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Forecasting Tourism Revenues in Tanzania: A Comparative Analysis of Support Vector Machine and Artificial Neural Network Performance

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Abstract

The tourism industry is a vital pillar of Tanzania's economy, necessitating reliable revenue forecasts for effective policy and investment decisions. This study analyses and compares the performance of two machine learning models, Support Vector Machine (SVM) and Artificial Neural Network (ANN) in forecasting Tanzania's tourism revenues. Based on historical annual data from 1970 to 2024, both models were developed, and their performance was evaluated using the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) metrics. The comparative analysis shows that the Support Vector Machine model outperformed the Artificial Neural Network model, as evidenced by lower error rates. The findings suggest that SVM is a highly effective predictive tool for this domain, offering significant practical implications for the strategic management of Tanzania's tourism sector.

1. Introduction

Tourism serves as an essential component of Tanzania's economy, contributing significantly to GDP, employment, and foreign currency earnings [1]. Tanzania is a country with many attractions, including the Serengeti National Park, the sandy beaches north and south of Dar es Salaam, the Spice Islands of Zanzibar and deep-sea fishing at Mafia and Pemba Islands. These natural features attract millions of travellers annually from around the globe. The 2024 Economic Impact Research (EIR) conducted by the World Travel & Tourism World Travel & Tourism Council (WTTC) highlights a surge in Tanzania's travel and tourism industry. Research shows that in 2023, the sector contributed a record of TZS 18.6 trillion to the national GDP, marking a 4% increase from the 2019 peak and accounting for 9.5 percent of the total economic output. In terms of spending, it

reveals unprecedented levels of international visitors' expenditures, reaching TZS 8 trillion, surpassing 2019 figures by 11.1%. Employment figures in 2023 also show a significant rise, with the sector employing over 1.4 million people [2].

Despite this potential, tourism revenue is nevertheless vulnerable to external shocks, such as world economic downturns, fluctuations in exchange rates, health crises (e.g., COVID-19), and shifting travel advisories [3]. These shocks make tourism revenue forecasting challenging for policymakers and stakeholders. Therefore, reliable forecasting approaches are essential for policymakers, investors, and industry stakeholders to mitigate risks and capitalize on growth opportunities.

Traditional forecasting methods, such as autoregressive integrated moving average (ARIMA) and regression models, have been widely used to predict tourism demand [4]. Although these methods work well for linear trends, they often fail to consider nonlinear trends and high-dimensional data that are present in tourism ecosystems, such as social media sentiment, airline pricing dynamics, and geopolitical events [5]. On the other hand, machine learning models such as artificial neural networks (ANN) and support vector machines (SVM) have sophisticated capabilities to decipher intricate patterns and increase prediction accuracy. ANNs are always superior at modelling nonlinear relationships through layered frameworks, while SVMs use kernel functions to classify or regress high-dimensional data with minimal overfitting [6].

Recent studies on Tanzania's tourism forecasting have extensively employed the traditional Box-Jenkins model, that is, ARIMA/SARIMA [7]. Machine learning (ML) approaches offer a promising substitute due to their ability to manage large datasets, detect hidden patterns, and adjust to changing dynamics [8]. They can provide projections that are more accurate by considering the real-time variables like flight bookings, sentiment on social media, and climate patterns [9].

This study examines the performance of SVM and ANN on forecasting tourism revenues in Tanzania. The selection of ANN and SVM for this comparative analysis was deliberate and grounded in their status as two foundational philosophically distinct machine learning paradigms. ANN, inspired by biological neural networks, excels at learning complex, hierarchical feature representations through its layered architecture. In contrast, SVM, grounded in statistical learning theory, seeks to find an optimal hyperplane that maximizes the margin between classes. This fundamental difference makes their comparison particularly insightful for understanding which learning strategy is more suited to the characteristics of dataset.

2. Literature review

In this section, the discussion of tourism forecasting, support vector machine approaches for tourism forecasting, and artificial neural networks for tourism forecasting are presented. Also, studies on comparative assessment of methods are discussed.

2.1 Tourism forecasting

Tourism revenue forecasting is essential for economic planning, particularly in developing nations like Tanzania, where the sector makes a substantial contribution to GDP and employment [10]. ARIMA and other traditional statistical forecasting techniques can be effective in predicting simple patterns over time, but they frequently fall short in making precise predictions when the data becomes more complex. Research by Irandoust [11] and Xu et al. [12] show that the demand for tourism is affected by a number of variables, such as geopolitical stability, exchange rates, and economic conditions, which calls for more sophisticated modelling methods.

Recent developments in machine learning (ML) have enhanced the forecast accuracy of tourism demand and revenue by managing complex and non-linear relationships in data [13]. Machine learning models have been inspired by numerous applications across several disciplines. They have demonstrated a superior performance on complicated data and tasks; thus, forecasting systems are adopting them [14]. For example, Claveria et al [15] showed that when it comes to mid- and long-term forecasting, machine learning (ML) models result in better forecast accuracy. Moreover, Li et al. [9] said that machine learning (ML) can yield more accurate findings than conventional methods. Therefore, machine learning methods are helpful tools for governments, tourist stakeholders, and investors, among others, to improve strategic and investment decisions [16].

Machine learning techniques have been effectively used in forecasting tourism demand [17]. The two most widely used machine learning methods are ANN and SVM. Applications of these methods are numerous, primarily in the areas of forecasting, regression, and classification [18].

2.3 Artificial Neural Networks (ANN) in Tourism Forecasting

One machine learning technique that has been predicting time series effectively is SVM. It is a powerful ML tool widely used for both linear and nonlinear classification as well as for regression and outlier detection tasks [19]. SVMs are particularly effective because they focus on finding the maximum separating hyperplane between the different classes in the target feature, making them robust for binary and multiclass classification.

According to several findings, SVM has demonstrated a high degree of accuracy in predicting international tourist arrivals [20]. SVMs use the so-called kernel trick to map data into the feature space with a higher dimension, creating a linear separating hyperplane. The mean forecasting error is reduced by the SVM model using a set of candidates and training at every forecasting stage [21]. The proper selection of SVM's parameter values, such as the kernel function, kernel parameter, and regularization parameter, is crucial in improving the model's performance [22].

ANN model is an effective and precise tool for determining nonlinear relationships among a number of inputs and one or more outputs. This approach has been successfully applied for optimizing, predicting, forecasting, and controlling many complex systems. Çuhadar [23] used ANN to forecast tourism revenue in Turkey and discovered that it outperformed ARIMA and exponential smoothing.

ANNs are versatile, non-linear, all-purpose statistical tools that can understand the intricate relationships that arise in the social processes related to tourism. This is in contrast to traditional statistical models, which fail to capture complex data. Compared with other approaches, such as linear models or ARIMA time series models [24], ANNs offer higher competitive advantages.

2.4 Comparative performance assessments on SVM and ANN

Several studies compare the performance of ANN and SVM models. Kandananond [25] discovered that ANN can be a better option than SVM when processes are stationary. For non-stationary data, however, SVM outperforms ANN. Furthermore, SVM works well for short datasets with clear trends, whereas ANN performs better for big, dynamic datasets that integrate pandemic recovery tendencies. Madhu et al. [26] showed that when the projected and real option prices are in good agreement, the ANN model outperforms the SVM model. Also, studies show that SVM and ANN are important in stock forecasting, and their hybrid models can further improve forecasting accuracy [27]. Therefore, between SVMs and

ANNs, there is no single optimal model in all situations. The specific dataset, the nature of the problem, and the intended result all have a significant influence on the best models.

2.5 Research Gap and Contribution

There are a few studies on modelling and forecasting tourism revenues. Akal [28] used a suitable ARMAX model to predict Turkey's foreign tourism earnings for the economic crisis that followed 2001. Anh and Huy [29] used linear regression as a method to estimate Vietnam's tourism revenue. The ARIMA technique was applied by Ahmed et al. [30] to predict tourism revenue in Bangladesh. Zaki [31] used the ARIMA model to predict Egypt's total tourism demand and revenue. Chen et al. [32] also used the Grey Markov Chain to forecast tourism revenue in Macau.

Even though machine learning is increasingly being used in tourism forecasting, no research has employed SVM and ANN to examine the forecasting performance on Tanzania's tourism revenues. The majority of current research focuses on developed countries' markets. No research compares the performance of these models in Tanzania, which presents a different infrastructure and economic challenges. This paper aims to close this gap.

3. Methodology of the study

This section presents the comprehensive methodology for SVM and ANN applied to tourism revenue forecasting. The methodology includes the data source and preprocessing, model development for SVM and ANN. Then, the performance metrics are specifically tailored for revenue prediction tasks.

3.1 Data sources

The study uses secondary annual data of Tanzania tourism revenue from 1970 to 2024.The set of data includes the COVID-19 downside effect in 2020. The sources of data are from Lwoga [33] and NBS [34]. All tourism revenues are in US$. The data set is split into two groups. The data from 1970 to 2019 are categorized as the training dataset, and those from 2020 to 2024 are categorized as testing data. We observed that the anomalous data point of revenues in 2020 was caused by the COVID-19 pandemic as an exogenous shock. According to Chandola [35], the correction of an outlier applies linear interpolation between adjacent revenues R_t in the year t ($t = 2019, 2020, \text{and } 2021$) as

$$R_{2020} = (R_{2019} + R_{2021})/2. \quad (1)$$

This arithmetic mean approach preserves the local trend while eliminating the distortion caused by extraordinary events. According to Hyndman and Athanasopoulos [36], simple interpolation methods are often preferred for time series outliers when the underlying trend is stable, as they minimize the introduction of artificial patterns.

Then, the logarithmic scaling is applied. The implementation of logarithmic scaling in tourism revenue analysis provides a mathematically sound visualization of exponential growth patterns while supporting economic interpretation of constant growth rate behaviour. The approach aligns with established statistical principles for variance stabilization and multi-scale pattern recognition in time series data.

3.2 Models Developments

The model development provides a rigorous foundation for tourism revenue forecasting. The SVM approach offers strong theoretical guarantees and robustness, while the ANN provides powerful and flexible approximation capabilities, making both methods well-suited for tackling the challenges of revenue prediction.

3.2.1. Support Vector Machine (SVM)

The SVM aims at finding a function:

$$f(t) = \omega^T \Phi(t) + b, \quad (2)$$

Where ω^T is a weight matrix, b is a bias vector, and Φ is a non-linear activation function (e.g., logistic sigmoid, ReLU, or softmax for the output layer). Equation 2 approximates tourism revenue in a year R_t while maintaining the model's simplicity.

SVM solves a primal convex optimization problem defined as

$$\min_{\omega,b,\xi,\xi_t^*} \left\{ \frac{1}{2}\|\omega\|^2 + C\left(\sum_{t=1}^{T}(\xi - \xi_t^*)\right)\right\} \quad (3)$$

Subject to:

$$R_t - \omega^T(t) - b \leq \epsilon + \xi_t, \quad (4)$$

$$\omega^T \phi(t) + b - R_t \leq \epsilon + \xi_t^*, \quad (5)$$

$$\xi_t, \xi_t^* \geq 0, t = 1, 2, \ldots, T.$$

R_t represents tourism revenue at time t and $C > 0$ is the regularization parameter that controls the trade-off between model complexity and error tolerance.

For practical computation, the dual problem is derived, which facilitates the use of kernels to capture non-linearity. The dual problem of Equation (3) maximizes the following expression:

$$\max_{a,a^*} -\frac{1}{2}\sum_{t,t\prime=1}^{T}(\alpha_t - \alpha_t^*)(\alpha_{t'} - \alpha_{t'}^*)K(t,t') -$$

$$\epsilon\sum_{t=1}^{T}(\alpha_t + \alpha_t^*) + \sum_{t=1}^{T} R_t(\alpha_t - \alpha_t^*), \quad (6)$$

(6)Subject to:

$$\sum_{t=1}^{T}(\alpha_t - \alpha_t^*) = 0, \quad (7)$$

$$0 \leq \alpha_t, \alpha_t^* \leq C,$$

For $t = 1970, 1971, \ldots, 2024$. Here, $K(t,t')$ is the Radical Basic Function (RBF) kernel for revenue forecasting, defined by

$$K(t,t') = exp\left(-\gamma\|x_i - x_j\|\right), \quad (8)$$

where γ is a parameter that sets the spread of the kernel. The kernel in Equation (8) effectively captures non-linear tourism revenue growth. Therefore, the predicted tourism revenues for the new time point are given by

$$\hat{R}_t = \sum_{t'=1}^{T}(\alpha_t - \alpha_t^*)K(t',t) + b. \quad (9)$$

3.2.2 Artificial Neural Network (ANN)

ANN offers a flexible function approximation approach. The architecture for this study consists of an input layer (the temporal feature t), two hidden layers with 100 and 50 neurons, respectively, using ReLU activation functions, and an output layer producing the predicted revenue $\hat{R}_t$. Forward propagation proceeds layer-wise: the input is transformed as

$$z^{(1)} = \omega^{(1)}t + b^{(1)}, \quad (10)$$

and

$$a^{(1)} = max(0, z^{(1)}), \quad (11)$$

followed by similar computations for the subsequent layers until the final output

$$\hat{R}_t = z^{(3)} = \omega^{(3)}a^{(2)} + b^{(3)}, \quad (12)$$

is obtained.

The network is trained by minimizing a loss function that combines the mean squared error

with ℓ_2 regularization. The backpropagation algorithm computes the gradients necessary for weight updates. The gradients for the output layer are then propagated backwards to the hidden layers using the chain rule. The Adam optimization algorithm, which utilizes moving averages of gradients and squared gradients, is used for efficient and adaptive learning.

3.2.3 Measures of forecasting accuracy

Model performance is evaluated using standard metrics. Several studies have recommended the use of Mean Absolute Error (MAE) and Root Mean Square Error to evaluate and compare time series predictions [37]. These metrics are calculated as

$$\mathrm{MAE} = \frac{1}{\mathrm{T}}\sum_{\mathrm{t=1}}^{\mathrm{T}}\left|\mathrm{R_t} - \widehat{\mathrm{R}}_\mathrm{t}\right| \qquad (13)$$

and the Root Mean Square Error (RMSE) as

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{T}}\sum_{\mathrm{t=1}}^{\mathrm{T}}\left(\mathrm{R_t} - \widehat{\mathrm{R}}_\mathrm{t}\right)^2} \qquad (14)$$

4. Numerical Results

This section presents the empirical findings of the comparative study between ANN and SVM in forecasting Tanzania's tourism revenue. The model performance and practical implications for tourism policymakers are examined.

4.1 Data cleaning and scaling

As shown by Figure 1, the 2020 outlier has been cleaned by Equation (1). The value of revenue in 2020 has been raised a bit compared to the original value. The original 2020 value is $714,590,000, and after interpolation, it is replaced by $1,957,420,000.

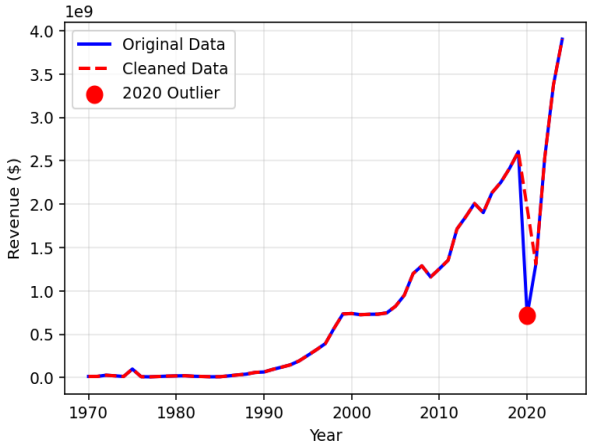


Figure 1. Tourism revenue (970-2024) original vs cleaned data.

On the other hand, the logarithmic scaling has been carried out to stabilize the variance. Figure 2 displays the results.

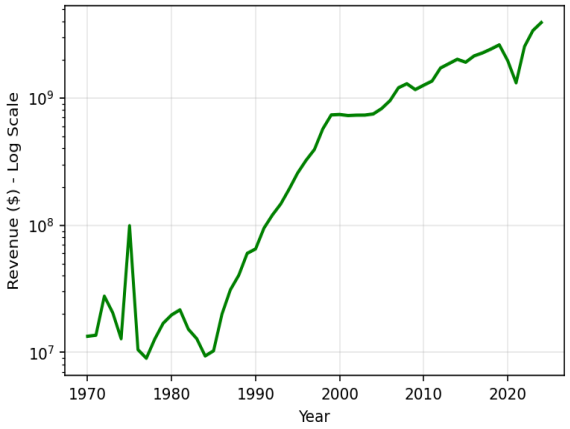


Figure 2. Tourism revenue (Log scale).

4.2 Model performance

The study applied test data to evaluate the performance of each model. As shown by Figure 3, SVM performed better than ANN. The forecasted values for SVM lie in a similar trend to the original trend before the pandemic.

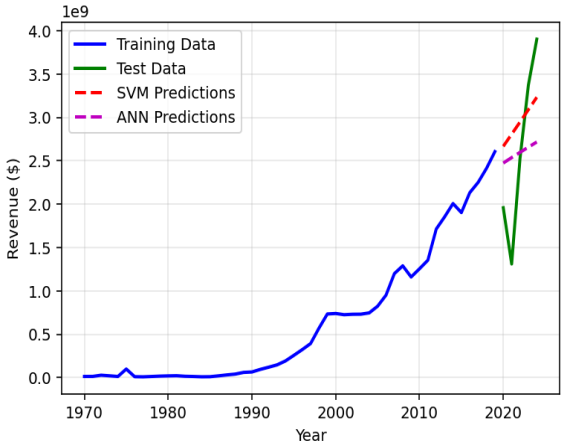


Figure 3. Model performance on test data (2020-2024).

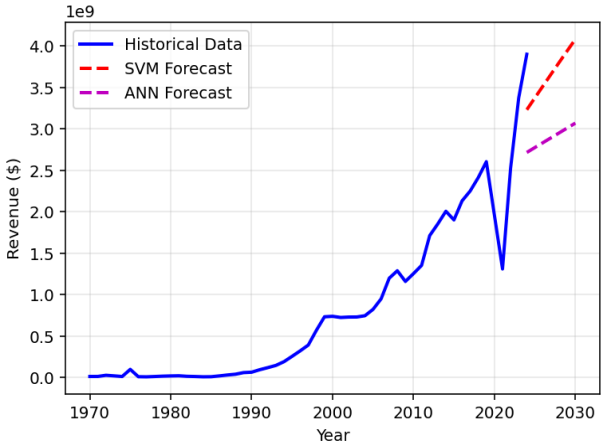


Figure 4. Revenue forecast (2024-2030).

Also, the study uses metric measures to assess the performance of SVM and ANN. Multiple metrics enables getting a complete picture of model performance [38]. Table 1 displays the results.

Table 1. Metric measures.

Metric measures	SVM	ANN
MAE	$715,210,027	$742,353,043
RMSE	$829,535,728	$859,034,999

The SVM has improved the MAE error of ANN by approximately 4% and RMSE by 3%. This demonstrates that SVMs perform better in forecasting tourism revenues in Tanzania.

4.3 Forecasting tourism revenues

Figure 4 presents the tourism revenues from 2024 to 2030. The Figure shows the increase in tourism revenues from 2024 to 2030. While the historical growth rate (2019-2023) is 6.68%, the SVM projected growth rate (2024-2030) at 3.97% and the ANN projected growth rate (2024-2030) at 2.06%. Both models demonstrate that the tourism sector will continue to increase and, therefore contribute to national economic growth. Thus, the government and other stakeholders should maintain strategies to ensure the sustainability of the tourism industry [33].

5. Discussion

The observed superiority of the SVM over ANN, as evidenced by Figure 3, and lower Mean Absolute Error and Root Mean Square Error, is a consequence of the specific data characteristics and the inherent inductive biases of each algorithm. A primary reason for this outcome is the issue of model complexity relative to dataset size. Bi et al. [13] recommended that SVM works well for short datasets.

ANNs are known to be expressive models that can require large amounts of data to generalize effectively without overfitting. In low-data, low-dimensionality regimes, they are prone to memorizing noise and idiosyncrasies in the training set rather than learning the underlying trend, a phenomenon well-documented in modern machine learning literature [39]. The fluctuations present in the historical revenue data likely caused the ANN to overfitting, degrading its performance on the test set.

In contrast, kernel-based methods like SVM often demonstrate stronger performance in such

scenarios due to their effective regularization and stability with limited samples [40]. The theoretical foundation of SVM is based on structural risk minimization, which provides a built-in mechanism for better generalization. This principle aims to minimize an upper bound on the generalization error, rather than just the training error (empirical risk minimization is common in ANN training). This makes SVM particularly robust when dealing with smaller datasets [41].

Also, the use of Radial Basic Function kernel was particularly advantageous for this problem. The RBF kernel is adept at capturing smooth, non-linear trends, which perfectly describe the long-term exponential growth pattern of tourism revenue. By implicitly mapping the single-time feature into a high-dimensional space, it allows for a linear fit there, which corresponds to a sophisticated non-linear fit in the original space. This approach is often more sample-efficient for such patterns than the more brute-force function approximation of a standard ANN.

6. Conclusion

The tourism industry is important in contributing to a country's GDP, employment and foreign currency. In 2020, the industry was greatly affected by COVID-19 due to travel restrictions imposed by many countries. As has been shown by several studies and reports, Tanzania's tourism revenue will keep on growing in the future [2]. Effective forecasting is required for the smooth planning of the industry. This study shows that Tanzanian tourism revenue forecasting accuracy can be greatly improved by machine learning techniques, especially Artificial Neural Networks.

Despite the fact that there are numerous studies on the use of machine learning to forecast tourism demands, little research has been conducted on the use of machine learning models to forecast tourism revenue. This study will advance our understanding of how to use machine learning to predict tourism revenue, particularly for developing nations like Tanzania. Machine learning models enhance the forecasting accuracy that can be used for tourism revenue, particularly in developing countries.

The adoption of the Support Vector Machine forecasting model is a critical step toward modernizing the governance of Tanzania's tourism sector. It enables a shift from reactive decision-making to proactive, strategic management. By leveraging this data-driven advantage, Tanzania can maximize tourism revenues, enhance the visitor experience, and ensure the long-term sustainability of one of its most vital economic assets. In essence, the government and other stakeholders may use our results to enhance their strategies in improving the contribution of tourism to the national economy.

Future studies may investigate into using hybrid and deep learning models to improve forecasting accuracy and strengthen the research contribution. Additionally, qualitative external factors such as international conditions, government policies, and natural disasters may be considered to strengthen and expand our dataset.

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