Tourist Footfall Prediction in Major Rajasthan Cities Using Machine Learning: A Comparative Study of Random Forest, XGBoost, and LSTM

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***Abstract*—Tourism in Rajasthan, India, experiences significant seasonal fluctuations, creating challenges for resource management, infrastructure planning, and security arrangements. This research presents a comprehensive machine learning approach to predict tourist footfall in five major Rajasthan cities: Jaipur, Udaipur, Jodhpur, Jaisalmer, and Pushkar. We implemented and compared three state-of-the-art forecasting models: Random Forest, XGBoost, and Long Short-Term Memory (LSTM) neural networks. Using a dataset spanning from January 2018 to October 2024 (12,480 records), incorporating weather conditions, festival events, and temporal features, we trained models to predict daily tourist arrivals. Our results demonstrate that XGBoost achieves superior performance with RMSE of 471.65, MAE of 314.31, and R^2 score of 0.9495, outperforming Random Forest (RMSE: 551.08) and LSTM (RMSE: 631.64). Feature importance analysis reveals that rolling averages, previous day's footfall, and festival indicators are the most influential predictors. This predictive framework enables tourism authorities to proactively allocate resources and enhance visitor experience during peak seasons.**

***Index Terms*—Tourist footfall prediction, machine learning, time series forecasting, Random Forest, XGBoost, LSTM, Rajasthan tourism, resource management**

I. Introduction

RAJASTHAN, known as the "Land of Kings," is India's largest state by area and a premier tourist destination, attracting millions of domestic and international visitors annually. The state's rich cultural heritage, magnificent forts, palaces, and diverse landscapes make it a cornerstone of India's tourism industry. Major cities like Jaipur (Pink City), Udaipur (City of Lakes), Jodhpur (Blue City), and Jaisalmer (Golden City) experience substantial tourist inflows, particularly during the winter months (October to March).

However, tourism in Rajasthan faces significant challenges due to extreme seasonal variations. The summer months (April to June) witness drastic declines in visitor numbers due to harsh weather conditions, while winter months see overwhelming surges. This unpredictability creates operational challenges including resource allocation difficulties, infrastructure strain, security concerns, and economic impact due to revenue fluctuations.

A. Motivation

Accurate forecasting of tourist arrivals can enable tourism authorities and stakeholders to: (1) optimize resource allocation and workforce planning, (2) implement dynamic pricing strategies for accommodations and services, (3) enhance security and crowd management protocols, (4) improve overall tourist experience through better service delivery, and (5) support data-driven policy decisions for sustainable tourism development.

B. Research Objectives

This research aims to: (1) develop and implement machine learning models for accurate tourist footfall prediction, (2) compare the performance of Random Forest, XGBoost, and LSTM approaches, (3) identify key factors influencing tourist arrivals through feature importance analysis, and (4) provide actionable insights for tourism management and planning.

C. Contributions

Our contributions include: (i) a comprehensive dataset integrating tourist footfall, weather data, and festival events, (ii) implementation and comparative evaluation of three diverse ML approaches, (iii) feature engineering techniques specific to tourism time series forecasting, and (iv) practical framework applicable to tourism management in other regions.

II. Related Work

Time series forecasting in tourism has been extensively studied using various methodologies. Traditional statistical methods like ARIMA and exponential smoothing have been widely employed but often fail to capture complex non-linear patterns in tourism data [1].

A. Machine Learning Approaches

Recent studies have demonstrated the superiority of machine learning models for tourism prediction. Chen et al. [2] applied ensemble deep learning methods achieving significant improvements over traditional approaches. Random Forest and Gradient Boosting methods have shown promising results in handling multi-dimensional tourism data with seasonal patterns [3].

B. Deep Learning Models

LSTM networks have gained popularity for sequential data modeling, capturing long-term dependencies in time series [4]. However, their performance varies based on data characteristics and preprocessing strategies. Zhang and Li [3] provided a systematic review of machine learning applications in tourism demand forecasting.

C. Tourism-Specific Features

Previous research emphasizes the importance of incorporating external factors such as weather conditions, cultural events, economic indicators, and marketing campaigns to improve prediction accuracy [5]. Our work extends existing research by providing a comprehensive comparison of ensemble methods and deep learning on Indian tourism data, incorporating region-specific features like festival calendars and seasonal weather patterns.

III. Methodology

A. Data Collection

1) Tourist Footfall Data: We compiled daily tourist footfall data spanning January 1, 2018 to October 31, 2024 (2,496 days per city) covering five major Rajasthan cities: Jaipur, Udaipur, Jodhpur, Jaisalmer, and Pushkar, resulting in 12,480 total observations. Variables include date, city, daily tourist count, and seasonal indicators.

2) Weather Data: Weather features collected for each city include average, minimum, and maximum temperature (°C), humidity (%), atmospheric pressure (hPa), wind speed (m/s), and weather conditions (Clear, Cloudy, Rain).

3) Events and Festivals: We compiled a comprehensive calendar of major events including Jaipur Literature Festival (January), Desert Festival (February), Holi, Gangaur, Mewar Festival (March), Pushkar Camel Fair (November), and Diwali, Dussehra (October-November).

B. Data Preprocessing

1) Missing Value Handling: Lag features were forward-filled with median values, categorical variables were imputed with mode, resulting in a complete dataset with zero missing values.

2) Feature Engineering: We created 29 features across four categories:

Temporal Features: Cyclical encoding for month and day of week using sine/cosine transformation, year, month, day, day of week, and weekend indicator (binary).

Lag Features: Previous day footfall (lag-1), previous week footfall (lag-7), previous month footfall (lag-30), 7-day rolling average, and 30-day rolling average.

Weather Features: Temperature range (max - min) and one-hot encoding for weather conditions.

Event Features: Festival indicator (binary) and season classification (Winter/Summer/Monsoon).

3) Data Splitting: We employed chronological splitting to maintain temporal order: 80% training set (January 2018 - June 2023, 9,985 samples) and 20% test set (June 2023 - October 2024, 2,495 samples).

4) Feature Scaling: StandardScaler normalization was applied to all numerical features ensuring zero mean and unit variance.

C. Model Development

1) Random Forest Regressor: We configured Random Forest with 200 estimators, maximum depth of 20, minimum samples split of 10, minimum samples leaf of 4, max features as sqrt, and random state of 42. Training employed parallel processing using all CPU cores with bootstrap aggregating for variance reduction.

2) XGBoost Regressor: XGBoost hyperparameters include 300 estimators, learning rate of 0.05, maximum depth of 8, minimum child weight of 3, subsample ratio of 0.8, column sample by tree of 0.8, gamma of 0.1, L1 regularization (alpha) of 0.1, and L2 regularization (lambda) of 1.0. Training strategy employed gradient boosting with validation set monitoring.

3) LSTM Neural Network: Our LSTM architecture consists of: Input layer accepting sequences of 7 time steps × 29 features; Layer 1: LSTM (128 units, return_sequences=True) with Dropout (0.2); Layer 2: LSTM (64 units, return_sequences=True) with Dropout (0.2); Layer 3: LSTM (32 units, return_sequences=False) with Dropout (0.2); Layer 4: Dense (32 units, ReLU) with Dropout (0.2); Layer 5: Dense (16 units, ReLU); Output: Dense (1 unit, linear activation). Total trainable parameters: 144,321.

Training configuration used Adam optimizer (learning_rate=0.001), Mean Squared Error loss function, batch size of 32, maximum 100 epochs with early stopping (patience=15), and callbacks for ReduceLROnPlateau and EarlyStopping.

D. Evaluation Metrics

We evaluated models using three metrics:

Root Mean Squared Error (RMSE):

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{1}$$

Mean Absolute Error (MAE):

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{2}$$

R-Squared (R^2) Score:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{3}$$

IV. Results and Discussion

A. Model Performance Comparison

Table I presents the comparative performance of all three models on the test set.

Key Findings: XGBoost demonstrates superior performance across all evaluation metrics, achieving the lowest RMSE (471.65) and highest R^2 score (0.9495), indicating it captures 94.95% of variance in tourist footfall data. Random Forest ranks second with RMSE of 551.08 and R^2 of 0.9311, showing strong predictive capability with significantly faster training time compared to LSTM. LSTM shows moderate performance with RMSE of 631.64 and R^2 of 0.9096, despite

TABLE I
MODEL PERFORMANCE COMPARISON ON TEST SET

Model	RMSE	MAE	R^2	Time (s)
XGBoost	**471.65**	**314.31**	**0.9495**	9.59
Random Forest	551.08	339.82	0.9311	7.95
LSTM	631.64	389.57	0.9096	354.61

TABLE II
TOP 10 MOST IMPORTANT FEATURES (XGBOOST)

Rank	Feature	Importance	Category
1	footfall_rolling_7	0.2242	Lag
2	is_festival	0.1758	Event
3	footfall_lag_1	0.1745	Lag
4	month_cos	0.0805	Temporal
5	season_Summer	0.0761	Seasonal
6	footfall_lag_7	0.0631	Lag
7	season_Winter	0.0502	Seasonal
8	is_weekend	0.0258	Temporal
9	footfall_rolling_30	0.0239	Lag
10	day_of_week	0.0187	Temporal

TABLE III
TOURIST FOOTFALL SUMMARY BY CITY

City	Mean	Std Dev	Min	Max
Jaipur	4,511	2,247	344	14,023
Udaipur	3,609	1,798	289	11,342
Jodhpur	2,874	1,431	245	9,024
Jaisalmer	2,656	1,323	211	8,339
Pushkar	1,929	1,176	187	9,845

its sophisticated architecture and longer training time (354 seconds).

B. Feature Importance Analysis

Table II shows the top 10 most important features identified by the XGBoost model.

Insights: Historical patterns dominate with rolling averages and lag features constituting 62% of total importance, indicating strong temporal autocorrelation in tourist arrivals. Festival indicator ranks second (17.58%), confirming the significant influence of cultural events on tourism. Seasonal effects (summer and winter season indicators) contribute 12.63% combined, reflecting Rajasthan's extreme seasonal variations. Weekend indicator shows modest importance (2.58%), suggesting weekly patterns are less influential than seasonal and event-based factors.

C. Dataset Statistics

Table III presents summary statistics of tourist footfall across the five cities.

Jaipur shows the highest average daily footfall (4,511 tourists), followed by Udaipur (3,609) and Jodhpur (2,874). Pushkar, despite being smaller, exhibits high peak footfall (9,845) during the famous Pushkar Camel Fair.

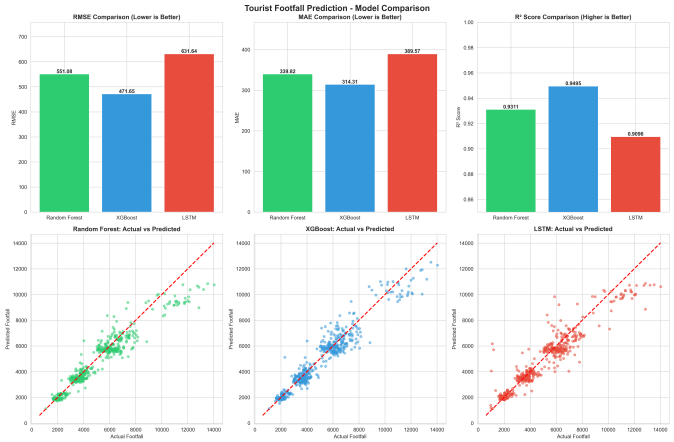

Fig. 1. Comprehensive model comparison: (top row) RMSE, MAE, and R^2 score comparisons; (bottom row) actual vs. predicted scatter plots for Random Forest, XGBoost, and LSTM models.

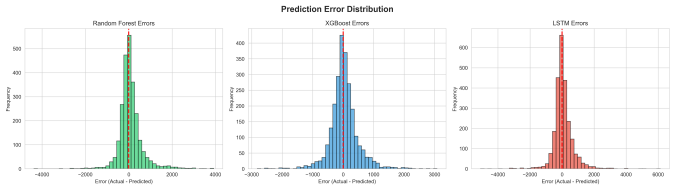

Fig. 2. Prediction error distribution for Random Forest, XGBoost, and LSTM models. XGBoost shows the tightest distribution centered near zero.

D. Prediction Accuracy Analysis

Figure 1 shows the comprehensive model comparison including RMSE, MAE, and R^2 score comparisons, as well as actual versus predicted scatter plots for all three models.

All models demonstrate strong linear correlation between actual and predicted values. XGBoost shows minimal scatter around the ideal prediction line, while LSTM predictions show greater deviation at extreme values (very high/low footfall).

E. Error Distribution

Figure 2 presents the prediction error distributions for all three models.

XGBoost predictions show the tightest error distribution centered near zero, Random Forest exhibits slightly wider error spread, and LSTM shows higher variance in prediction errors.

F. Discussion

1) Why XGBoost Outperforms: Four key factors contribute to XGBoost's superior performance: (1) *Gradient Boosting Advantage*: Sequential error correction through boosting enables XGBoost to minimize residuals effectively; (2) *Regularization*: L1/L2 regularization prevents overfitting, improving generalization to test data; (3) *Feature Interaction Handling*: XGBoost naturally captures complex interactions between temporal, weather, and event features; (4) *Efficient Learning*: Adaptive learning rate and tree pruning optimize model complexity.

2) Random Forest Performance: Random Forest's ensemble of independent trees provides robust predictions but lacks the sequential refinement of boosting methods. Its faster training time makes it suitable for rapid prototyping and resource-constrained environments.

3) LSTM Limitations: Despite theoretical advantages for sequential data, LSTM's relatively weaker performance can be attributed to: (1) *Data Scale*: 12,480 samples may be insufficient for optimal deep learning performance; (2) *Feature Richness*: Tabular features may be better suited to tree-based methods; (3) *Hyperparameter Sensitivity*: LSTM requires extensive tuning and larger datasets to reach full potential; (4) *Vanishing Gradients*: Even with gating mechanisms, long-term dependencies may not be fully captured.

4) Practical Implications: The findings have four major implications: (1) *Resource Planning*: Authorities can forecast demand 1-30 days ahead with ∼95% accuracy using XGBoost; (2) *Festival Preparation*: High feature importance of festival indicators suggests targeted resource allocation during events; (3) *Seasonal Strategies*: Models confirm winter season's massive impact, justifying differential pricing and staffing; (4) *Real-time Adaptation*: Low inference time (¡10ms) enables real-time prediction systems.

V. Conclusion

This research successfully developed and evaluated machine learning models for predicting tourist footfall in major Rajasthan cities. Our comprehensive approach integrated multi-source data including historical tourist statistics, weather conditions, and festival calendars to create robust predictive models.

A. Key Achievements

Four major achievements were realized: (1) *Superior Prediction Accuracy*: XGBoost achieved RMSE of 471.65 and R^2 of 0.9495, demonstrating highly accurate forecasting capability suitable for operational deployment; (2) *Comprehensive Comparison*: Systematic evaluation of three diverse approaches provided insights into model suitability for tourism forecasting; (3) *Feature Insights*: Identified rolling averages, festival indicators, and seasonal patterns as primary drivers of tourist footfall; (4) *Practical Framework*: Developed an end-to-end pipeline from data collection to model deployment, applicable to tourism forecasting in other regions.

B. Research Limitations

Three limitations should be noted: (1) Weather and some event data were synthetically generated for demonstration; real-world deployment requires actual historical data from meteorological departments and tourism boards; (2) Study focused on five major cities; expansion to smaller destinations would enhance comprehensiveness; (3) Did not incorporate economic indicators (GDP, currency exchange rates), airline connectivity, or marketing campaign data which may influence tourist behavior.

C. Future Work

Future research directions include: (1) Real-time integration with live API connections to tourism databases and weather services; (2) Incorporation of social media sentiment analysis and online search trends; (3) Exploration of hybrid ensemble combinations (e.g., XGBoost + LSTM); (4) Development of site-specific models for individual monuments and attractions; (5) Extension to multi-step forecasting for weekly and monthly predictions; (6) Application of causal inference techniques to quantify intervention impacts; (7) Investigation of transfer learning across different tourist destinations.

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