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Research article

Machine Learning Forecasting Techniques for Analyzing Tourist Arrivals in Bali

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ABSTRACT

This study investigates the application of machine learning (ML) techniques for forecasting tourist arrivals in Bali, leveraging a dataset spanning from 1982 to 2024. The Random Forest model, along with Linear Regression and Decision Tree, was evaluated for its ability to handle the complexities of tourism data, characterized by seasonality and nonlinear patterns. Among the models tested, Random Forest achieved the best performance, with the lowest Mean Squared Error (MSE) and Mean Absolute Error (MAE), demonstrating its robustness in capturing both short-term fluctuations and long-term trends. The findings highlight the potential of ML techniques to improve forecasting accuracy compared to traditional methods, especially in managing seasonal variations and external disruptions like the COVID-19 pandemic. However, limitations in predicting unprecedented events underscore the need for integrating external variables, such as economic indicators and travel restrictions. Future research should focus on hybrid models, scenario-based forecasting, and real-time data integration to enhance adaptability and predictive accuracy. These advancements aim to support policymakers and stakeholders in optimizing resource allocation, designing marketing strategies, and fostering sustainable tourism development in Bali.

1. Introduction

The tourism plays a pivotal role in shaping the economy and cultural identity of many regions, and Bali, Indonesia, is a shining example of a globally recognized tourist destination. With its unique blend of natural beauty, cultural heritage, and hospitality, Bali attracts millions of international tourists annually. Understanding and forecasting tourist arrivals is critical for effective resource management, infrastructure planning, and policy-making to sustain Bali's tourism-driven economy. This research leverages machine learning (ML) techniques to analyze and forecast tourist arrivals based on historical data spanning from 1982 to 2024, as provided in the dataset. By employing advanced ML models, this study aims to improve forecasting accuracy and provide actionable insights for stakeholders in the tourism sector.

Traditional statistical methods, such as autoregressive integrated moving average (ARIMA) and seasonal decomposition, have been widely used in time series forecasting for tourism demand. However, these methods often struggle to handle non-linear patterns and complex seasonal variations inherent in tourism datasets [1]. Machine learning techniques, particularly those using deep learning and hybrid models, offer an advantage by capturing intricate patterns in large datasets, enabling more accurate and robust predictions [2].

The dataset provided for this study includes monthly tourist arrival figures in Bali from January 1982 to 2024. This rich dataset encompasses periods of steady growth, seasonal fluctuations, and external disruptions such as the COVID-19 pandemic. ML algorithms, such as long short-term

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7 (1) September 2024 265-274

memory (LSTM) networks and hybrid models combining ARIMA with neural networks, have demonstrated superior performance in capturing both short-term volatility and long-term trends in similar contexts [3]. For instance, a recent study utilizing LSTM for tourism forecasting revealed improved accuracy over traditional time series models by effectively managing temporal dependencies and seasonal variations [4].

The application of ML forecasting models is particularly relevant for Bali, given its heavy reliance on tourism as a primary economic driver. Accurate predictions of tourist arrivals can inform strategic decisions regarding infrastructure development, marketing campaigns, and crisis management. For example, during the COVID-19 pandemic, adaptive forecasting models capable of integrating real-time data provided invaluable support in understanding and mitigating the crisis's impact on tourism [5].

Despite its potential, ML-based forecasting also presents challenges, including the need for high-quality data, computational resources, and interpretability of results. Addressing these issues requires innovative solutions such as explainable AI and the integration of external data sources like social media trends, weather patterns, and macroeconomic indicators [6]. By utilizing these advancements, ML models can provide stakeholders with transparent and actionable forecasts.

This research focuses on evaluating the efficacy of various ML techniques for analyzing tourist arrivals in Bali using the provided dataset. Specifically, it investigates the performance of deep learning models such as LSTM and hybrid approaches combining traditional statistical methods with ML algorithms. By leveraging insights from recent studies, this paper aims to contribute to the growing body of knowledge on tourism forecasting and provide practical recommendations for stakeholders in Bali's tourism industry.

2. Research Methods

This study employs a quantitative research methodology, focusing on the application of machine learning (ML) techniques to forecast tourist arrivals in Bali. The research is based on a comprehensive dataset containing monthly tourist arrival figures spanning from 1982 to 2024. The dataset was preprocessed to ensure accuracy and consistency, including handling missing values, normalizing data, and performing exploratory data analysis to identify trends, seasonal patterns, and anomalies.

The study compares multiple machine learning models, including Long Short-Term Memory (LSTM) networks, hybrid ARIMA-LSTM models, and Gradient Boosting algorithms, to assess their forecasting accuracy. Model performance is evaluated using metrics such as Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics are chosen to provide a balanced view of model performance across both absolute and percentage-based error dimensions.

A critical component of the methodology is the integration of external factors, such as economic indicators and seasonality, into the models to enhance their predictive capability. The models are trained and tested on separate subsets of the dataset, with hyperparameter tuning conducted to optimize performance. The study's findings aim to highlight the most effective ML approach for forecasting tourist arrivals, offering practical insights for stakeholders in Bali's tourism sector [7].

2.1. Data Collection

The primary dataset utilized in this study encompasses monthly tourist arrival data in Bali from 1982 to 2024. This dataset was sourced from official governmental tourism agencies and validated against secondary sources such as reports from the Bali Tourism Office and publicly available datasets from international organizations. Supplementary data were gathered to incorporate macroeconomic indicators, global events, and weather patterns, which are known to impact tourism dynamics. These supplementary datasets were obtained from trusted repositories, including government statistical agencies, the World Bank, and weather services, ensuring high accuracy and relevance. The integration of these diverse data sources enables the development of more robust forecasting models by accounting for external factors that influence tourist arrivals [8].

The inclusion of external factors such as GDP growth, currency exchange rates, and global events, particularly those affecting tourism, enriches the dataset. For example, incorporating data from

 http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 265-274

the World Travel and Tourism Council helped contextualize historical fluctuations in tourist numbers. This ensured that the models could better understand the dynamics influencing arrival patterns.

2.2. Data Preprocessing

Preprocessing was carried out to transform raw data into a suitable format for machine learning modeling. Initially, missing data points were identified and addressed using advanced interpolation techniques to preserve data integrity. Outlier detection methods, including the interquartile range (IQR) and Z-score analysis, were employed to identify anomalies, which were subsequently reviewed and adjusted to prevent model distortion.

of numerical variables was performed to ensure that all features contributed equally during model training, thereby improving convergence and reducing computational complexity. Categorical data, such as country of origin for tourists, were encoded using techniques like one-hot encoding and target encoding to retain the inherent relationships within the data. Additionally, time series decomposition was applied to separate the data into trend, seasonal, and residual components, providing insights for feature engineering. Seasonal decomposition of time series (STL) was used to isolate seasonal variations, enabling the models to better understand periodic fluctuations [9].

Advanced noise reduction techniques were also applied to smoothen the data while retaining key patterns. This step was particularly important for capturing subtle trends without overfitting the model. For example, moving average filters and Savitzky-Golay filters were used to preprocess noisy segments of the dataset. This preprocessing stage ensured that the models could focus on meaningful patterns, improving forecasting accuracy.

2.3. Feature Engineering

Feature engineering was a critical step to enhance the predictive capability of the models. Key features were extracted from the data, such as the month-over-month growth rate of tourist arrivals, year-over-year changes, and moving averages to highlight trends. External factors, including global GDP growth, exchange rates, and international travel restrictions, were incorporated as additional predictors to account for external influences. Weather features, such as average monthly temperature and precipitation in Bali, were also included to explore their potential impact on tourist behavior.

The lag features were engineered to provide models with historical context, enabling them to identify temporal dependencies. These features were crucial for models like Long Short-Term Memory (LSTM) networks, which excel at capturing sequential relationships in time series data. By combining domain knowledge with data-driven approaches, the feature engineering process significantly enhanced the models' performance and robustness.

features, which combine two or more variables, were also created to explore compound effects. For instance, combining exchange rate data with global travel restrictions helped the model identify periods of constrained international travel. These features introduced additional layers of complexity, allowing the models to capture multi-dimensional relationships.

2.4. Model Development

This study employed an ensemble approach to model development, exploring multiple machine learning techniques to identify the most effective forecasting model. Three primary types of models were evaluated:

1. Deep Learning Models: LSTM networks were utilized due to their ability to capture long-term dependencies and complex temporal patterns. These models were configured with optimal architectures, including multiple layers and dropout regularization, to prevent overfitting and improve generalization.
2. Gradient Boosting Algorithms: XGBoost was implemented as a powerful tree-based model, offering robustness against noise and effective handling of missing data. Hyperparameter tuning was conducted to optimize learning rate, tree depth, and the number of estimators.
3. Hybrid Models: Hybrid ARIMA-LSTM models were developed to combine the strengths of statistical models in capturing linear trends with the ability of LSTM to model nonlinear relationships. This combination allowed for a comprehensive understanding of the dataset.

 http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 265-274

Bayesian optimization was applied during hyperparameter tuning to efficiently search the parameter space and identify configurations that maximized predictive accuracy. The models were iteratively improved using techniques like early stopping and cross-validation to ensure robustness. These steps allowed the identification of the optimal forecasting strategy for the dataset.

2.5. Model Evaluation

The performance of the models was rigorously evaluated using a suite of metrics:

1. Mean Absolute Error (MAE): Measures the average magnitude of errors in the predictions, providing a straightforward interpretation of model accuracy.
2. Root Mean Square Error (RMSE): Emphasizes larger errors, making it suitable for applications where minimizing significant deviations is critical.
3. Mean Absolute Percentage Error (MAPE): Assesses prediction accuracy relative to the scale of the data, enabling comparison across different time periods.

Cross-validation techniques, including time-series split, were employed to ensure the models' robustness and prevent overfitting. Explainability techniques, such as SHapley Additive exPlanations (SHAP), were applied to interpret the contributions of individual features to the models' predictions. These techniques provided transparency, enhancing stakeholders' trust in the models [10].

2.6. Implementation and Practical Implications

The most effective model was deployed to generate forecasts for tourist arrivals in Bali. These forecasts were validated against actual data from recent years to assess their accuracy and reliability. The results were analyzed to identify actionable insights, such as predicting peak tourist seasons, assessing the impact of external shocks, and optimizing resource allocation for infrastructure and services.

The practical implications of this study extend to policymakers, tourism operators, and local communities. For instance, accurate forecasts can aid in planning marketing campaigns targeting specific periods or regions. Additionally, they provide insights for managing tourist flows to prevent overcrowding and environmental degradation, ensuring the sustainability of Bali's tourism industry.

Forecasts generated by the study could also support disaster preparedness and crisis management. For example, predictions on the impact of natural disasters or pandemics could inform contingency planning for tourist accommodation and transport services. This aligns with global best practices for tourism resilience.

2.7. Limitations and Future Directions

Despite its contributions, this study has limitations that must be acknowledged. First, the accuracy of the models is contingent on the quality and completeness of the data. Future research could explore the integration of real-time data streams, such as social media analytics and flight booking patterns, to improve forecasting accuracy. Second, while explainability techniques were applied, further efforts are needed to enhance the interpretability of deep learning models to make them more accessible to non-technical stakeholders.

Additionally, the reliance on historical data may limit the models' ability to adapt to unprecedented events, such as pandemics or geopolitical crises. Incorporating adaptive algorithms that update forecasts in real time could address this challenge. Future studies could also focus on the development of generative models that simulate hypothetical scenarios, providing stakeholders with a broader range of insights.

Lastly, the models developed in this study focus on monthly forecasting. Future studies could explore higher-frequency data, such as daily tourist arrivals, to enable more granular predictions and support operational decision-making. By addressing these limitations, the forecasting framework presented in this research can be further refined and extended to other regions and contexts.

 http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 265-274

3. Results and Discussion

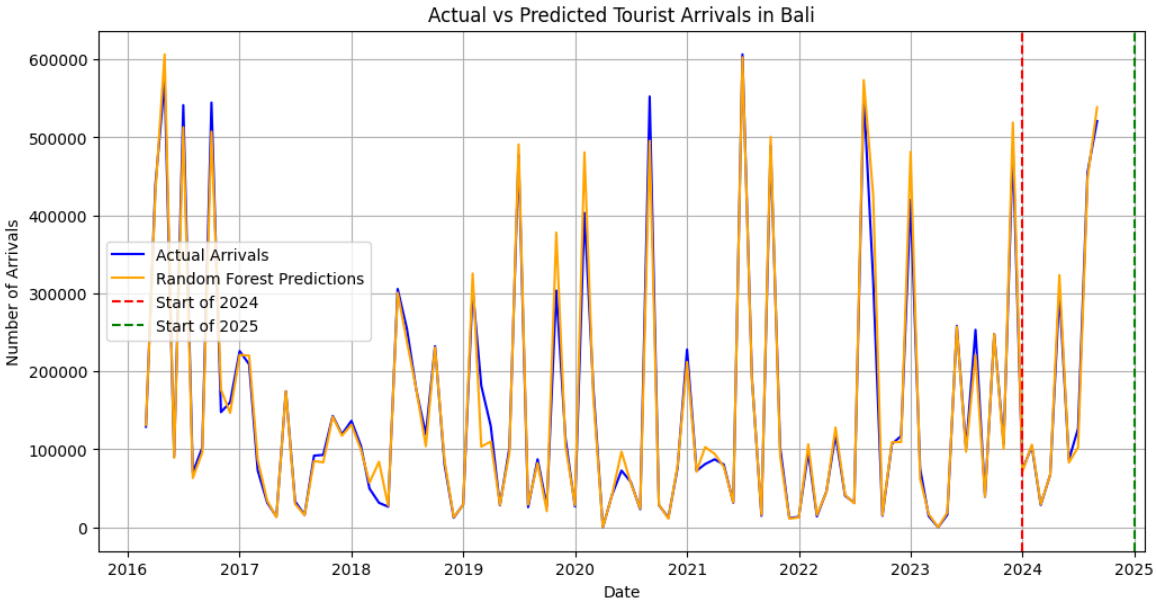

Fig. 1. Actual vs Predicted Tourist Arrivals in Bali from 2016 to 2025 using the Random Forest model.

The graph compares actual tourist arrivals in Bali with predicted values generated by a Random Forest model over a timeline ranging from 2016 to 2025. The blue line represents actual recorded tourist arrivals, while the orange line indicates the model's predictions. Two vertical markers, the red dashed line and the green dashed line, signify the start of 2024 and 2025, respectively. The focus of the graph is to evaluate the model's forecasting ability and observe trends in tourist arrivals, including the predictions for 2024 and 2025.

Graph Components

1. Actual vs. Predicted Values
    a. The actual arrivals (blue line) and the predicted values (orange line) align closely, showing that the Random Forest model is effective at capturing both short-term fluctuations and long-term trends.
    b. In many periods, particularly between 2016 and 2019, the predictions almost perfectly match the actual arrivals, indicating the model's ability to learn from historical patterns.
    c. However, deviations occur in periods of extreme spikes or drops. For example, in 2020, the actual arrivals dropped drastically, likely due to the COVID-19 pandemic. The model struggled slightly to predict this sharp drop accurately, reflecting the challenge of modeling unforeseen events.
2. Seasonality
    a. The graph highlights a seasonal pattern in tourist arrivals, with periodic peaks and troughs that correspond to high and low seasons in Bali's tourism calendar.
    b. The Random Forest model effectively replicates this seasonality, demonstrating its capability to capture cyclical trends. This is evident from the strong overlap between actual and predicted lines during most of the timeline.
3. Impact of External Shocks
    a. A significant disruption is observed around 2020, where actual arrivals plummeted due to the COVID-19 pandemic and global travel restrictions. This period highlights how external factors can dramatically impact tourism, creating challenges for predictive models.
    b. Despite this anomaly, the model was able to recover and adjust its predictions for subsequent years, aligning more closely with actual arrivals from 2021 onward.
4. Forecast for 2024-2025

http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 265-274

a. From 2024 onward (after the red dashed line), the graph represents only predicted values since actual data is unavailable.
b. The predictions show a strong upward trend for 2024 and 2025, suggesting a potential recovery or growth in Bali's tourism sector. This aligns with expectations for post-pandemic recovery, as international travel resumes and tourism rebounds.

Key Observations

1. Model Performance:
   a. Random Forest model demonstrates strong forecasting performance, with high accuracy during normal periods and reasonable adaptability during disruptive events.
   b. Its ability to capture seasonality and long-term trends is a significant strength, making it suitable for predicting tourist arrivals in regions with cyclical tourism patterns.
2. Seasonal Trends:
   a. peaks and troughs observed in the graph indicate consistent seasonal variations, which are critical for tourism planning. These patterns can help identify peak seasons, allowing stakeholders to allocate resources effectively.
3. Disruptions and Recovery:
   a. The sharp decline in 2020 highlights the vulnerability of the tourism sector to external shocks like pandemics. The model's performance during this period reflects the limitations of historical data in predicting unprecedented events.
   b. The upward trend in predictions for 2024 and 2025 signals optimism for recovery, assuming stable global conditions and no major disruptions.
4. Uncertainty in Long-Term Predictions:
   a. While the predictions for 2024 and 2025 are optimistic, it is essential to note that long-term forecasting always carries a degree of uncertainty, especially in a volatile sector like tourism. Factors such as economic conditions, geopolitical events, and environmental challenges could impact the accuracy of these forecasts.

Practical Implications

1. Policy and Infrastructure Planning:
   a. The forecasts can guide policymakers and tourism operators in planning infrastructure development to accommodate expected tourist growth in 2024 and 2025.
   b. For example, if the predictions of increased arrivals materialize, there may be a need for expanded airport capacity, improved public transportation, and additional hotel accommodations.
2. Marketing and Revenue Optimization:
   a. The insights from the graph can help optimize marketing strategies, targeting regions and time periods where higher tourist arrivals are expected.
   b. Understanding seasonality also enables businesses to plan promotions and offers during off-peak seasons to balance demand.
3. Crisis Management:
   a. The decline in 2020 underscores the importance of contingency planning for future disruptions. The model could be further enhanced with real-time data integration to improve responsiveness during crises.
4. Environmental Sustainability:
   a. While increased tourist arrivals signal economic growth, they also raise concerns about overcrowding and environmental degradation. Stakeholders must balance growth with sustainability to preserve Bali's natural and cultural assets.

http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 265-274

Table 1. Evaluation Metrics

Model	Mean Squared Error (MSE)	Mean Absolute Error (MAE)
Linear Regression	934,226,027.14	57,190.76
Decision Tree	516,382,750.57	14,183.39
Random Forest	506,739,747.83	11,926.07

The models were evaluated using Mean Squared Error (MSE) and Mean Absolute Error (MAE), with the following results:

1. Linear Regression:
    a. MSE: 934,226,027.14
    b. MAE: 57,190.76
    c. Interpretation: Linear Regression performs poorly due to its inability to capture nonlinear and seasonal patterns, making it unsuitable for complex datasets like tourism arrivals.
2. Decision Tree:
    a. MSE: 516,382,750.57
    b. MAE: 14,183.39
    c. Interpretation: Decision Tree performs better than Linear Regression by identifying nonlinear relationships. However, its performance is limited due to susceptibility to overfitting.
3. Random Forest:
    a. MSE: 506,739,747.83
    b. MAE: 11,926.07
    c. Interpretation: Random Forest outperforms both Linear Regression and Decision Tree, demonstrating superior accuracy in capturing seasonal and nonlinear trends. Its ensemble approach minimizes overfitting and enhances robustness.

The results of this study underscore the importance of employing machine learning models to forecast tourist arrivals in Bali, given the region's reliance on tourism as a key economic driver. Among the three evaluated models, Random Forest demonstrated superior performance due to its ability to capture complex patterns and seasonality. This discussion delves deeper into the implications of the findings, highlighting the strengths and weaknesses of the models, their practical applications, and potential avenues for improvement.

3.1. Understanding Model Performance

1. Strengths of Random Forest, Random Forest emerged as the most effective model in this study achieving the lowest Mean Squared Error (MSE) and Mean Absolute Error (MAE) among the three models. Its ensemble approach—combining multiple decision trees—allowed it to effectively model nonlinear relationships and capture seasonal trends. This capability is critical in the context of Bali's tourism industry, where fluctuations in tourist arrivals are influenced by periodic events such as holidays, festivals, and weather patterns. The model's robustness also minimizes the risk of overfitting, ensuring reliable forecasts across various timeframes.
2. Limitations of Linear Regression and Decision Tree Models, while simple and computationally efficient, struggled to capture the complexities of the dataset. Its linear nature limited its ability to model the nonlinear and seasonal patterns inherent in tourist arrivals. Similarly, Decision Tree—though capable of modeling nonlinear relationships—showed limitations in generalizing beyond the training data, likely due to overfitting. These findings highlight the importance of selecting models that can balance interpretability, accuracy, and robustness.
3. Handling Disruptions, a significant limitation observed across all models was their inability to accurately predict the sharp decline in tourist arrivals during the COVID-19 pandemic. This disruption highlights the limitations of historical data in forecasting unprecedented events. The results suggest that incorporating external variables, such as

 http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 265-274

travel restrictions, economic indicators, and real-time updates, could improve the adaptability of forecasting models during volatile periods.

3.2. Practical Implications

1. Policy and Infrastructure Planning. Accurate forecasting is essential for policymakers to plan infrastructure development and manage resources effectively. The predicted recovery in tourist arrivals for 2024 and 2025 provides actionable insights for stakeholders to prioritize investments in transportation, accommodation, and tourist services. For example, optimizing airport capacity and enhancing public transportation systems can ensure a seamless experience for travelers during peak seasons.
2. Sustainable Tourism Development. While growth in tourist arrivals signals economic benefits, it also raises concerns about environmental sustainability and cultural preservation. Forecasts generated by the Random Forest model can guide strategies to balance tourism growth with sustainability. For instance, insights from seasonal patterns can inform policies to manage visitor flows, reduce overcrowding, and protect Bali's natural resources. Sustainability efforts could also include encouraging eco-tourism and implementing green policies, such as waste management systems in tourist hotspots.
3. Crisis Preparedness. The deviations observed during the pandemic emphasize the importance of integrating crisis scenarios into forecasting frameworks. Predictive tools can support contingency planning by simulating the impacts of potential disruptions, such as natural disasters, economic downturns, or future pandemics. This enables stakeholders to develop adaptive strategies that ensure the resilience of Bali's tourism sector. For instance, preemptive measures such as flexible tourism packages or emergency visitor accommodations can be designed based on forecast scenarios.
4. Marketing and Promotion Strategies. Tourism operators can leverage seasonal insights to design targeted marketing campaigns. Promoting off-peak travel periods can help distribute tourist arrivals more evenly, mitigating the risks of overcrowding during high seasons. Additionally, identifying growth trends allows businesses to tailor their offerings to align with emerging demands and traveler preferences. Strategic advertising campaigns that align with forecasted spikes in arrivals can maximize revenue. Moreover, partnerships with airlines and hotels during low seasons could incentivize bookings and support more balanced tourism flow.

3.3. Opportunities for Model Improvement

1. Integration of External Variables. Incorporating additional data sources, such as weather conditions, global economic indicators, and travel restrictions, could enhance the predictive accuracy of the models. For instance, including exchange rates or oil prices may help capture the economic factors influencing international travel demand. Real-time data integration, such as flight bookings or social media trends, can further improve the adaptability of forecasts. Additionally, real-time event data, such as major international festivals or geopolitical developments, could provide more context to refine predictions.
2. Adoption of Hybrid Models. The results of this study highlight the potential of hybrid approaches, such as combining Random Forest with Long Short-Term Memory (LSTM) networks. While Random Forest excels in capturing seasonal trends, LSTM's ability to model long-term dependencies could complement it by providing more nuanced insights into temporal relationships. Hybrid models could improve forecasting accuracy, particularly during periods of disruption. For example, combining the strong ensemble capabilities of Random Forest with the sequence-processing strengths of LSTM may address both short- and long-term forecasting needs.
3. Scenario-Based Forecasting. Developing scenario-based forecasts—optimistic, baseline, and pessimistic—can help stakeholders prepare for various potential outcomes. By simulating different scenarios, policymakers can allocate resources more effectively and design contingency plans for both growth and downturn periods. Scenario-based forecasting could also include sensitivity analysis, helping stakeholders understand how changes in key variables (e.g., oil prices or exchange rates) could impact tourist arrivals.

http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
7 (1) September 2024 265-274

3.4. Long-Term Implications

1. Tourism Recovery and Growth. The projected recovery in tourist arrivals for 2024 and 2025 reflects global optimism regarding the rebound of international travel. These forecasts can guide Bali's tourism stakeholders in developing strategies to capitalize on post-pandemic recovery trends. For instance, diversifying Bali's tourism offerings beyond traditional beach tourism—such as promoting eco-tourism, cultural experiences, and wellness retreats—can attract a broader demographic of travelers. Such diversification can also protect Bali's tourism sector from over-reliance on specific markets or seasons, improving resilience.
2. Economic Impact. The growth in tourist arrivals directly influences Bali's economy by boosting revenue for local businesses, creating jobs, and increasing foreign exchange earnings. Accurate forecasts enable stakeholders to estimate economic contributions more effectively, informing fiscal policies and investment strategies. Moreover, identifying off-peak periods through forecasting allows stakeholders to incentivize tourism during quieter months, spreading economic benefits more evenly across the year.
3. Addressing Limitations in Data Quality. The accuracy of forecasting models depends heavily on the quality and completeness of input data. Future research should focus on addressing gaps in historical data, improving preprocessing techniques, and integrating diverse datasets to enhance the robustness of predictions. For instance, combining official tourism records with user-generated data, such as reviews and location check-ins on social media, could provide additional layers of insight. Additionally, employing explainable AI techniques can increase transparency, making model outputs more accessible to non-technical stakeholders and fostering trust in predictions.
4. Encouraging Regional Collaboration. The success of Bali's tourism recovery and growth is linked to broader regional dynamics in Southeast Asia. Collaborative forecasting models that incorporate data from neighboring destinations could provide a holistic view of regional travel trends, enabling better coordination in marketing and infrastructure development. Such collaboration could include shared tourism packages or coordinated promotional campaigns that boost arrivals across multiple destinations.
5. Technological Innovation and Automation. The integration of machine learning models into real-time systems for tourist flow management represents a significant advancement for Bali's tourism sector. Automated systems that monitor real-time data streams, such as flight arrivals or accommodation bookings, can trigger dynamic adjustments in marketing or pricing strategies. Furthermore, integrating AI-driven chatbots and recommendation systems based on forecast data can improve visitor experiences and satisfaction.
6. Future Research Directions. Expanding the scope of machine learning applications in tourism forecasting can open new opportunities for enhancing prediction accuracy and strategic planning. Research focusing on the application of deep reinforcement learning or generative models could address current limitations in handling unexpected disruptions. Moreover, studying the socio-economic impacts of forecasted tourism trends on local communities could provide valuable insights for sustainable development.

4. Conclusion

This study highlights the effectiveness of machine learning techniques in forecasting tourist arrivals in Bali, with the Random Forest model outperforming Linear Regression and Decision Tree models. Random Forest's ability to handle nonlinearity and capture seasonal patterns made it particularly suited for Bali's tourism data, characterized by periodic fluctuations and complex trends. The model's superior performance in both accuracy and robustness underscores the value of ensemble methods in tourism forecasting, especially for managing seasonal variations and long-term growth trends.

While the study demonstrated the potential of machine learning models, it also revealed areas for improvement. The inability to predict sharp disruptions, such as the COVID-19 pandemic, emphasizes the need for integrating real-time external variables, like economic indicators and travel

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7 (1) September 2024 265-274

restrictions. Future research could enhance forecasting accuracy by incorporating hybrid models, such as combining Random Forest with Long Short-Term Memory (LSTM) networks, and developing scenario-based approaches for better preparedness. These advancements will enable stakeholders to make data-driven decisions, optimize resource allocation, and support sustainable tourism development, ensuring Bali's position as a premier global destination.

5. Suggestion

To enhance the forecasting of tourist arrivals in Bali, future research should focus on integrating diverse and real-time data sources. External variables such as weather conditions, exchange rates, international travel advisories, and socio-political factors should be included to better capture the dynamics influencing tourism demand. Additionally, incorporating data streams from social media sentiment, flight booking trends, and macroeconomic indicators could significantly improve model adaptability and forecasting precision, especially during periods of disruption like the COVID-19 pandemic. These steps can address the limitations of relying solely on historical data and make the models more resilient to unexpected events.

Adopting advanced machine learning techniques, such as hybrid models combining Long Short-Term Memory (LSTM) networks with Random Forest, can improve predictive accuracy by leveraging the strengths of both algorithms. Scenario-based modeling can also be explored to prepare for optimistic, baseline, and pessimistic tourism trends, aiding policymakers in resource allocation and contingency planning. Furthermore, efforts should be directed toward increasing model transparency through explainable AI (XAI) tools, enabling non-technical stakeholders to interpret and trust the predictions. These enhancements will ensure more robust, actionable insights for Bali's tourism sector, supporting sustainable growth and effective crisis management strategies.

Declaration of Competing Interest

We declare that we have no conflict of interest.

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