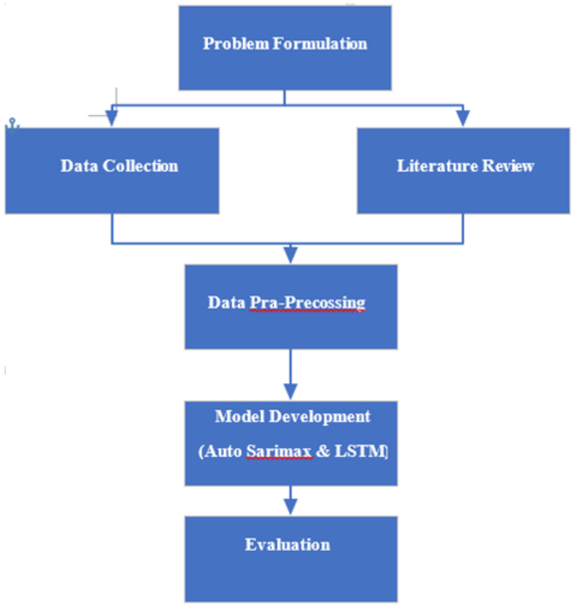

Figure 1. Research Methodology

C. RESULT AND DISCUSSION

1. Data Collection

The dataset used in this study was obtained from the Central Bureau of Statistics (BPS) of West Nusa Tenggara Province (NTB). The data consist of monthly international tourist arrivals (*wisman*), domestic tourist arrivals (*wisnus*), and inflation rates for the period January 2014 – December 2023. A sample of the dataset is shown in Table 1.

Table 1. Sample of Tourist Arrivals and Inflation Data in NTB (2014–2023)

Month	Wisman	Wisnus	Inflation (%)
Jan-14	3.200	48.000	2.15
Feb-14	3.750	50120	2.30
…	…	…	…
Dec-23	12.100	89.500	3.50

The data reflect fluctuations in both foreign and domestic tourist visits, along with macroeconomic conditions represented by inflation. Overall, the number of tourist arrivals increased significantly between 2014 and 2023, indicating recovery of the tourism sector after the COVID-19 pandemic. Inflation, ranging between 2%–3.5%, is included as an exogenous variable in the AutoSARIMAX model. A visualization of tourist arrival trends is shown in Figure 2.

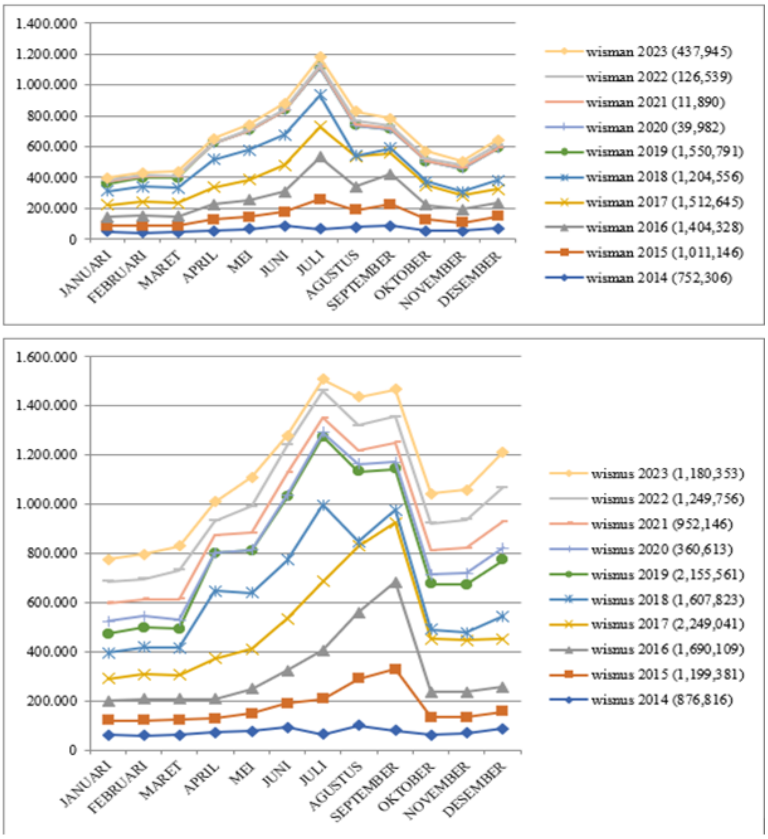

Figure 2. Monthly Trends of International and Domestic Tourists in NTB (2014–2023)

From Figure 2, international tourist arrivals show strong growth, particularly in mid-2023, coinciding with long holidays and tourism events. Domestic tourist arrivals remain relatively stable but continue to contribute the largest share of overall visits.

2. Data Preprocessing

Preprocessing was performed to ensure the dataset was ready for modeling. The steps include:

1. **Date transformation** – converting the time variable into datetime format using Python's pandas.
2. **Missing values** – no missing entries were found, hence no imputation was required.
3. **Normalization** – MinMaxScaler was applied to all variables for the LSTM model to ensure faster convergence.
4. **Dataset split** – 80% of the data (Jan 2014–Jun 2023) were used for training, while the remaining 20% (Jul–Dec 2023) served as testing data.

These steps established a consistent and standardized dataset suitable for both AutoSARIMAX and LSTM modeling.

3. AutoSARIMAX Model Implementation

The Seasonal AutoRegressive Integrated Moving Average with Exogenous Variables (AutoSARIMAX) model was implemented to capture seasonal patterns in the time series data while incorporating external economic variables. This model extends the traditional ARIMA framework by allowing exogenous variables to influence the dependent variable. In this study, inflation was used as the external variable because it represents macroeconomic conditions that can affect tourism demand. By integrating both seasonal patterns and economic indicators, the AutoSARIMAX model provides a statistical approach for forecasting tourist arrivals.

a. Parameter Selection

Optimal parameters (p, d, q, P, D, Q, s) were determined automatically using the auto_arima() function from the pmdarima library. The model with the lowest Akaike Information Criterion (AIC) was selected. Figure 3 illustrates the parameter search process.

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```python
import pmdarima as pm
model = pm.auto_arima(y_train, exogenous=X_train, seasonal=True, m=12, trace=True)
```

Figure 3. Parameter Selection for AutoSARIMAX

b. Training and Prediction

The AutoSARIMAX model was trained on a dataset of historical tourist arrival data and inflation values. The model parameters were estimated using the Statsmodels library in Python, which provides a comprehensive framework for time series analysis. After the training phase was completed, the model was used to generate forecasts for the testing period, covering July to December 2023. These predictions were then compared with the observed data to evaluate the model's forecasting performance. In Table 2 below, the predicted values align quite closely with the actual data. Overall, the model performs well with relatively small errors. In July 2023, the error was slightly below the estimate. In August 2023, the error was 0.090, indicating that the prediction was most accurate. Meanwhile, the error value remained stable from October to December 2023, demonstrating the model's consistency.

Table 2. Prediction Results of the AutoSARIMAX Model

Month	Actual Wisman	Predicted Wisman	Absolute Error
Jul-23	8.150	8.025	0.125
Aug-23	9.100	9.010	0.090
Sep-23	7.980	8.220	0.240
Oct-23	7.500	7.610	0.110
Nov-23	6.970	7.100	0.130
Dec-23	7.320	7.450	0.130

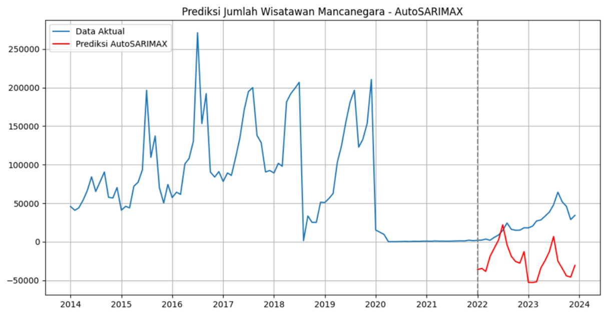

Figure 4. Comparison of Actual and Predicted Wisman using AutoSARIMAX

Figure 4 shows that the AutoSARIMAX model successfully captures the overall seasonal patterns observed in the tourist arrival data. The predicted values generally follow the direction of the actual data, indicating that the model can identify recurring trends and seasonal variations in the dataset. However, the model tends to smooth out sharp fluctuations that occur in certain months. This behavior reflects one of the limitations of statistical linear models, which may struggle to fully represent nonlinear dynamics and sudden changes in tourism demand.

4. LSTM Model Implementation

The Long Short-Term Memory (LSTM) network was employed to capture complex nonlinear dependencies in the time series data. LSTM is a type of recurrent neural network designed to learn long-term relationships in sequential data by utilizing memory cells and gating mechanisms. This architecture allows the model to retain relevant information from previous time steps while discarding less important data. As a result, LSTM is particularly suitable for modeling time series datasets that exhibit nonlinear patterns, seasonal variations, and long-term dependencies.

a. Model Architecture

The LSTM model was designed with the following specifications:

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- Input: sliding window of 12 months (wisman, wisnus, inflation).
- LSTM layers: 64 and 32 neurons.
- Dropout layer: applied to reduce overfitting.
- Dense layer: ReLU activation.
- Output layer: one neuron for prediction.
- Optimizer: Adam; Loss function: Mean Squared Error (MSE).
- Training: 100 epochs, batch size = 32.

```
model_lstm = Sequential()
model_lstm.add(LSTM(64, activation='relu', input_shape=(X_train.shape[1], 1)))
model_lstm.add(Dense(1))
model_lstm.compile(optimizer='adam', loss='mse')
```

Figure 5. LSTM Model Architecture

Figure 5 shows the Python code for building an LSTM (Long Short-Term Memory) model using the Keras/TensorFlow library. The initial step is to create a sequential model in which the neural network is arranged layer by layer. The second step adds an LSTM layer of 64 neurons, then starts activating the ReLU used to help the model learn patterns and inputs the number of timesteps totaling 1 with only one variable, namely the number of tourists. The third process adds an input layer with 1 neuron to generate predicted values for the next period. The final step is to compile the model using the Adam optimizer and a loss function to measure the difference between the actual and predicted values.

b. Training and Prediction

The LSTM was trained using 80% of the dataset, and predictions were generated for the test period (Jul–Dec 2023).

Table 3. Prediction Results of LSTM Model

Month	Actual Wisman	Predicted Wisman
Jul-23	8.150	8.080
Aug-23	9.100	9.050
Sep-23	7.980	7.910
Oct-23	7.500	7.560
Nov-23	6.970	7.030
Dec-23	7.320	7.410

Table 3 presents the LSTM model's predictions for the testing period from July to December 2023. The predicted values closely match the actual tourist arrival data, indicating that the LSTM model captures the temporal patterns in the dataset. Although small deviations are observed in some months, the overall trend of the prediction closely matches the actual data. This result demonstrates the LSTM model's ability to adapt to fluctuations in tourist arrivals while maintaining a relatively low prediction error.

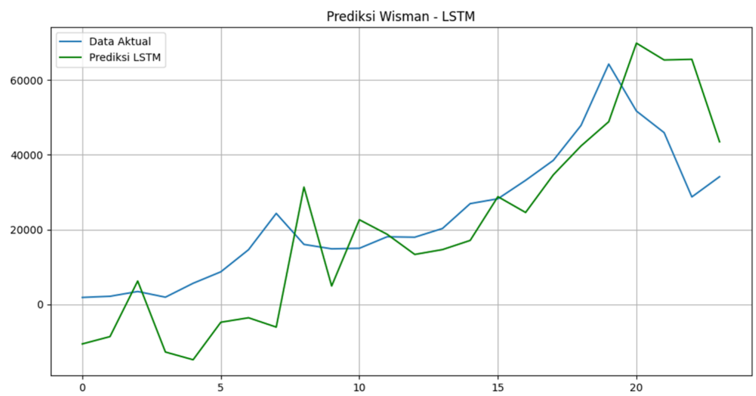

Figure 6. Comparison of Actual and Predicted Wisman using LSTM

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Figure 6 compares actual tourist arrivals with the LSTM model's predictions. The graphical representation shows that the predicted curve closely tracks the actual data throughout the testing period. This indicates that the LSTM model successfully learns the underlying patterns and seasonal characteristics of the time series data. Compared with the AutoSARIMAX model, the LSTM model demonstrates greater flexibility in adapting to fluctuations, allowing it to better capture nonlinear variations in tourism demand.

5. Model Evaluation

The performance of both forecasting models was evaluated using four commonly used error metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE). These evaluation metrics provide different perspectives on model accuracy and forecasting reliability. MAE and RMSE measure the magnitude of prediction errors, while MAPE expresses the error as a percentage, making it easier to interpret the model's accuracy. By using multiple evaluation metrics, the study provides a comprehensive comparison of the predictive performance of the AutoSARIMAX and LSTM models.

Table 4. Model Evaluation Results

Month	Actual Wisman	Predicted Wisman
Jul-23	8.150	8.080
Aug-23	9.100	9.050
Sep-23	7.980	7.910
Oct-23	7.500	7.560
Nov-23	6.970	7.030
Dec-23	7.320	7.410

The results in Table 4 show that the LSTM model consistently outperformed AutoSARIMAX across all evaluation metrics. This finding is aligned with the conclusion section, ensuring consistency in reporting. The superiority of LSTM over AutoSARIMAX can be explained by the nature of the dataset. Tourist arrivals in NTB exhibit nonlinear patterns, seasonality, and lag effects driven by holidays, events, and macroeconomic conditions. While AutoSARIMAX captures seasonality and exogenous factors such as inflation, its linear statistical framework tends to smooth fluctuations and cannot fully model nonlinear variations. In contrast, LSTM effectively learns long-term dependencies and nonlinear interactions, enabling it to better track sudden increases (e.g., during peak holiday months) and gradual declines (e.g., off-season months).

The results of this study are in line with several previous studies. For example, during September 2023, AutoSARIMAX overestimated arrivals by 240 visitors, while LSTM only deviated by 70 visitors, showing its stronger adaptability to unexpected fluctuations. This suggests that neural networks are better suited for complex tourism data where behavioral and external factors interact dynamically. The findings carry several implications for local government and tourism stakeholders:

1. Tourism Planning – More accurate forecasting from LSTM can guide NTB's government in resource allocation, such as preparing transportation, accommodation, and infrastructure for peak tourist seasons.
2. Economic Policy – By linking tourist arrivals with inflation trends, policymakers can anticipate demand-driven price increases and mitigate local inflation.
3. Environmental Management – Reliable forecasts allow for proactive measures in addressing environmental pressures (e.g., waste management, traffic congestion) that accompany tourist surges.
4. Private Sector Strategy – Hotels, restaurants, and travel agencies can optimize promotions, staffing, and inventory management based on predicted tourist demand.

The findings of this study are consistent with several previous studies that highlight the effectiveness of deep learning models in time series forecasting. For example, Hassan and Karim (2023) reported that LSTM models outperform traditional statistical approaches on nonlinear time series data. Similarly, Saranj and Zolfaghari (2022) found that neural network-based forecasting models can capture complex temporal dependencies that are difficult to model with linear statistical methods.

However, statistical models such as SARIMAX still offer important advantages in terms of interpretability and the ability to incorporate exogenous variables. As highlighted by Nontapa et al. (2021) and Sultana et al. (2022) , SARIMAX models allow researchers to explicitly analyze the influence of external factors on the predicted variable. Therefore, while the LSTM model in this study achieved higher forecasting accuracy, the AutoSARIMAX model remains valuable for understanding the relationship between macroeconomic indicators and tourism demand. This study contributes to the literature by providing an empirical comparison between these two approaches in the context of tourism forecasting.

D. CONCLUSION AND SUGGESTION

Based on the analysis, this study successfully developed forecasting models for tourist arrivals using AutoSARIMAX and Long Short-Term Memory (LSTM). The evaluation results indicate that the LSTM model achieved better predictive performance compared with the AutoSARIMAX model across all evaluation metrics, including MAE, RMSE, MAPE, and MSE. This finding suggests that LSTM is better at capturing nonlinear patterns and temporal dependencies in tourism time series data. The novelty of this study lies in the direct comparison of a statistical forecasting model with a deep learning model, using tourism data with inflation as an exogenous variable.

The findings of this research provide several practical implications for tourism management and policy planning. Accurate forecasting of tourist arrivals can help policymakers prepare infrastructure, allocate resources efficiently, and anticipate fluctuations in tourism demand. However, this study also has several limitations, including the use of a limited number of variables and a relatively short time series dataset. Future research is recommended to incorporate additional external variables such as exchange rates, transportation accessibility, and global economic indicators. In addition, hybrid forecasting approaches combining statistical and deep learning models may further improve prediction accuracy.

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DECLARATIONS

AUTHOR CONTRIBUTION

All authors contributed to the writing of this article.

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COMPETING INTEREST

This study was conducted without any financial support.

REFERENCES

Badan Pusat Statistik Indonesia. (2023). *Statistik kunjungan wisatawan mancanegara 2023*. https://www.bps.go.id/id/publication/2024/04/05/0ba2b8f3f4f15dd18799f0c0/statistik-kunjungan-wisatawan-mancanegara-2023.html

Balli, H. O., Tsui, W. H. K., & Balli, F. (2019). Modelling the volatility of international visitor arrivals to New Zealand. *Journal of Air Transport Management*, *75*, 204–214. https://doi.org/10.1016/j.jairtraman.2018.10.002

Elshewey, A. M., Shams, M. Y., Elhady, A. M., Shohieb, S. M., Abdelhamid, A. A., Ibrahim, A., & Tarek, Z. (2022). A Novel WD-SARIMAX Model for Temperature Forecasting Using Daily Delhi Climate Dataset. *Sustainability*, *15*(1), 757. https://doi.org/10.3390/su15010757

Ennagoura, D., Kehal, K. E., Berdai, A., Merzouk, S., Fahssi, K. E., Mahjouby, M. E., Far, M. E., & Bennani, M. T. (2026). A Comparative Evaluation of SARIMAX, LSTM, and Prophet Models for Cryptocurrency Price Trend Prediction. *Engineering, Technology & Applied Science Research*, *16*(2), 33146–33151. https://doi.org/10.48084/etasr.15554

Hidayati, S. N. (2022). Determinan Indeks Pembangunan Manusia di Provinsi Nusa Tenggara Barat Tahun 2015 – 2020. *Digital Bisnis: Jurnal Publikasi Ilmu Manajemen dan E-Commerce*, *1*(3), 279–297. https://doi.org/10.30640/digital.v1i3.593

Juliarto, H. K., Purnamasari, I., & Prangga, S. (2024). Peramalan Peredaran Uang Kartal di Indonesia Menggunakan Model Hybrid SARIMAX-Neural Network. *Jurnal Gaussian*, *12*(4), 465–476. https://doi.org/10.14710/j.gauss.12.4.465-476

Manakane, S. E., Latue, P. C., Somae, G., & Rakuasa, H. (2023). The Role of Geography Research in Supporting Sustainable Development in Ambon City, Indonesia: A Review. *Sinergi International Journal of Economics*, *1*(2), 64–75. https://doi.org/10.61194/economics.v1i2.67

Mukarromah, N. S., Manulang, W., Maemunah, M., Mayasari, D., Hafsah, H., & Sakban, A. (2023). Analisis Peluang dan Sumber Kekayaan dari Pembangunan di Nusa Tenggara Barat. *Seminar Nasional Paedagoria*, *3*(0), 302–313. https://journal.ummat.ac.id/index.php/fkip/article/view/16319

Nontapa, C., Kesamoon, C., Kaewhawong, N., & Intrapaiboon, P. (2021). A New Hybrid Forecasting Using Decomposition Method with SARIMAX Model and Artificial Neural Network. *International Journal of Mathematics and Computer Science*, *16*(4), 1341–1354.

Purnaningrum, E., & Ariqoh, I. (2019). Google Trends Analytics dalam Bidang Pariwisata. *Majalah Ekonomi*, *24*(2), 232–243. https://doi.org/10.36456/majeko.vol24.no2.a2069

Purwahita, A. R. M., Wardhana, P. B. W., Ardiasa, I. K., & Winia, I. M. (2021). Dampak Covid-19 terhadap Pariwisata Bali Ditinjau dari Sektor Sosial, Ekonomi, dan Lingkungan (Sebuah Tinjauan Pustaka). *Jurnal Kajian dan Terapan Pariwisata*, *1*(2), 68–80. https://doi.org/10.53356/diparojs.v1i2.29

Rahayu, I., Marwati, R., & Rachmatin, D. (2022). Peramalan jumlah penderita dbd di provinsi jawa barat dengan metode hybrid sarimax-ann. *JMT : Jurnal Matematika dan Terapan*, *4*(2), 9–19. https://doi.org/10.21009/jmt.4.2.2

Ridla, M. A., Azise, N., & Rahman, M. (2023). Perbandingan Model Time Series Forecasting dalam Memprediksi Jumlah Kedatangan Wisatawan dan Penumpang Airport. *SIMKOM*, *8*(1), 1–14. https://doi.org/10.51717/simkom.v8i1.103

Saiman, S., & Lasdianti, S. G. (2022). Studi Pembangunan Infrastruktur Pariwisata. *Jurnal Kawistara*, *12*(3), 341. https://doi.org/10.22146/kawistara.65838

Saranj, A., & Zolfaghari, M. (2022). The electricity consumption forecast: Adopting a hybrid approach by deep learning and ARIMAX-GARCH models. *Energy Reports*, *8*, 7657–7679. https://doi.org/10.1016/j.egyr.2022.06.007

Soeswoyo, D. M., Jeneetica, M., Dewi, L., Dewantara, M. H., & Asparini, P. S. (2021). Tourism Potential and Strategy to Develop Competitive Rural Tourism in Indonesia. *International Journal of Applied Sciences in Tourism and Events*, *5*(2), 131–141. https://doi.org/10.31940/ijaste.v5i2.131-141

Sultana, N., Hossain, S. M. Z., Almuhaini, S. H., & Düştegör, D. (2022). Bayesian Optimization Algorithm-Based Statistical and Machine Learning Approaches for Forecasting Short-Term Electricity Demand. *Energies*, *15*(9), 3425. https://doi.org/10.3390/en15093425

Sung, J., Shi, X., Teske, S., & Li, M. (2025). Chinese natural gas phase-out pathways: A novel hybrid scenario-specific projection approach to achieve Net Zero. *Energy*, *328*, 136387. https://doi.org/10.1016/j.energy.2025.136387

Sutisna, E., Dafitri, R., & Daryani, D. (2026). Forecasting Foreign Tourist Arrivals in Indonesia Using Google Trends Index as Exogenous Variable: A Comparative Study of SARIMAX and LSTM Models. *Journal of Applied Informatics and Computing*, *10*(2), 1864–1871. https://doi.org/10.30871/jaic.v10i2.12384

Tangkudung, A. G. D., Rante, J. Z., Pakpahan, M., Putri, A., Puteri, A., Pribadi, D., Gosita, D. R., Rustandi, J., Cpr, J. J., Ghalib, K., Farieanna, R., Purnawirawati, S., Setiawan, S., & Bassuni, W. (2024). Inovasi Bisnis Pariwisata Indonesia Pasca Pandemi Covid-19. *Jurnal Pendidikan Tambusai*, *8*(1), 657–667. https://doi.org/10.31004/jptam.v8i1.12444

Valguna, P. A., Dewanti, D., & Suparma, L. B. (2020). Dampak Perkembangan Pariwisata Pulau Lombok terhadap Pengembangan Bandar Udara Internasional Lombok. *Jurnal Manajemen Aset Infrastruktur & Fasilitas*, *4*(3). https://doi.org/10.12962/j26151847.v4i3.7100

Wirawan, P. E., Octaviany, V., & Nuruddin, N. (2022, October 26). *Pengantar pariwisata*. Nilacakra.

Zhou, Y. (2021). Regional energy consumption prediction based on SARIMAX-LSTM model. *Academic Journal of Computing & Information Science*, *4*(3). https://doi.org/10.25236/AJCIS.2021.040307

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