IAES International Journal of Artificial Intelligence (IJ-AI)
Vol. 14, No. 2, April 2025, pp. 1022~1030
ISSN: 2252-8938, DOI: 10.11591/ijai.v14.i2.pp1022-1030

Predicting tourist arrivals to a tropical island using artificial intelligence

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Article Info

Article history:

Received Apr 24, 2024
Revised Nov 12, 2024
Accepted Nov 24, 2024

Keywords:

AI methodologies
East Java
East Java province
Temporal trends
Tourism forecasting

ABSTRACT

This research leverages artificial intelligence (AI) techniques to develop a predictive model for forecasting tourist arrivals in East Java Province, Indonesia, using a comprehensive dataset encompassing historical tourism statistics from 2018 to 2020, seasonal trends, promotional campaigns, and various economic and social variables. The study evaluates three AI methodologies: artificial neural network (ANN), extreme learning machine (ELM), and Jordan recurrent neural network (JRNN), each known for their distinct strengths in processing complex data and adapting to changing trends. The comparative analysis reveals that the JRNN model outperforms others with the highest precision, achieving an average prediction deviation of just 2.98% from actual data, effectively capturing temporal and seasonal trends. The ANN follows closely with a deviation of 3.31%, showing strong capabilities in handling complex, nonlinear relationships. In contrast, the ELM, though fastest in training, exhibits a larger deviation of 10.51%, indicating a trade-off between speed and accuracy. These results highlight the potential of AI to significantly enhance the accuracy and operational efficiency of tourism forecasts, offering robust tools for stakeholders to engage in informed strategic planning and resource allocation in dynamic market conditions.

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1. INTRODUCTION

Indonesia's tourism industry is a crucial sector contributing to the national economy. As such, understanding the factors that influence foreign tourist arrivals is vital for strategic planning and development. A range of factors influence the number of foreign tourists visiting Indonesia. Ulfah *et al*. [1] found that gross domestic product (GDP) per capita, economic distance, relative prices, and security significantly affect tourist numbers, while exchange rates and travel warnings have no significant impact. Santamaría [2] further identified tourist expenditure, consumer price index (CPI), terrorism, and COVID-19 as significant negative factors, and exchange rates and GDP per capita as significant positive factors. Westoby *et al.* [3] emphasized the importance of tourism destinations and human resources in sustainable tourism implementation, particularly in popular destinations like Bali. These studies collectively highlight the need for stable economic conditions, effective marketing, and high-quality tourism products and services to attract more foreign tourists to Indonesia.

However, the COVID-19 pandemic has reshaped the global tourism landscape, bringing significant changes and challenges to the sector. The pandemic has significantly impacted tourist numbers due to a dual causality between the virus spread and tourist arrivals [4]. This linkage has reduced travel willingness, influenced by perceptions of severity and personal impacts [5]. The pandemic has also altered attitudes toward tourism, where COVID-19 statistics and media coverage have played a substantial role [6]. These changes have negatively affected the tourism industry, including in protected and conserved areas [7]. The pandemic has not only disrupted travel but also forced a reevaluation of how tourism interacts with health, safety, and environmental concerns globally.

The digital revolution has fundamentally transformed various sectors of life, including tourism. In the last decade, technological advancements, particularly in the field of artificial intelligence (AI), have opened significant new opportunities for understanding and enhancing the competitiveness of tourism. A range of studies have explored the use of AI in predicting tourist numbers. Petrović *et al*. [8] utilized machine learning, achieving notable outcomes in the prediction of tourist flows. Lu *et al.* [9] achieved a high prediction accuracy using genetic algorithm-convolutional neural network-long-short-term memory network (GA-CNN-LSTM) algorithm. Zhong [10] focused on the application of a 10-layer backpropagation neural network model to predict tourist arrivals in Queensland, Australia, showing promising results. Lastly, Sovia *et al.* [11] combined multiple linear regression and artificial neural networks (ANN) to predict tourist visits, achieving a high level of accuracy. These studies collectively demonstrate the potential of AI in accurately forecasting tourist numbers.

However, despite the advances in AI applications for forecasting tourist numbers, there remain significant gaps in research, particularly regarding the prediction of both local and international tourist flows to Indonesia in the post-COVID era. Previous studies have predominantly focused on individual aspects of tourist behavior or specific technological models without fully addressing the integrative effects of global pandemics like COVID-19 on tourism dynamics. The aim of future research should therefore be to develop a novel, comprehensive AI-based forecasting model that incorporates a wide range of variables influenced by pandemic outcomes. This model should not only consider economic indicators and health statistics but also adapt to new patterns of tourist behavior and expectations that have emerged as a result of the pandemic. By addressing these gaps, the research could provide more robust tools for tourism stakeholders to anticipate changes and plan more effectively, thereby enhancing the resilience and sustainability of Indonesia's tourism industry.

2. METHOD

In this study, the predictive system will utilize three AI methodologies: ANN, extreme learning machine (ELM), and Jordan recurrent neural network (JRNN) as comparative frameworks. The adoption of these methods is due to their superior capabilities in forecasting tourist arrivals by learning complex patterns from historical data and adaptively adjusting to the evolving trends in tourism. This chapter will elaborate on the methodologies employed, providing a detailed examination of each technique's architecture, the rationale behind their selection, and their respective roles in enhancing the accuracy and reliability of the tourism prediction system being developed.

2.1. Artificial neural networks

ANNs are highly effective in forecasting future tourist arrivals by analyzing complex patterns in historical and contextual data [12], [13]. By inputting diverse factors such as past tourism statistics, economic indicators, environmental conditions, and social media trends into the network, ANNs can learn to identify intricate relationships and dependencies that influence tourism demand. The network architecture typically includes multiple layers: an input layer to receive the data, several hidden layers that process the data through weighted connections and non-linear activation functions, and an output layer that predicts future tourist numbers. During the training phase, the network adjusts its weights based on the error in its predictions, improving its accuracy over time. This capability allows ANNs to provide reliable predictions on tourist arrivals, helping stakeholders in the tourism industry to plan resources, marketing strategies, and policies effectively in anticipation of future trends.

The formula shown in (1) used in ANNs is crucial for processing inputs to predict future tourist arrivals [14], [15]. In this context, each xi represents a different input feature such as past tourism data, economic indicators, environmental conditions, and social media trends. The wi are the weights assigned to each of these features, reflecting their relative importance in predicting tourism demand. The process involves multiplying each feature by its corresponding weight and summing all these values. The bias term b is then added to this sum to provide additional flexibility, allowing the activation function to adjust the threshold at which the neuron activates. This sum, z, becomes the input to the activation function in a neuron of the hidden layer, which then processes it to contribute to the final prediction output. By adjusting these weights and biases during training, based on the prediction error, the ANN learns to accurately forecast tourist numbers, aiding stakeholders in strategic planning and decision-making.

$$z = \sum_{1=i}^{n} w_i x_i + b \tag{1}$$

2.2. Extreme learning machine

ELM offers a promising approach to forecasting future tourist arrivals due to its rapid training capabilities and adeptness in managing complex data interactions [16]–[18]. ELM streamlines the learning process by randomly assigning and fixing weights and biases to the hidden neurons from the outset, thereby eliminating the need for iterative adjustments typical of traditional neural networks. In the context of tourism forecasting, ELM can handle a variety of inputs like historical tourist numbers, economic conditions, seasonal variations, and environmental factors. This method uses a single-layer feedforward network where the inputs undergo transformation through nonlinear activation functions in the hidden layer, enabling the capture of complex and nonlinear relationships in the data. The critical computational step in ELM involves determining the output weights connecting the hidden layer to the output layer using a least squares method. This method efficiently adjusts these weights by minimizing the error between actual and predicted tourist arrivals, computed swiftly through the pseudoinverse of the hidden layer's output matrix. The simplicity and computational efficiency of ELM make it an attractive tool for rapidly generating reliable tourist arrival forecasts, aiding stakeholders in the tourism industry to make informed decisions quickly, especially in dynamic market conditions.

In the context of using the ELM for predicting tourist arrivals, the formula shown in (2) plays a crucial role. Here, X represents the matrix of input data, which could include variables such as historical tourism data, economic indicators, weather conditions, and other factors relevant to predicting tourist numbers. The W and b are the randomly assigned weights and biases for the neurons in the hidden layer of the ELM, which are fixed and not adjusted during the training process. The function g is a non-linear activation function, such as the sigmoid or hyperbolic tangent, applied to the linear combination $XW + b$. This step transforms the input data into the hidden layer output H, which encapsulates the non-linear interactions between the inputs [19], [20]. The output H is then used to compute the output weights that connect the hidden layer to the output layer, ultimately predicting the number of tourist arrivals. This methodology allows the ELM to quickly and efficiently model complex relationships in the data, providing fast and reliable forecasts essential for tourism management and planning.

$$H = g(XW + b) \tag{2}$$

2.3. Jordan recurrent neural network

JRNN are particularly effective for forecasting future tourist arrivals due to their recurrent architecture, which can process sequential data and retain information from previous outputs [21]–[23]. By feeding back the output from the network's previous steps into the input for subsequent predictions, JRNNs are adept at capturing the temporal dynamics and seasonality of tourism data. This feature allows the network to utilize not just current data such as economic indicators, weather conditions, and event schedules, but also to remember and integrate past tourist numbers into its forecasting model. During training, JRNNs continuously adjust their weights to minimize prediction errors, enhancing their accuracy over time. This ability to refine its understanding of complex temporal patterns makes JRNN an invaluable tool for stakeholders in the tourism industry, enabling them to predict future trends more accurately and optimize planning and resource management in response to anticipated changes in tourist arrivals.

The formula shown in (3) used in JRNN effectively captures the dynamics of tourist arrival predictions by integrating past outcomes into future forecasts [24], [25]. Here, xt represents the input at time t, which might include various predictors such as current economic conditions, seasonal factors, and other relevant tourism indicators. Wh and Wy are the weights applied to the current input and the output from the previous time step ($yt - 1$), respectively. This reflects how past tourism numbers (represented by $yt - 1$) and current data influence the prediction for the next period. The bias b_h adjusts the threshold level of the activation function σ, which is typically a nonlinear function like sigmoid or tanh, helping to model complex, nonlinear relationships in the data. By recalculating the hidden state h_t at each time step using both new input and feedback from the previous output, JRNNs provide a powerful mechanism for predicting tourist arrivals with increased accuracy, capturing trends and cyclic behavior crucial for effective tourism management and planning.

$$h_t = \sigma\,(Whxt + Wyyt - 1 + b_h) \tag{3}$$

2.4. Tourism visitor prediction using machine learning techniques

The diagram presents a structured workflow for predicting tourism visitor numbers by leveraging machine learning techniques. The process begins with the collection of tourism visitor data spanning from 2018 to 2020, which is then subjected to data processing and modeling to prepare it for analysis. Following this, a method selection phase occurs where one can choose from three different machine learning models: ANN, ELM, or JRNN. Once a model is selected, an analysis of tourism data constraints is performed to assess the model's fit to the data. If the model is not fitting well (no pathway), the process iteratively returns to the data processing and modeling phase to adjust and refine the model or data. On achieving a satisfactory fit (yes pathway), the process concludes, resulting in a predictive model capable of forecasting future tourism visitor numbers. This workflow shown in Figure 1 exemplifies a systematic approach to model selection and validation in the context of tourism data analysis, ensuring that the chosen model is well-suited to the underlying patterns and characteristics of the data.

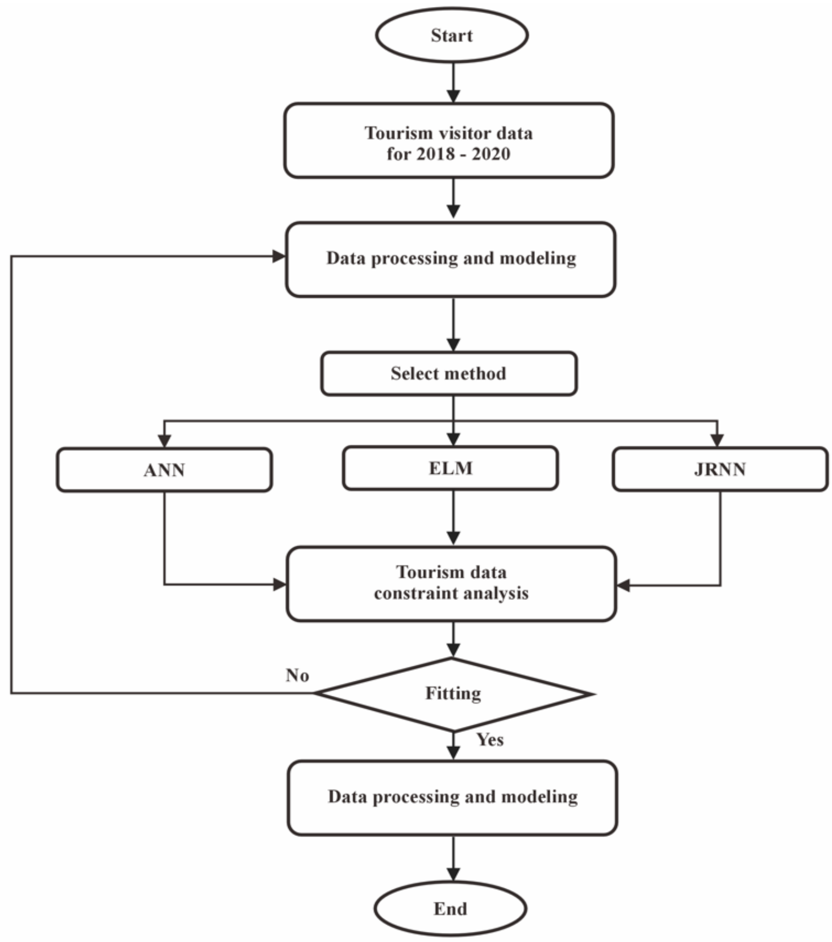
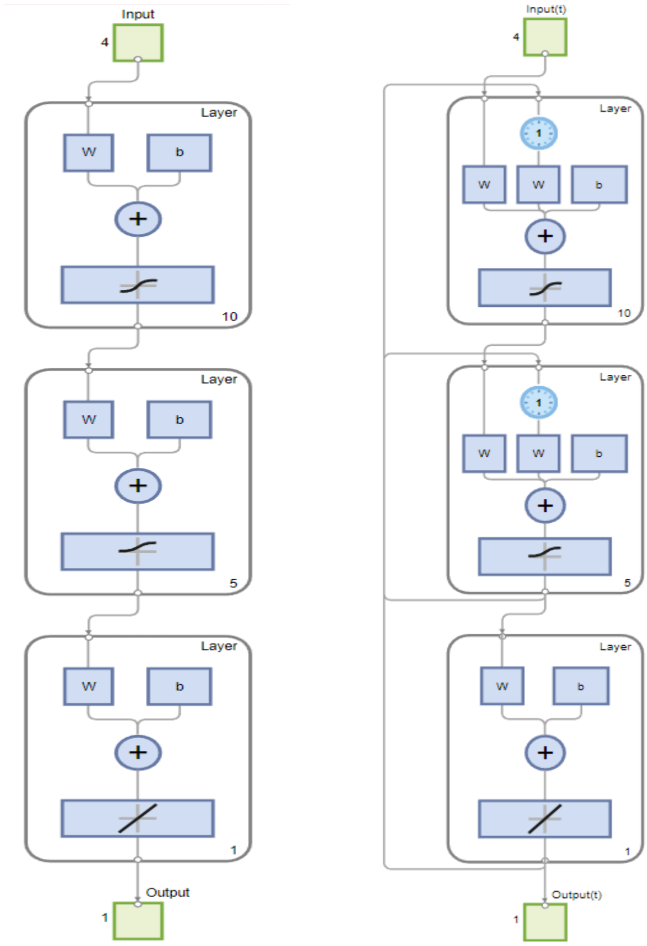


Figure 1. Flowchart of machine learning techniques

The architectures of ANN and JRNN are distinctive, yet both are rooted in the foundational concept of neural computation. ANNs consist of an input layer, one or more hidden layers, and an output layer, with each layer composed of interconnected neurons that process information through weighted connections and biases. This configuration enables ANNs to learn from and adapt to data by adjusting these weights during the training phase, as depicted in Figure 2(a). JRNNs, as illustrated in Figure 2(b), augment this architecture by incorporating feedback loops. These loops channel the output of the network back into the input for subsequent time steps, endowing the network with a form of memory regarding previous outputs. This architecture is particularly beneficial for time-series data, such as the figures for tourist arrivals, because it captures the temporal dependencies that are often present within such data. The respective architectures of each model are purposefully designed to harness different dimensions of data structure and the inherent patterns therein, which promotes effective learning and forecasting capabilities.



(a) (b)

Figure 2. Architecture of (a) ANN and (b) JRNN

3. RESULTS AND DISCUSSION

A comparative analysis of results obtained using ANN, ELM, and JRNN models in predicting tourist numbers in East Java in 2021 offers valuable insights regarding the effectiveness and efficiency of each method in the context of temporal and fluctuating data like tourism statistics. The ANN model shows good capability in capturing complex and non-linear patterns from historical data, producing relatively accurate predictions compared to actual data. The training process, which involves backpropagation, allows the model to iteratively adjust its weights based on prediction errors, thereby enhancing the model's generalization ability to new data. However, the complexity and time required for ANN training may be a consideration, especially if the available data is very large or if the model needs frequent updates. On the other hand, ELM offers significant training speed as an advantage. By initializing hidden weights randomly and not altering them, ELM speeds up the training process without the need for iterative weight adjustments as in ANN. The prediction results from ELM show that despite its simpler approach, this method can still produce competitive estimates with ANN. This points to ELM as an appealing choice for applications where training speed is a priority, though it may require further adjustments to improve accuracy. JRNN, with its architecture that allows retaining information from previous inputs through backward connections, proves effective in modeling temporal data with long-term dependencies. JRNN produces predictions that are very close to reality, reflecting its ability to understand and project patterns in time-series data. The uniqueness of JRNN in considering temporal context makes it highly suitable for predicting tourist numbers, which may be influenced by seasonal factors or long-term trends.

From Table 1 and Figure 3, it's clear that the ANN, ELM, and JRNN models all have varying degrees of success in predicting the monthly tourist numbers. The JRNN seems to be the closest in tracking the actual data throughout the year, which suggests its proficiency in capturing the temporal dependencies and underlying trends in the tourism data. This capability is particularly valuable in tourism forecasting, where past trends can influence future outcomes. The ANN predictions also follow the trend of the actual data closely, with some discrepancies that are more pronounced in months where tourist numbers change sharply, such as April, July, and December. This might indicate that while ANN is proficient at understanding complex patterns, it may need more data or perhaps a different architecture to capture rapid changes more effectively.

Table 1. Comparative data on the number of tourists in east java for the years 2018-2021, along with predictions from ANN, ELM, and JRNN models

Month	Number of East Java tourist (people)						
	2018	2019	2020	2021			
	Actual	Actual	Actual	Actual	ANN	ELM	JRNN
January	605,515	663,168	764,903	1,261	1,506	1,510	1,202
February	696,021	678,159	526,944	6,039	5,676	5,554	6,163
March	795,296	706,825	236,170	10,245	10,291	10,722	10,109
April	803,669	721,315	728	15,586	15,663	15,986	15,730
May	769,881	672,688	442	12,944	12,901	12,804	12,954
June	773,485	783,361	1,042	13,630	13,644	15,808	13,902
July	1,020,834	924,733	3,218	5,518	5,503	5,491	5,689
August	945,717	915,852	4,507	1,107	1,180	1,014	1,239
September	860,528	852,251	7,519	4,083	4,038	5,570	3,833
October	814,872	804,758	9,889	13,739	13,971	11,046	13,615
November	670,738	725,912	14,382	18,983	19,148	19,089	18,543
December	778,514	782,240	22,026	16,696	16,291	15,261	16,762
Total	9,535,070	9,231,262	1,591,770	119,831	119,812	119,855	119,741

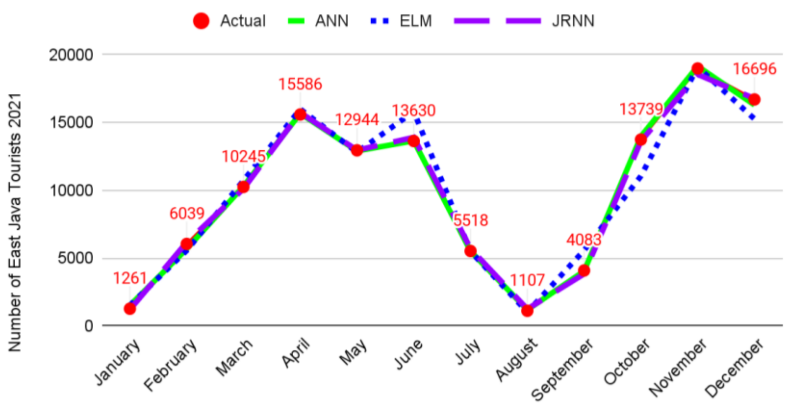


Figure 3. Comparative graph of the number of tourists in East Java for the year 2021

ELM, while generally less accurate than JRNN and ANN, still tracks the overall trend of the data. It's noteworthy that the ELM model predictions are remarkably close to those of ANN in most months, which is impressive given that ELM's primary advantage is its rapid training time. This makes ELM an attractive option when speed is a priority, and near-real-time predictions are required, though it may not be the best choice when the highest accuracy is needed. Analyzing the cumulative performance over the entire year, the JRNN model appears to offer the best balance between accuracy and responsiveness to changes in the data. It closely mirrors the actual data's seasonal peaks and troughs, which indicates a robust understanding of the time series data's characteristics.

JRNN's ability to retain and utilize past information effectively contributes to its strong performance, especially in contexts where the sequence and timing of past events are significant predictors of future events, such as in tourism. In summary, when we consider the proximity of the predicted data to the actual figures, JRNN emerges as the superior model among the three. Its strength in modeling long-term dependencies and capturing complex temporal patterns makes it the most accurate for the fluctuating and seasonal nature of tourism data. However, when operational constraints such as time and computational resources are also considered, ELM's fast training capabilities present a valuable trade-off for slightly less accuracy. The choice between these models would ultimately be driven by the specific requirements of a forecasting task-whether the premium is on accuracy, speed, or perhaps a balance of both, which might even involve an ensemble of these models to harness their collective strengths. The performance analysis of AI models for predicting tourist arrivals in East Java, Indonesia, illustrates distinct capabilities among the three examined techniques. The JRNN model emerges as the most precise, with an average prediction deviation of just 2.98%, underscoring its adeptness at handling time-series data with complex temporal dependencies. Meanwhile, the ANN also demonstrates commendable accuracy with a slightly higher average deviation of 3.31%, indicating robust pattern recognition capabilities for complex datasets. In contrast, the ELM, while the fastest in terms of training, shows a higher average deviation of 10.51%, reflecting a trade-off between speed and precision. This comparative insight highlights the importance of model selection based on specific needs-accuracy versus training speed-guiding stakeholders in choosing the right tool for enhancing strategic planning and operational efficiency in tourism management.

4. CONCLUSION

This research provides a nuanced comparison of three distinct AI models-ANN, ELM, and JRNN-for forecasting tourist numbers in East Java. The analysis demonstrates that each model possesses specific strengths suited to different aspects of tourism forecasting. The JRNN model emerges as the most accurate, with the lowest average deviation from actual data (2.98%), proving its capability in capturing temporal and seasonal trends effectively. This makes it particularly valuable for long-term planning where understanding cyclical patterns is crucial. In contrast, the ANN model, with an average deviation of 3.31%, also performs robustly, especially in deciphering complex and non-linear relationships within the data. This model is ideal for scenarios that require deep learning capabilities to interpret intricate data layers. Meanwhile, the ELM model, though less accurate with a 10.51% deviation, offers the fastest training times, making it suitable for situations where speed in forecasting is prioritized over pinpoint accuracy. Overall, the selection among these models should be guided by the specific needs of the stakeholders, balancing between accuracy, speed, and the complexity of data. The JRNN's superior ability to handle time-related data suggests it as the best fit for accurate and dynamic tourism forecasting, while ELM provides a practical solution for quick predictions, and ANN stands out when complex data analysis is needed. This comparison not only underscores the diverse capabilities of AI in enhancing tourism predictions but also assists in strategic decision-making, ensuring that stakeholders can align their choices with their operational demands and forecasting objectives.

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