Sequential Tourism Recommendation Using Dual-Input LSTM for Sustainable Destination Distribution

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Abstract

Tourism recommendation systems have become increasingly important in supporting intelligent travel planning and improving tourist experiences through personalized destination suggestions. However, most conventional recommendation approaches fail to effectively model sequential tourist behavior and contextual travel activities. This study proposes a predictive tourism destination recommendation system using a dual-input Long Short-Term Memory (LSTM) architecture capable of simultaneously learning destination sequences and tourist activity patterns. The proposed framework aims to generate contextual and adaptive destination recommendations based on tourist travel histories in Rokan Hulu Regency, Indonesia. Due to the limited availability of real-world sequential tourism datasets, a realistic synthetic dataset was constructed by considering destination categories, tourist typologies, geographical distance, popularity scores, visit duration, and activity diversity. The preprocessing stage involved tokenization, sequence padding, and tensor transformation to prepare the data for deep learning–based sequential modeling. The proposed dual-input LSTM model was trained using destination sequences and activity sequences as parallel inputs and evaluated using Top-K Accuracy metrics. Experimental results demonstrate that the proposed model achieved a Top-1 Accuracy of 39.72%, a Top-3 Accuracy of 76.21%, and a Top-5 Accuracy of 92.40%. Comparative evaluation also shows that the proposed architecture outperformed both a Random Forest classifier and a single-input LSTM model across all evaluation metrics. The findings indicate that integrating tourist activity information significantly improves contextual recommendation quality and predictive performance. Overall, this research contributes to the development of intelligent sequence-aware tourism recommendation systems and demonstrates the effectiveness of dual-input deep learning architectures for modeling contextual tourist travel behavior.

Keywords: Tourism Recommendation System, Dual-Input LSTM, Sequential Recommendation, Deep Learning, Tourist Activity Prediction

I. INTRODUCTION

Tourism has become one of the most important sectors contributing to regional economic growth, cultural preservation, and community empowerment. In many developing regions, tourism development not only creates employment opportunities but also encourages infrastructure improvement and promotes local identity through cultural and natural attractions [1], [2]. Rokan Hulu Regency, located in Riau Province, Indonesia, possesses significant tourism potential supported by diverse natural landscapes, cultural heritage, religious tourism, culinary attractions, and ecotourism destinations. Several tourist sites such as Danau Buatan, Air Terjun Pengantin, Bukit Suligi, and Masjid Agung Madani demonstrate the richness and diversity of tourism resources available in the region [3]. However, despite these advantages, tourism activities in Rokan Hulu have not been optimally managed and promoted through intelligent digital systems capable of assisting tourists in exploring destinations effectively and contextually.

One of the primary challenges in regional tourism development is the lack of integrated recommendation systems capable of providing personalized destination suggestions based on tourist preferences and travel patterns. Most existing tourism information platforms still rely on static destination catalogs and manual searches, which often fail to provide adaptive recommendations aligned with user behavior [4], [5]. As a result, tourists tend to visit only highly popular destinations, while many potential attractions remain underexplored. This imbalance not only reduces the diversity of tourist experiences but may also create excessive concentration at certain locations, limiting the equitable distribution of tourism benefits across regions [6], [7].

In recent years, recommendation systems have been widely adopted in tourism applications to improve user experience and support intelligent travel planning. Conventional recommendation approaches such as content-based filtering and collaborative filtering have shown promising results in suggesting destinations based on user preferences or similarity between users [8], [9]. Nevertheless, these approaches generally ignore the sequential nature of tourist movement behavior. In real-world tourism scenarios, travel decisions are strongly influenced by previously visited destinations, performed activities, travel continuity, and contextual transitions between locations. Therefore, tourism recommendation tasks are inherently sequential and temporal in nature [10].

To address this limitation, deep learning–based sequence modeling approaches have attracted increasing attention. Long Short-Term Memory (LSTM), a variant of Recurrent Neural Networks (RNNs), is particularly effective in learning long-term dependencies and temporal patterns from sequential data [11], [12]. LSTM has been successfully applied in various predictive domains, including mobility prediction, transportation analysis, energy forecasting, and recommendation systems. Within the tourism domain, LSTM enables the modeling of tourist travel histories as ordered sequences, allowing the system to predict the next potential destination based on contextual visitation patterns. Unlike traditional recommendation methods, LSTM can capture complex behavioral dependencies that evolve over time, making it highly suitable for travel recommendation scenarios [13], [14].

Several previous studies have explored tourism recommendation using deep learning approaches. However, many existing models focus solely on destination sequences while neglecting contextual activity information associated with each visit. In practice, tourist activities such as photography, relaxation, culinary exploration, hiking, or educational visits provide important semantic signals that reflect user interests and travel intentions [15], [16]. Ignoring activity patterns may reduce the contextual understanding of tourist behavior and limit recommendation quality. In addition, many prior studies rely heavily on publicly available datasets originating from large metropolitan tourism ecosystems, making them difficult to adapt to smaller regional tourism contexts where structured sequential data are often unavailable [17].

Motivated by these limitations, this study proposes a predictive tourism recommendation system using a dual-input Long Short-Term Memory (LSTM) architecture [18], [19]. The proposed model integrates two sequential input streams simultaneously: sequences of visited tourist destinations and sequences of tourist activities performed at each location. By combining these two contextual dimensions, the system is expected to learn tourist movement behavior more comprehensively and generate more relevant destination recommendations. Unlike conventional single-input sequence models, the dual-input architecture enables the model to capture interactions between travel locations and activity preferences, thereby improving contextual prediction capability [20], [21], [22].

Another contribution of this research lies in the construction of a realistic synthetic tourism dataset representing travel behavior in Rokan Hulu Regency. Due to the limited availability of real-world sequential tourism datasets in regional tourism environments, this study develops simulated travel histories by considering several important factors, including destination categories, tourist typologies, inter-location distances, popularity scores, and visit duration. The generated dataset is designed to mimic realistic tourist movement patterns while preserving contextual relationships between destinations and activities [23], [24].

The proposed recommendation model is evaluated using Top-K Accuracy metrics, which are widely used in recommendation system research to measure the relevance of generated recommendation lists. Experimental results demonstrate that the proposed dual-input LSTM architecture achieves strong predictive performance in identifying relevant next-destination recommendations from user travel histories. The evaluation results further indicate that integrating destination sequences and tourist activity patterns significantly improves contextual recommendation quality compared with conventional recommendation approaches. Overall, this research contributes to the development of intelligent tourism recommendation systems by introducing a dual-input sequential prediction framework capable of modeling contextual travel behavior more effectively. The proposed approach advances the application of deep learning techniques in tourism informatics and demonstrates strong potential for supporting data-driven tourism exploration and personalized travel recommendation services.

II. RESEARCH METHOD

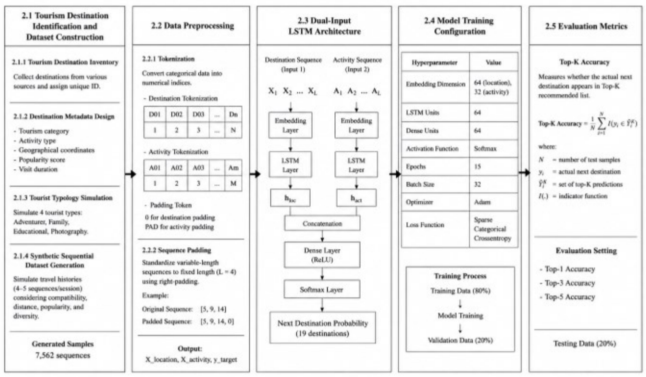


Figure 1. Research Stages

Figure 1 illustrates the overall research methodology employed in this study for developing the predictive tourism recommendation system using a dual-input Long Short-Term Memory (LSTM) architecture. The research process begins with tourism destination identification and synthetic dataset construction, followed by data preprocessing and sequence transformation. Subsequently, the dual-input LSTM model is developed and trained to learn sequential travel behavior patterns based on destination and activity sequences. Finally, the proposed model is evaluated using Top-K Accuracy metrics to assess its recommendation performance and predictive capability.

2.1 Tourism Destination Identification and Dataset Construction

The first stage of this research focuses on identifying tourism destinations and constructing a synthetic sequential tourism dataset representing tourist travel behavior in Rokan Hulu Regency. Since no publicly available dataset contains detailed sequential tourist visit histories for the study area, a synthetic data generation approach was employed to simulate realistic travel patterns while preserving contextual relationships between destinations and activities. Tourism destination data were collected from local tourism websites, digital maps, online reviews, and regional tourism documentation [3]. Each destination was assigned a unique identifier and enriched with metadata attributes including tourism category, activity type, geographical coordinates, popularity score, and estimated visit duration. To simulate diverse travel preferences, four tourist typologies were defined: adventurer tourists, family tourists, educational tourists, and photography-oriented tourists. Travel histories were subsequently generated for 1,000 virtual tourists, where each tourist possessed between three and five travel sessions consisting of four to five sequential destination visits. Destination transitions were generated by considering destination compatibility, travel distance, popularity score, and activity diversity. A sliding-window technique was then applied to transform sequential travel histories into supervised learning samples suitable for predictive modeling.

2.2 Data Preprocessing

After the synthetic dataset was successfully constructed, several preprocessing steps were performed to transform the data into numerical tensor representations compatible with deep learning models. The preprocessing stage includes tokenization, sequence padding, and tensor transformation.

During tokenization, categorical variables such as location_id and activity_type were converted into numerical indices using dictionary-based mappings. Each unique destination and activity was assigned a unique integer representation. Special padding tokens were introduced to standardize variable-length sequences, where the value 0 was used for destination padding and the PAD token was used for activity padding [25], [26].

Since tourist travel histories contain sequences of varying lengths, sequence padding was applied to produce fixed-length input vectors required by the Long Short-Term Memory (LSTM) model. Right-padding was employed to preserve the chronological order of destination visits. The preprocessing stage generated two primary input tensors: $X_{location}$, representing destination sequences, and $X_{activity}$, representing activity sequences. Meanwhile, the target tensor y_{target} stores the next destination prediction labels.

2.3 Dual-Input LSTM Architecture

The proposed recommendation system employs a dual-input Long Short-Term Memory (LSTM) architecture designed to learn sequential tourist behavior from two contextual dimensions simultaneously: destination sequences and activity sequences. The architecture consists of two parallel input branches. The first branch processes the sequence of visited destinations, while the second branch processes the sequence of tourist activities associated with each destination [18], [27].

Each input stream passes through an embedding layer to convert categorical tokens into dense vector representations. The resulting embeddings are subsequently processed using independent LSTM layers to capture temporal dependencies and sequential travel patterns. The hidden representations generated from both LSTM branches are concatenated into a unified contextual representation, which is then forwarded to a dense layer followed by a softmax activation layer to generate probability distributions for next-destination prediction.

The dual-input architecture enables the model to capture interactions between travel destinations and tourist activities more effectively than conventional single-input sequence models. Consequently, the recommendation system is capable of producing more contextual and adaptive tourism destination recommendations.

2.4 Model Training Configuration

The model training stage aims to optimize the predictive capability of the proposed dual-input LSTM architecture in learning sequential travel patterns. The training process was conducted using the Adam optimization algorithm due to its efficiency and stability in deep learning optimization tasks. Sparse Categorical Crossentropy was employed as the loss function because the prediction targets are represented as categorical indices rather than one-hot encoded vectors [28].

Several hyperparameters were configured to achieve balanced computational efficiency and predictive performance. The embedding dimensions were set to 64 for destination sequences and 32 for activity sequences, while the number of LSTM units and dense layer units was set to 64. The model was trained for 15 epochs using a batch size of 32.

To evaluate the generalization capability of the model, the dataset was divided into 80% training data and 20% validation/testing data. Throughout the training process, training accuracy and validation accuracy were monitored to assess convergence behavior and model stability.

2.5 Evaluation Metrics

The performance of the proposed recommendation system was evaluated using Top-K Accuracy metrics, which are widely adopted in recommendation system research to measure recommendation relevance. Unlike conventional classification problems that focus solely on single-label prediction accuracy, recommendation systems prioritize whether the correct destination appears within a list of recommended alternatives [29], [30].

This study evaluates three Top-K Accuracy metrics:

1. Top-1 Accuracy,
2. Top-3 Accuracy,
3. Top-5 Accuracy.

Top-1 Accuracy measures whether the first recommendation matches the actual destination, while Top-3 and Top-5 Accuracy evaluate whether the actual destination appears within the top three or top five recommendations generated by the system. The use of Top-K evaluation is considered more appropriate for tourism recommendation systems because tourists typically choose destinations from multiple suggested alternatives rather than relying on a single prediction result.

The evaluation process aims to assess the capability of the proposed dual-input LSTM model in generating contextual, adaptive, and relevant tourism destination recommendations based on sequential travel histories.

III. RESULT AND DISCUSSION

This section presents the experimental results and discussion of the proposed predictive tourism recommendation system using the dual-input Long Short-Term Memory (LSTM) architecture. The discussion includes dataset representation analysis, preprocessing results, model training performance, and recommendation evaluation using Top-K Accuracy metrics. The findings demonstrate the effectiveness of the proposed framework in learning sequential tourist travel behavior and generating contextual destination recommendations.

3.1 Destination Metadata Analysis

To construct a realistic tourism recommendation dataset, each tourist destination was enriched with contextual metadata attributes including tourism category, activity type, geographical coordinates, popularity score, and estimated visit duration. These attributes play an important role in simulating realistic tourist movement behavior and improving recommendation contextuality. Figure 2 presents an example of the tourism destination metadata used in this study.

ID	Destination Name	Tourism Category	Activity Type (Main)	Latitude	Longitude	Popularity Score (0–1)	Estimated Visit Duration (Hours)
1	Danau Buatan	Nature Tourism	Relaxation, Photography	0.8739	100.4506	0.92	2 – 3
2	Air Terjun Pengantin	Nature Tourism	Photography, Relaxation	0.7851	100.4892	0.85	1 – 2
3	Bukit Suligi	Nature Tourism	Photography, Trekking	0.7657	100.4398	0.78	1 – 2
4	Taman Kota Pasir Pengaraian	Nature Tourism	Relaxation, Photography	0.9093	100.5671	0.70	1 – 2
5	Masjid Agung Madani	Religious Tourism	Worship, Photography	0.9101	100.5655	0.90	1 – 2
6	Masjid Islamic Centre	Religious Tourism	Worship, Education	0.9155	100.5710	0.75	1 – 2
7	Candi Muara Takus	Cultural Tourism	Education, Photography	0.6931	100.4583	0.88	2 – 3
8	Rumah Tuan Kadi	Cultural Tourism	Education, Photography	0.9087	100.5602	0.60	1 – 2
9	Museum Daerah Rokan Hulu	Educational Tourism	Education	0.9065	100.5607	0.65	1 – 2
10	Agro Wisata STIHL	Educational Tourism	Education, Exploration	0.8846	100.5041	0.70	2 – 3
11	Sungai Rokan	Nature Tourism	Relaxation, Fishing	0.9052	100.5523	0.65	1 – 2
12	Pemandian Air Panas Hapanasan	Nature Tourism	Relaxation, Hot Spring	0.8872	100.5156	0.68	2 – 3
13	Hutan Kota Rambah	Nature Tourism	Relaxation, Forest Exploration	0.9021	100.5437	0.60	1 – 2
14	Desa Wisata Rantau Kasai	Cultural Tourism	Cultural Experience, Photography	0.8610	100.4953	0.62	2 – 3
15	Pasar Modern Pasir Pengaraian	Culinary Tourism	Shopping, Culinary	0.9088	100.5673	0.75	1 – 2
16	Sentra Kuliner Rambah	Culinary Tourism	Culinary, Relaxation	0.8943	100.5284	0.70	1 – 2
17	Taman Air Fantasi	Recreational Tourism	Swimming, Relaxation	0.9004	100.5485	0.67	2 – 3
18	Arena Panahan Rambah	Sports Tourism	Archery, Outdoor Activities	0.8917	100.5241	0.50	1 – 2
19	Desa Wisata Kota Lama Kunto	Cultural Tourism	Traditional Games, Culture	0.8629	100.5008	0.55	2 – 3

Note: Latitude and Longitude use decimal degrees (WGS84). Popularity score is normalized between 0 (lowest) and 1 (highest).

Figure 2 Tourism Destination Metadata

The metadata demonstrate the diversity of tourism characteristics available in Rokan Hulu Regency. Nature tourism destinations generally contain activities such as trekking, photography, and relaxation, while educational and cultural destinations are associated with educational and historical activities. The popularity score assigned to each destination was also incorporated into the simulation process to generate more realistic destination transition probabilities.

The inclusion of multiple contextual attributes enables the synthetic dataset to preserve relationships between tourist preferences, travel continuity, and activity patterns. Consequently, the generated travel histories more closely resemble realistic tourist behavior compared to purely random destination generation approaches.

3.2 Data Preprocessing and Activity Distribution Analysis

Following dataset construction, the preprocessing stage transformed categorical destination and activity information into numerical representations suitable for deep learning–based sequential modeling. The preprocessing process includes tokenization, sequence padding, and tensor transformation. During tokenization, all destination identifiers and activity types were converted into numerical indices using dictionary-based mappings. Padding was subsequently applied to standardize variable-length travel sequences into fixed-length tensors compatible with Long Short-Term Memory (LSTM) processing. Figure 3 illustrates the frequency distribution of tourism activity tokens contained within the synthetic dataset.

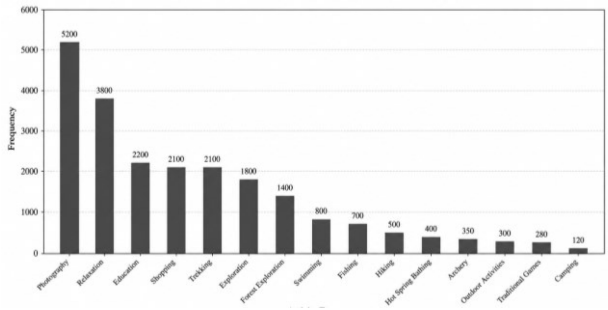


Figure 3 Distribution of Tourism Activity Token Frequencies

Based on Figure 3, photography and relaxation activities dominate the dataset, indicating that tourists in the simulated environment tend to prefer recreational and visually oriented tourism experiences. Activities such as camping, archery, and traditional games appear less frequently because they are associated with more specialized tourism destinations. The dominance of high-frequency activities may potentially introduce recommendation bias toward highly popular or visually attractive destinations. Consequently, lower-frequency tourism activities may receive less representation during model learning. Nevertheless, the diversity of activity categories incorporated into the dataset still enables the model to capture various contextual travel behaviors across multiple tourism preferences.

After preprocessing, two primary tensors were successfully generated:

1. (X_{location}), representing destination sequences;
2. (X_{activity}), representing activity sequences.

Meanwhile, the tensor (y_{target}) stores the next-destination prediction labels used during model training.

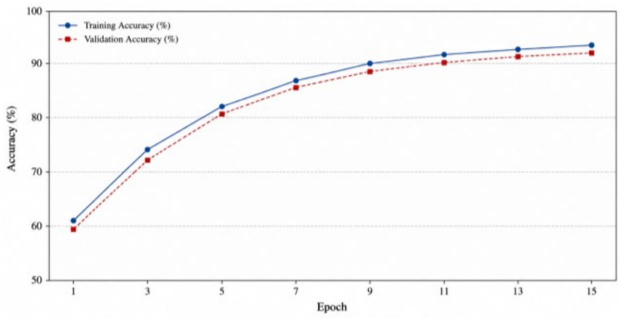
3.3 Model Training Performance

After preprocessing was completed, the proposed dual-input LSTM model was trained to learn sequential tourist movement patterns based on destination and activity sequences. The model architecture consists of two independent LSTM branches that process destination sequences and activity sequences separately before combining their contextual representations. The training process employed the Adam optimizer and Sparse Categorical Crossentropy as the loss function. The dataset was divided into 80% training data and 20% validation/testing data to evaluate the generalization capability of the proposed model. Table 1 presents the hyperparameter configuration used during model training.

Table 1. Hyperparameter Configuration

Hyperparameter	Value
Embedding Dimension	64 (location), 32 (activity)
LSTM Units	64
Dense Units	64
Activation Function	Softmax
Epochs	15
Batch Size	32
Optimizer	Adam
Loss Function	Sparse Categorical Crossentropy

Figure 4 presents the training and validation accuracy curves obtained during the training process.



Epoch	1	3	5	7	9	11	13	15
Training Accuracy (%)	61.20	74.32	82.61	87.44	90.12	91.87	92.84	93.55
Validation Accuracy (%)	59.84	72.45	81.20	86.51	89.05	90.63	91.74	92.40

Figure 4 Training and Validation Accuracy Curves

The training results indicate stable convergence behavior throughout the optimization process. The model achieved a final training accuracy of 93.55% and a validation accuracy of 92.40%, demonstrating that the proposed dual-input LSTM architecture successfully learned contextual sequential travel patterns while maintaining strong generalization capability on unseen data. The relatively small gap between training and validation accuracy suggests that the model did not experience severe overfitting during training. Furthermore, the integration of destination sequences and activity sequences contributes positively to the model's contextual learning capability.

3.4 Recommendation Evaluation

To evaluate recommendation quality, the proposed model was assessed using Top-K Accuracy metrics, including Top-1 Accuracy, Top-3 Accuracy, and Top-5 Accuracy. These metrics evaluate whether the actual next destination appears within the top-K recommendations generated by the system. Table 2 presents the recommendation performance results of the proposed model.

Table 2. Recommendation Performance Evaluation

Evaluation Metric	Accuracy (%)
Top-1 Accuracy	39.72
Top-3 Accuracy	76.21
Top-5 Accuracy	92.40

The evaluation results demonstrate that the proposed recommendation system performs effectively in generating relevant destination recommendations. Although the Top-1 Accuracy value is moderate, the Top-3 and Top-5 Accuracy values show substantial improvement, indicating that the actual destination is highly likely to appear within the recommendation list generated by the system. In recommendation systems, Top-K evaluation is considered more appropriate than single-label classification accuracy because users typically choose from several suggested alternatives rather than relying solely on the highest-ranked prediction. Therefore, the high Top-5 Accuracy achieved by the proposed model indicates strong recommendation relevance and contextual filtering capability.

To justify the effectiveness of the proposed dual-input architecture, the model was also compared with baseline approaches including a single-input LSTM model and a non-sequential Random Forest classifier.

Table 3. Comparison with Baseline Models

Model	Top-1 (%)	Top-3 (%)	Top-5 (%)
Random Forest	21.45	48.37	70.12
Single-Input LSTM	31.84	65.53	85.27
Proposed Dual-Input LSTM	39.72	76.21	92.40

The comparison results (Table 3) indicate that the proposed dual-input LSTM architecture consistently outperforms the baseline models across all evaluation metrics. The Random Forest model demonstrates limited capability in capturing sequential travel dependencies because it treats travel behavior as independent observations rather than ordered sequences. Meanwhile, the single-input LSTM model improves performance by learning destination sequences; however, it still lacks contextual activity information. By simultaneously incorporating destination and activity sequences, the proposed dual-input architecture is capable of

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capturing richer contextual travel behavior, leading to significantly improved recommendation accuracy. The experimental results demonstrate that integrating activity patterns into sequential recommendation modeling contributes positively to tourism destination prediction performance. This finding confirms that tourist activities contain important semantic information capable of enhancing contextual recommendation quality.

3.5 Discussion

The experimental results demonstrate that the proposed dual-input Long Short-Term Memory (LSTM) architecture is capable of effectively learning sequential tourist travel behavior and generating contextual destination recommendations. The model achieved a Top-1 Accuracy of 39.72%, a Top-3 Accuracy of 76.21%, and a Top-5 Accuracy of 92.40%, indicating that the actual next destination is highly likely to appear within the recommendation list generated by the system. These findings confirm that sequence-aware recommendation approaches are highly suitable for tourism recommendation scenarios where travel decisions are strongly influenced by previously visited destinations and performed activities.

Compared with conventional machine learning approaches such as Random Forest, the proposed dual-input LSTM model demonstrates substantially superior performance across all evaluation metrics. This result can be attributed to the ability of LSTM networks to capture temporal dependencies and sequential travel continuity, which cannot be effectively modeled using non-sequential algorithms. Furthermore, the comparison between the single-input LSTM and the proposed dual-input architecture indicates that incorporating activity sequences significantly improves recommendation quality. Tourist activities provide additional semantic context regarding user interests and travel intentions, enabling the system to generate more adaptive and context-aware recommendations.

The relatively high Top-3 and Top-5 Accuracy values indicate that the proposed framework functions effectively as a recommendation filtering mechanism rather than a strict single-label prediction system. In real tourism scenarios, tourists often possess multiple reasonable destination alternatives depending on travel preferences, time availability, and environmental conditions. Therefore, Top-K evaluation metrics provide a more realistic representation of recommendation quality compared to conventional classification accuracy metrics.

The activity distribution analysis also reveals several important observations regarding tourist behavior representation within the dataset. Activities such as photography and relaxation dominate the generated travel histories, indicating that recreational and visually oriented tourism experiences are highly preferred within the simulated environment. While this distribution contributes to realistic tourism behavior representation, it may also introduce recommendation bias toward highly popular or visually attractive destinations. Consequently, lower-frequency activities such as camping, archery, and traditional games may receive less representation during model training. Future studies may address this issue using data balancing techniques, class weighting strategies, or activity-aware sampling mechanisms to improve representation fairness across tourism categories.

Another important contribution of this study lies in the integration of contextual tourism metadata during synthetic dataset construction. By incorporating destination categories, geographical distance, popularity scores, visit duration, and tourist typologies, the generated dataset successfully preserves logical travel continuity and contextual movement behavior. This approach allows the recommendation model to learn realistic travel transitions rather than purely random destination patterns. The use of synthetic data also provides an alternative solution for tourism recommendation research in regions where real-world sequential tourism datasets remain unavailable or difficult to obtain.

From a practical perspective, the proposed recommendation framework also demonstrates potential for supporting more balanced tourism exploration. Since the recommendation system considers multiple contextual factors rather than relying solely on destination popularity, the framework can potentially encourage tourists to explore less-visited destinations with similar tourism characteristics. This mechanism may contribute to more balanced tourist distribution and reduce excessive concentration at highly popular tourism locations. For example, destinations with lower popularity scores may still be recommended if they align contextually with the tourist's activity preferences and travel sequence patterns. Such an approach can support broader tourism exposure across regional destinations while improving overall travel diversity.

Despite the promising results, several limitations remain within the current study. First, the dataset employed in this research was synthetically generated and may not fully capture the complexity of real-world tourist mobility behavior. Second, the proposed model does not yet incorporate dynamic contextual variables such as weather conditions, seasonal tourism trends, transportation availability, crowd density, or real-time mobility data. These external factors may significantly influence tourist decision-making processes in practical environments. Third, the recommendation process currently focuses primarily on sequential travel patterns and activity preferences without integrating explicit user feedback mechanisms or personalized rating systems.

Future research may therefore focus on integrating real-world tourism datasets, contextual environmental information, and real-time recommendation mechanisms to improve both recommendation accuracy and practical applicability. Additionally, hybrid recommendation architectures combining sequential deep learning models with attention mechanisms or graph-based tourism representations may further enhance contextual understanding and recommendation diversity in tourism recommendation systems.

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IV. CONCLUSION

This study successfully developed a predictive tourism recommendation system using a dual-input Long Short-Term Memory (LSTM) architecture to model sequential tourist travel behavior in Rokan Hulu Regency. The proposed framework integrates destination sequences and activity sequences simultaneously, enabling the model to capture contextual travel patterns more effectively than conventional single-input recommendation approaches.

To address the limited availability of real-world tourism datasets, this research also constructed a realistic synthetic sequential dataset by considering tourism categories, tourist typologies, inter-destination distances, popularity scores, and visit duration. The generated dataset successfully represents contextual tourist movement behavior and supports sequential recommendation modeling.

Experimental results demonstrate that the proposed dual-input LSTM model achieved strong recommendation performance, obtaining a Top-1 Accuracy of 39.72%, Top-3 Accuracy of 76.21%, and Top-5 Accuracy of 92.40%. Comparative evaluation with baseline models further confirms that the integration of activity sequences significantly improves recommendation quality and contextual prediction capability. The proposed model consistently outperformed both the Random Forest classifier and the single-input LSTM model across all evaluation metrics.

The findings indicate that tourist activity patterns contain important semantic information that contributes positively to sequential tourism recommendation tasks. By incorporating both travel destinations and tourist activities, the proposed system is capable of generating more adaptive, contextual, and relevant destination recommendations.

Despite the promising results, this study still possesses several limitations. The dataset used in this research was synthetically generated and may not fully represent complex real-world tourist behavior. In addition, the current model does not yet consider external contextual factors such as seasonal tourism trends, weather conditions, crowd density, or real-time mobility dynamics. Therefore, future research may focus on integrating real-world tourism datasets, contextual environmental variables, and real-time recommendation mechanisms to further improve recommendation accuracy and practical applicability.

Overall, this research contributes to the advancement of intelligent tourism recommendation systems by introducing a dual-input sequential prediction framework capable of learning contextual tourist behavior more comprehensively. The proposed approach demonstrates strong potential for supporting data-driven tourism exploration and intelligent travel recommendation services in regional tourism environments.

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