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SMART TOUR: SUSTAINABLE TOURISM MANAGEMENT AND RECOMMENDATION SYSTEM IN ROKAN HULU USING LONG SHORT-TERM MEMORY

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Abstract: *Rokan Hulu Regency possesses significant natural and cultural tourism potential; however, tourist visitation rates remain relatively low due to the lack of integrated destination information and concerns regarding environmental sustainability. This study aims to design and develop SMART TOUR, a sequence-prediction–based tourism recommendation system utilizing a deep learning approach. The system is designed to learn tourist travel patterns based on their visitation history by employing a dual-input Long Short-Term Memory (LSTM) model that integrates location and activity data. To address the limitations of real-world data, a synthetic dataset was constructed in a realistic manner by considering tourist preferences, inter-location distances, visit duration, and the popularity of tourist attractions. Experimental results indicate that the proposed recommendation system achieves competitive performance, with a Top-1 Accuracy of 39.7%, Top-3 Accuracy of 76.2%, and Top-5 Accuracy reaching 92.4%. Evaluation was conducted using the Top-K Accuracy approach, which is considered most relevant in the context of recommendation systems as it reflects user behavior in selecting from multiple alternatives. This study demonstrates that integrating LSTM models with predictive techniques can enhance the quality of tourism recommendations and support the development of more environmentally friendly and sustainable tourism practices. SMART TOUR is expected to serve as an innovative solution to strengthen the tourism appeal of Rokan Hulu and empower local communities through the adoption of technology.*

Keyword: *Recommendation System; Tourism; LSTM; Deep Learning; Rokan Hulu*

Abstrak: Kabupaten Rokan Hulu memiliki potensi wisata alam dan budaya yang besar, namun angka kunjungan wisatawan masih tergolong rendah akibat kurangnya informasi destinasi yang terintegrasi dan risiko terhadap keberlanjutan lingkungan. Penelitian ini bertujuan untuk merancang dan membangun SMART TOUR, sebuah sistem rekomendasi tujuan wisata berbasis prediksi sekuensial menggunakan pendekatan deep learning. Sistem ini dirancang untuk mempelajari pola perjalanan wisatawan berdasarkan histori kunjungan mereka, dengan memanfaatkan model Long Short-Term Memory (LSTM) dua-input yang menggabungkan data lokasi dan aktivitas. Untuk mengatasi keterbatasan data riil, digunakan dataset sintetik yang disusun secara realistis dengan mempertimbangkan preferensi wisatawan, jarak antar lokasi, durasi kunjungan, dan popularitas objek wisata. Hasil pengujian menunjukkan bahwa sistem rekomendasi yang dibangun mampu memberikan hasil yang kompetitif, dengan Top-1 Accuracy sebesar 39,7%, Top-3 Accuracy sebesar 76,2%, dan Top-5 Accuracy mencapai 92,4%. Evaluasi dilakukan menggunakan pendekatan Top-K Accuracy yang dianggap paling relevan dalam konteks sistem rekomendasi, karena mencerminkan perilaku pengguna yang memilih dari beberapa alternatif. Penelitian ini menunjukkan bahwa integrasi model LSTM dengan pendekatan prediktif dapat meningkatkan kualitas rekomendasi wisata dan mendukung pengembangan pariwisata yang lebih ramah lingkungan dan berkelanjutan. SMART TOUR diharapkan menjadi solusi inovatif untuk meningkatkan daya tarik wisata

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Rokan Hulu serta memberdayakan masyarakat lokal melalui pemanfaatan teknologi.

Kata kunci: Sistem Rekomendasi; Pariwisata; LSTM; Deep Learning; Rokan Hulu

INTRODUCTION

Rokan Hulu Regency, located in Riau Province, is a region rich in natural and cultural tourism potential. Its geographical landscape offers pristine natural beauty, ranging from dense tropical forests and clear river streams to captivating hilly areas. Destinations such as Danau Buatan, Air Terjun Pengantin, and the conservation area of Bukit Tigapuluh National Park reflect the abundance of the region's natural tourism assets. In addition, the diversity of local culture expressed through various festivals, performing arts, and traditional customs positions Rokan Hulu as an area with strong potential for development as a culture-based tourism destination (Dinas Pariwisata dan Kebudayaan Rokan Hulu, 2023; Visit Rokan Hulu, 2025).

Despite this potential, tourism in Rokan Hulu has not been fully optimized. Based on visitor data, the number of tourists recorded remains relatively low, at approximately 200,000 visitors per year (Badan Pusat Statistik (BPS) Provinsi Riau, 2024; Visit Rokan Hulu, 2025). This figure does not yet reflect the region's maximum potential. One contributing factor is the absence of an integrated, informative, and easily accessible tourism information system. Fragmented and unstructured information makes it difficult for potential visitors to obtain a comprehensive overview of available destinations, activities, and efficient travel routes (Anisa & Irfani Lindawati, 2024).

This information gap has a direct impact on the low motivation for tourist visits. Moreover, tourism development that is not accompanied by sustainable approaches may lead to adverse environmental and social effects. Such conditions contradict the principles of sustainable development as mandated in the Sustainable Development Goals (SDGs), particularly SDG 8, which emphasizes decent work and economic growth, and SDG 12, which promotes responsible consumption and production patterns (United Nations, 2025). Therefore, strategies for tourism development in Rokan Hulu must not only focus on increasing visitor numbers but also incorporate environmental conservation and community empowerment. In recent years, the use of information technology in the tourism sector has grown significantly (Choi & Kim, 2024). Tourism information systems, digital tour guide applications, and data-driven recommendation systems have been widely adopted to enhance tourist comfort and personalize their experiences (Efrizoni, Ali, et al., 2025).

Various approaches have been proposed, ranging from content-based filtering systems that recommend destinations similar to those previously visited, to collaborative filtering systems that rely on the preferences of tourists with similar characteristics. However, these approaches are generally static and often fail to capture the complex sequential patterns of tourist visit behavior (Efrizoni, Junadhi, et al., 2025). A sequence-aware recommendation approach using deep learning thus becomes highly relevant. The Long Short-Term Memory (LSTM) model, a variant of Recurrent Neural Networks (RNNs), is known for its capacity to process sequential data and identify temporal patterns. LSTM can retain contextual information over long sequences, making it well-suited for modeling tourist travel behavior that typically involves multiple destinations and stepwise activities (Al-Selwi et al., 2024). Through this approach, the system evaluates not only a tourist's preferences at a single point in time but also how those preferences evolve chronologically from one location to another (Wu et al., 2021).

This study proposes the development of SMART TOUR, an intelligent recommendation system utilizing a dual-input LSTM model to capture tourist travel patterns from two primary data types: visited locations and activity types. The system is designed to provide personalized, contextual, and adaptive recommendations tailored to tourist needs and preferences (Li et al., 2023). Thus, the system does not generate random tourist destination suggestions but instead considers the logical sequence of previously visited destinations (Ruiz-Meza & Montoya-Torres, 2022). A key challenge in developing this system lies in the limited availability of real-world tourist visit data in Rokan Hulu. To address this, the study constructs a synthetic dataset generated realistically by considering parameters such as user preferences, inter-location distances, visit time, and destination popularity (Goyal & Mahmoud, 2024a). Although synthetic, the dataset is structured to mimic real tourist behavior in a natural and representative manner.

The strengths of this approach lie not only in its ability to enhance recommendation quality but also in its potential contribution to sustainable tourism development. By providing more accurate and personalized recommendations, the system can encourage tourists to explore a wider range of destinations, including lesser-known yet attractive sites. This could help distribute economic benefits more evenly across locations and reduce pressure on major attractions susceptible to overtourism (Dowlut & Gobin-Rahimbux, 2023; Shafqat & Byun, 2020). The objective of this research is to design and develop a tourism recommendation system based on sequential prediction using a dual-input LSTM model that not only enhances tourist comfort and experience in Rokan Hulu but also supports environmentally friendly, inclusive, and sustainable tourism development (Lubis et al., 2024). This study is expected to contribute meaningfully to the integration of artificial intelligence technologies in advancing local tourism sectors in Indonesia (Crivellari & Beinat, 2020).

METHODS

The research methodology encompasses several key stages, including the design of the synthetic dataset, data preprocessing procedures, tokenization, padding, and the transformation of data into tensor formats. The study further elaborates on the dual-input Long Short-Term Memory (LSTM) model architecture employed, the model training process, and the performance evaluation strategies utilizing conventional accuracy metrics as well as Top-K Accuracy (Alizadegan et al., 2025; Camelia et al., 2024). This approach is designed to capture tourist travel patterns and generate contextually relevant destination predictions. Figure 1 presents the research stages undertaken in this study.

Figure 1 Research Stages

RESULT AND DISCUSSION

After completing the system design and model testing stages, this section presents the implementation results of the developed SMART TOUR system, including an analysis of model performance, visualization of prediction outcomes, and a discussion of the effectiveness of the adopted approach. The results are evaluated using the Top-K Accuracy metric to assess how well the system recommends tourist destinations based on patterns in users' travel histories. The discussion elaborates on the model's achievements, compares its

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performance with other relevant approaches, and identifies both the potential strengths and limitations of the proposed system.

Application Design for the Recommendation System

To construct a representative simulation dataset that closely reflects real-world conditions, each tourist destination in the system is enriched with a set of key attributes that capture its characteristics and contextual information. These attributes not only enhance the descriptive quality of each location but also function as input variables in the synthetic data generation process and predictive modeling. The attributes incorporated include tourism category, possible activity types, geographic coordinates, popularity level, and estimated visit duration. A more detailed explanation of each attribute is presented in Figure 2.

Figure 2 Tourist Attraction Destination Metadata

Figure 2 illustrates the diversity of tourism types in Rokan Hulu—ranging from nature and adventure to culinary and educational attractions—each with varying levels of popularity and visit duration. These attributes serve as a crucial foundation in constructing a synthetic dataset that realistically reflects tourist preferences and travel patterns.

Data Preprocessing and Mapping

Once the dataset was compiled in CSV format, the next stage involved preprocessing the data to transform all entries into numerical representations suitable for the Long Short-Term Memory (LSTM) model. This process includes tokenization to identify and organize data elements into units recognizable by the model, padding to standardize sequence lengths, and final conversion into fixed-dimensional numerical tensors that can be efficiently processed within a deep learning computational environment.

Tokenization of Categorical Columns

During the tokenization process, two primary categorical columns were converted into numerical representations: location_id and activity_type. Each unique value in the *location_id* column was mapped to an integer index through a location2idx dictionary, while the activity types in the *activity_type* column—such as swimming, photography, and dining—were converted into numerical indices using an activity2idx dictionary. These tokenization dictionaries were constructed based on the set of unique values present in the dataset.

To ensure format consistency and compatibility with padding operations, special values were assigned: the number 0 to mark padding for the *location_id* column, and the symbol PAD for the *activity_type* column. These tokens help maintain uniform sequence lengths during model training. Figure 3 presents a visualization of the activity token distribution.

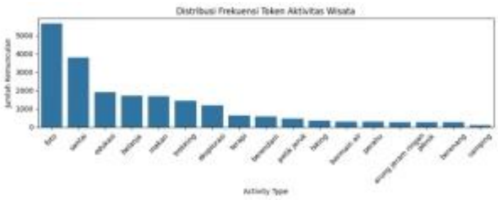

Figure 3 Activity Token Distribution Visualization

Figure 3 illustrates the frequency distribution of tourism activity tokens obtained from the tokenization process of the *activity_type* column in the dataset. This visualization highlights how often each activity type appears across the entire dataset, represented in the form of a bar chart. Based on the graph, the activity "photo" is the most dominant, with over 5,000 occurrences. Other frequently appearing activities include "relax", "education", and "shopping", indicating

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that tourists tend to prefer light, recreational, and informative activities.

Conversely, activities such as "camping", "swimming", and "sand play" show significantly lower frequencies, suggesting that these activities are limited to specific locations or performed by a narrower tourist segment. This distribution is important during model training because imbalanced activity frequencies may affect the model's ability to recognize and recommend low-frequency activities. Therefore, understanding this distribution provides the basis for considering additional measures such as data augmentation or class weighting to reduce potential bias within the recommendation system.

Padding and Tensor Transformation

In the dataset used, each tourist travel sequence varies in length, typically consisting of two to four destinations. This variation in input length is incompatible with deep learning models, particularly LSTMs, which require fixed-dimensional input sequences. Therefore, padding was applied to standardize all sequences to a length of four steps. This process involved adding special padding values to the end of each sequence (right-padding), ensuring that the temporal order of visits remained intact.

Following tokenization and padding, two primary input tensors were constructed as numerical representations of the model's input features:

1. X_location, representing the tokenized sequence of *location_id*, with dimensions [batch_size, 4];
2. X_activity, representing the tokenized sequence of *activity_type*, with the same dimensions.

These two tensors function as parallel inputs that are processed independently by the dual-input LSTM model. Meanwhile, the target output for model learning is stored in the y_target tensor, which contains the token ID of the next destination in the travel sequence. In other words, the system is trained to predict the subsequent destination based on the combination of previous locations and activities.

For training and evaluation purposes, the dataset is divided into two subsets: 80% for the training set and 20% for the validation/testing set. This split ensures that the model's generalization ability is assessed using previously unseen data. Figure 4 presents the resulting structure after the padding and tensor transformation process.

	X_location	X_activity	y_target
0	[11, 14, 0, 0]	[7, 9, 0, 0]	15
1	[11, 14, 15, 0]	[7, 9, 9, 0]	9
2	[5, 14, 0, 0]	[9, 9, 0, 0]	11
3	[5, 14, 11, 0]	[9, 9, 7, 0]	15
4	[5, 14, 11, 15]	[9, 9, 7, 9]	9

Figure 4 Tensor Input Format

Training the Tourist Destination Recommendation Model

After all data were successfully processed and transformed into fixed-dimensional tensors, the next stage of this research involved training the machine learning model to learn the sequential patterns of tourist visits and accurately predict subsequent destinations. The purpose of this training process is to enable the model to generalize travel patterns from the available historical data, allowing the system to provide relevant and context-aware destination recommendations that align with user preferences. The developed model is designed with two primary input pathways: (1) the tokenized sequence of tourist locations (location_id), and (2) the sequence of activity types performed at each location (activity_type). Each input pathway is processed independently through its own embedding layer and LSTM unit, enabling the model to capture sequential representations of each aspect in a more specialized manner. The outputs from these two pathways are then concatenated and passed to a fully connected (dense) layer to generate a probability distribution over all potential

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next destinations using the softmax activation function. This architectural structure allows the model to produce contextual predictions based on previously observed travel sequences. Figure 5 illustrates the architecture of the proposed recommendation system.

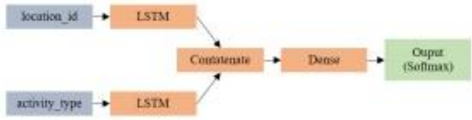

Figure 5 Recommendation System Architecture Design

The dual-input LSTM model was trained to learn sequential patterns of tourist locations and activities in order to predict the next destination. The training process employed the Adam optimizer and a categorical cross-entropy loss function, both of which are commonly used in multi-class classification tasks. Figure 6 presents the training and validation accuracy curves.

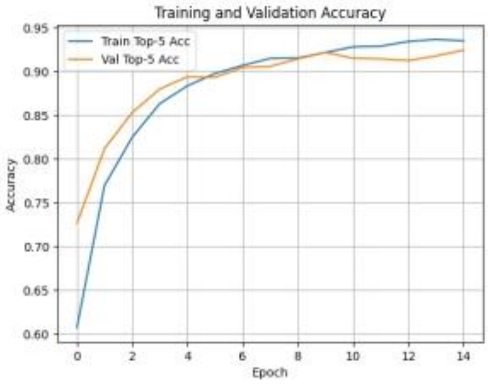

Figure 6 Training and validation accuracy graph

The dataset was divided into two portions, with 80% allocated for training and 20% for validation. This split aims to ensure that the model is not only capable of recognizing patterns in previously seen data but also able to generalize effectively to new, unseen data. The training results demonstrate strong performance. The model achieved a training accuracy of 93.55%, indicating that it successfully learned the relationships between sequences of locations and activities within the training set. Meanwhile, on the validation set, the model attained an accuracy of 92.40%, reflecting robust generalization capability. The model was also evaluated manually using test data to compute the top-1 accuracy, top-3 accuracy, and top-5 accuracy. Figure 7 presents the results of this evaluation.

```
y_preds = model.predict([X_loc_val, X_act_val])  # shape: (batch_size, vocab_size)
top_1_pred = np.argmax(y_preds, axis=1)
top_3_pred = np.argsort(y_preds, axis=1)[:, -3:]
top_5_pred = np.argsort(y_preds, axis=1)[:, -5:]

# Top-1 Accuracy
top1_acc = np.mean(top_1_pred == y_val)

# Top-3 Accuracy
top3_acc = np.mean([y in top3 for y, top3 in zip(y_val, top_3_pred)])

# Top-5 Accuracy
top5_acc = np.mean([y in top5 for y, top5 in zip(y_val, top_5_pred)])

print(f"Top-1 Accuracy: {top1_acc:.4f}")
print(f"Top-3 Accuracy: {top3_acc:.4f}")
print(f"Top-5 Accuracy: {top5_acc:.4f}")

48/48 ━━━━━━━━━━━━━━━━━━━━ 0s 6ms/step
Top-1 Accuracy: 0.3972
Top-3 Accuracy: 0.7621
Top-5 Accuracy: 0.9240
```

Figure 7 Evaluation

The recommendation model demonstrates strong performance, achieving a Top-1 Accuracy of 39.72%, Top-3 Accuracy of 76.21%, and Top-5 Accuracy of 92.40%. Although the first-ranked prediction is not always correct, the actual destination is almost consistently included within the top five suggestions, indicating that the model is effective in filtering and narrowing down the most plausible options. Unlike conventional classification systems that prioritize Top-1 accuracy, recommendation systems require a more contextual evaluation approach. First, a single travel history may lead to multiple reasonable next destinations. For example, after visiting Benteng Tujuh Lapis and the Butterfly Museum, a tourist may continue to Istana Rokan Hulu or Masjid Agung Madani both of which are historically and educationally relevant. Second, the purpose of the model is to function as a recommender system rather than a single-outcome predictor. Therefore, metrics such as Top-3 and Top-5 accuracy more accurately reflect the system's quality as a filtering mechanism, consistent with evaluation practices used in platforms like Spotify or YouTube.

With a Top-5 accuracy exceeding 90%, the SMART-TOUR system has demonstrated its effectiveness in providing users with relevant and useful recommendation lists. Figure 8 presents the top-k coverage accuracy graph.

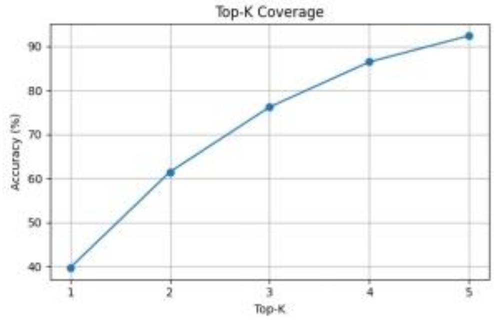

Figure 8 Top-K coverage accuracy graph

SMART-TOUR Application

As an implementation of the developed recommendation model, this study also produced a mobile application called SMART-TOUR. The application is designed to provide real-time tourist destination recommendations to users based on their visit history and previously selected activity preferences. SMART-TOUR was developed using the Kotlin programming language and built on the Android platform, ensuring optimal performance across a wide range of mobile devices.

The presence of this application represents a concrete step in bridging research outcomes with user needs while supporting the development of an intelligent, technology-driven tourism ecosystem in Rokan Hulu Regency. The following section describes the user interface, workflow, and key features of the SMART-TOUR application. Figure 9 presents the design layout of the SMART-TOUR application.

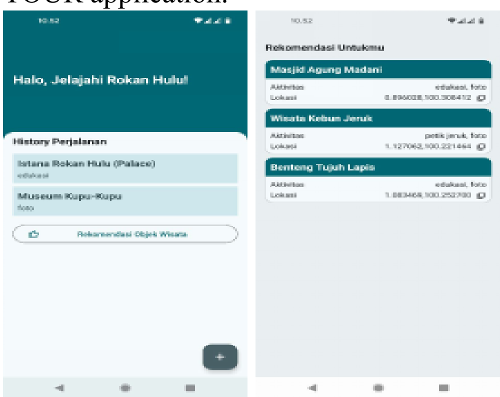

Figure 9 SMART-TOUR application

The operational workflow of the SMART-TOUR application is designed to be intuitive and user-friendly. Users in this case, tourists—are prompted to input their travel history, consisting of the destinations they have visited along with the activities performed at each location. This information is then processed by the application's embedded recommendation system, which utilizes a Long Short-Term Memory (LSTM)–based predictive model.

Based on the user's travel history, the application analyzes their movement patterns and automatically generates a list of the most relevant and preference-aligned next-destination recommendations. The recommendations are presented in a Top-K list format, allowing users to select from several suggested options. Through this approach, SMART-TOUR not only assists tourists in planning their visits more efficiently but also encourages them to explore potential destinations that may be lesser known or not commonly visited.

CONCLUSION

This research successfully designed and developed a sequential prediction–based tourism destination recommendation system using a deep learning approach, specifically a dual-input Long Short-Term Memory (LSTM) architecture that incorporates both location and activity information. The system is capable of learning travel patterns from historical visit data and generating contextually relevant destination recommendations. One of the key contributions of this study is the development of a realistic synthetic dataset that accounts for factors such as tourist preferences, inter-location distance, estimated visit duration, and destination popularity. This approach proved effective for simulating user behavior in scenarios where real-world data are not yet available. In terms of performance, the dual-input LSTM model demonstrates competitive results, achieving a Top-1 Accuracy of 39.7%, a Top-3 Accuracy of 76.2%, and a Top-5 Accuracy of 92.4%. Although the top-ranked prediction is not always correct, the system effectively provides multiple logical and relevant destination options to users. Furthermore, the use of Top-K Accuracy as an evaluation metric is considered highly appropriate, as it reflects real-world recommender system practices that present more than one alternative to users. Overall, this research offers a meaningful contribution to the development of sequence-based recommendation systems, both in terms of methodology and real-world applicability. Moving forward, the system has strong potential for further enhancement through the integration of real-time data and user feedback to continuously improve the accuracy and quality of its recommendations.

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