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Tourist Destination Recommendations Using Deep Learning

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Abstract

Personalized tourist attraction recommendations present a challenging problem in intelligent travel planning. Bangkok, the capital of Thailand, is a popular tourist destination offering a convenient metro system that enables travelers to plan their journeys easily. Leveraging this infrastructure, this study proposes a deep learning-based model designed to classify tourists into five categories: Nature Tourists, Cultural Tourists, Shopping Tourists, Historical Tourists, and Industrial Tourists. The model employs Neural Collaborative Filtering (NCF), utilizing deep neural networks to capture complex, non-linear patterns between users and destinations, surpassing the limitations of traditional matrix factorization methods. It integrates both user-related data, such as tourists' opinions on destinations, and location-based data from the attractions themselves. To evaluate the model, data were collected from 30 stations along Bangkok's Pink Line, covering the northern part of the city and Nonthaburi province, and 31 tourist attractions along the route. Experimental results demonstrate high classification accuracy across tourism types: 96.26% for Nature Tourists, 80.59% for Cultural Tourists, 93.78% for Historical Tourists, 70.35% for Industrial Tourists, and 97.66% for Shopping Tourists. Furthermore, the study proposes three optimized travel routes tailored to tourist preferences: one for Nature and Cultural Tourists, another for Cultural Tourists, and a third for Historical and Cultural Tourists. By categorizing tourists based on their interests and recommending destinations accordingly, the model supports more informed and personalized travel decision-making. However, this current study serves as a prototype model and can be further applied to problems related to public transportation systems, such as deployment in mobile applications and integration with GPS positioning systems to enhance convenience and accuracy in providing tourist destination recommendations.

Keywords: Deep Learning; Recommendation; Neural Collaborative Filtering (NCF); Tourism.

1. Introduction

Nowadays, tourists place great importance on researching destinations and travel routes before embarking on their journeys. They consider various factors that influence their travel experiences, such as travel time, entrance fees, and overall convenience. Many travelers choose public transportation, such as the metro system, for its accessibility and efficiency. Along metro routes, numerous shops and points of interest attract visitors.

Cultural tourism is becoming increasingly popular, particularly in Thailand—especially in Bangkok—which boasts a wealth of cultural attractions that are both educational and engaging. The newly operational Metro Pink Line serves as a crucial transit link between northern and eastern Bangkok, connecting Nonthaburi and Min Buri. It provides a convenient and efficient mode of transportation, offering quick access to numerous cultural and recreational attractions, including temples, museums, and shopping centers—making it especially beneficial for cultural tourists exploring Bangkok.

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AI is playing an important role in reshaping the tourism landscape, with continuous advancements in machine learning, deep learning, and big data analytics to enhancing efficiency, personalization, and decision-making. By leveraging deep learning, NLP, and IoT, tourism businesses can optimize efficiency, enhance customer satisfaction, and contribute to sustainable tourism development. As a result, numerous studies have been carried out to explore the impact of AI on various aspects of the tourism industry.

In terms of sentiment analysis and customer insights, Martín et al. [1] concluded that deep learning models, particularly Long Short-Term Memory (LSTM) networks, are highly effective for sentiment analysis of tourist reviews, achieving an accuracy of over 89%. These models outperform Convolutional Neural Networks (CNNs) and demonstrate superior capability in classifying positive sentiments. The findings emphasize the practical applications of these models in the tourism industry, including market positioning, proactive customer service, marketing, and risk management. By leveraging these tools, tourism businesses can gain valuable insights from electronic Word of Mouth (eWOM) platforms to improve services, address customer feedback, and enhance their reputation in competitive markets.

When it comes to hybrid deep learning for sentiment analysis, Wang et al. [2] proposed a hybrid deep learning model for analyzing sentiment in educational tourism reviews, a method integrating Parallel Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks with a multi-channel attention mechanism to extract key sentiment-related features, by leveraging Word2Vec for word embedding and filtering out noise, the model improves sentiment classification accuracy. Experimental results show that this approach significantly outperforms traditional machine learning and deep learning models in precision, recall, and F1-score, offering valuable insights for tourism management and improving customer satisfaction.

As for smart tourism systems and AI-based services, Li et al. [3] studied ai-based smart tourism service platform and find that the AI-based smart tourism service platform, designed with features such as smart access control, virtual reality (VR) scenic tours, and integrated mobile applications has been well-received by tourists. Among the users surveyed, it was revealed 96.65% expressed satisfaction, with 41.5% being very satisfied.

A study by Du [4] proposed an advanced smart tourism system that leverages big data, clustering algorithms (K-means), and visualization techniques to improve user experience and enhance tourism management. The study focuses on integrating real-time data processing, improving information accessibility for tourists, and optimizing decision-making for tourism enterprises. The proposed system significantly enhances data mining accuracy and user satisfaction, demonstrating its effectiveness in providing personalized recommendations, real-time analytics, and efficient resource management for smart tourism applications.

Moreover, Sun [5] highlighted the effectiveness of AI-assisted recommendation algorithms in enhancing tourism through personalized and accurate suggestions. Hybrid models perform best by combining content-based and collaborative filtering. Despite promising results, challenges like data privacy and algorithm bias persist.

Also, Mu et al. [6], who study AI in hotel & tourism analytics, confirm that big data analytics holds transformative potential for the tourism and hotel industry. By analysing diverse traveller data from booking patterns to feedback businesses can enhance customer experiences, improve operational efficiency, and drive strategic decision-making. Key factors like service quality, location, and room comfort strongly influence guest satisfaction. Lin Mu et al. propose that in the future, the integration of real-time analytics, sustainable travel trends, and AI will play a vital role in creating personalized, data-driven tourism experiences.

In relation to route planning and optimization, Damos et al. [7] worked on ACO for hilly area path optimization and propose an introducing enhanced Ant Colony Optimization (ACO) algorithm to optimize tourism path planning in hilly areas by incorporating dynamic objectives like temperature, atmospheric pressure, and health conditions alongside static objectives such as distance and elevation. Tested in Sudan’s Jebel Marra region, the improved ACO outperforms traditional ACO and Genetic Algorithms (GA), achieving shorter paths, faster execution times, and better adaptability to real-time environmental factors. The findings emphasize its potential for creating safer, more efficient, and tailored travel routes in complex terrains, highlighting its significance for advancing tourism experiences in hilly regions.

In the same respect, Sirirak & Pitakaso [8] presented an approach to tourism route planning and marketplace location allocation using the Adaptive Large Neighborhood Search (ALNS) algorithm, which is applied to a case study in Chiang Rai, Thailand. By balancing popular and less popular attractions and integrating suitable marketplace locations, the proposed methodology minimizes travel distances while supporting local economic development. The ALNS algorithm exhibits strong performance, producing solutions that closely match exact methods while significantly reducing computational time. This approach effectively addresses the challenges of tourism planning, promoting economic opportunities for underserved areas and enhancing tourist satisfaction through optimized route designs and strategic marketplace placement.

Furthermore, Qi & Wang [9] proposed an improved Genetic Algorithm (IGA) for optimizing tourism route selection. Their approach addresses the limitations of traditional genetic algorithms, such as premature convergence and poor local search ability, by integrating the ant colony algorithm for initialization, adaptive crossover probability adjustment, and the 2-opt optimization method. As a result, IGA enhances route planning efficiency. Experimental results confirm its effectiveness in reducing travel costs and time while improving tourist experience. Also, Cao [10] proposed an Improved Genetic Algorithm (IGA) to minimize travel time and costs while selecting the best route through multiple tourist attractions. It highlights how traditional methods like dynamic programming and simulated annealing have limitations when solving large-scale problems and propose enhancements to genetic algorithms to improve accuracy and efficiency. The results show that the IGA performs better than standard genetic algorithms and neural network-based approaches in optimizing tourist routes. The findings have practical implications for intelligent tourism route planning, reducing costs, and enhancing travel experiences.

Moreover, Lu & Zhou [11] presented a study in which traditional methods mainly consider single factors, such as scenic spots. However, their approach integrates multiple elements, including hotels and geographic constraints, to enhance planning accuracy. It proposes that a self-balancing PSO mechanism enhances global search efficiency and parallel computing to speed up the solution process. The study highlights that PSO-based algorithms surpass conventional methods by dynamically optimizing route selection while incorporating real-world geographic data. The results confirm that this approach significantly improves the feasibility and practicality of tourism route planning.

Besides, Sun et al. [12] proposed a multi-objective travel route recommendation framework that efficiently suggests optimal travel routes by leveraging mobile phone signaling data. The framework identifies popular attractions and frequent travel sequences using a frequent pattern mining method and then applies an improved Ant Colony Optimization (ACO) algorithm to generate optimal routes based on attraction popularity and travel time. The experimental results demonstrate that the framework successfully provides effective travel recommendations. However, the study acknowledges limitations, including the lack of consideration for real-time traffic conditions, crowd levels, and user preferences.

Regarding tourism demand prediction and market insights, a study by Yu & Chen [13], which investigates tourism demand forecasting via SAE-LSTM, proposes an advanced model for predicting tourism demand. The proposed Stacked Autoencoder-Long Short-Term Memory (SAE-LSTM) model enhances traditional LSTM networks by incorporating autoencoders for unsupervised pretraining. The study evaluates its performance using mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE). Experimental results show that SAE-LSTM outperforms standard LSTM models in forecasting accuracy, demonstrating its effectiveness in optimizing resource allocation and strategic planning in the tourism industry.

Another study by Wang et al. [14], which focuses on a train passenger load factor prediction model using the LightGBM algorithm, integrates weather conditions, train attributes, and passenger flow time sequences. The study finds that LightGBM outperforms traditional models, such as ARIMA, XGBoost, and RandomForest, in terms of accuracy. The analysis highlights key influencing factors such as departure time, mileage, and seasonal variations. This approach provides a valuable tool for optimizing train operations, ticket revenue calculations, and passenger demand forecasting.

Moreover, a study on AI-based Airbnb Pricing Models by Camatti et al. [15] showed that AI models, particularly random forests and neural networks, outperform traditional methods in predicting Airbnb prices. Still, traditional models are useful for understanding key factors. Financial history data greatly improves predictions, and combining models may further enhance accuracy.

In respect of rural and cultural tourism development, a study by Yang & Dong [16] employed e-commerce and intelligent algorithms to improve rural tourism planning and infrastructure. It finds that the development model for rural tourism, based on multi-objective planning and intelligent optimization algorithms, is effective in addressing the complexities of rural tourism planning. By leveraging advanced Internet technologies, e-commerce, and intelligent optimization methods, the proposed model enhances tourism experiences while fostering economic growth and improving infrastructure in rural areas. The experimental results validate its ability to optimize tourism paths, improve service efficiency, and promote sustainable rural development, highlighting its potential for broader application in the tourism industry.

Moreover, Wang et al. [17] proposed a hierarchical clustering-based method to classify rural tourism characteristics to develop a classification index system that includes factors like tourist density, infrastructure, economic impact, and environmental resources; by using hierarchical clustering, the model improves the rational zoning of rural tourism attractions, leading to better management and higher revenue. The experimental results indicate that this method significantly increases daily tourism income (by over 261,900 yuan) compared to traditional classification approaches, demonstrating its effectiveness in promoting rural tourism.

Furthermore, Xiao [18] proposed an Apriori algorithm that can be applied to analyze and optimize rural tourism development. It identifies key driving factors such as demand, resource availability, and economic influence, integrating them into a dynamic system for sustainable rural tourism growth. The study demonstrates that the Apriori algorithm enhances data mining efficiency, outperforming traditional methods like SVM and CD algorithms by reducing database size and improving record reading speed. The findings support improved urban-rural tourism planning, enabling policymakers to optimize tourism routes and allocate resources more efficiently.

Also, Jiang & Dai [19] adopted a cultural tourism attraction recommendation model based on an optimized weighted association rule algorithm, incorporating dynamic time and seasonal weights to enhance recommendation accuracy and personalization. Experimental results demonstrate that the model significantly outperforms traditional algorithms like NARM and Bpr-MF in terms of accuracy, recall, F1 value, and convergence efficiency. By addressing the limitations of conventional recommendation systems, such as neglecting user preferences and seasonal variations, the model provides intelligent and tailored suggestions that effectively encourage tourist travel.

Besides, Li & Lyu [20] proposed a Quantum Genetic Algorithm-Backpropagation (QGA-BP) neural network model to classify ethnic traditional sports tourism resources. It focuses on Yunnan Province, using SWOT analysis, surveys, and machine learning to improve classification accuracy. Compared to traditional classification methods, the QGA-BP model achieves higher accuracy and efficiency, overcoming issues like manual classification inefficiencies. The model shows potential in optimizing tourism planning and preserving ethnic cultural heritage by better categorizing sports-related tourism resources and,

In relation to AI-driven classification and security enhancements, Luo & Zhang [21] adopted a deep learning-based approach for classifying tourism-related questions. It integrates Word2Vec for word vector representation and employs an attention-based Long Short-Term Memory (LSTM) model to enhance text feature extraction. The Softmax classifier is used to determine question categories, and cross-entropy loss function improves classification accuracy. Experimental results indicate that this method significantly outperforms traditional models, achieving high accuracy (0.943), recall (0.867), and F1-score (0.903), making it a more effective solution for automatic classification of tourism-related queries.

Moreover, Chenghu & Thammano [22] introduced a hybrid model combining K-Means and neural networks to handle overlapping data, enhancing classification accuracy. Tested on various datasets, the model consistently outperforms traditional K-Means, proving its robustness and wider applicability.

Furthermore, a study by Xiao et al. [23] demonstrated that deep learning significantly enhances real-time intrusion detection in smart grids, particularly for protecting Data Processing Units (DPUs). Among the evaluated models, Random Forest achieves the highest accuracy (F1-score = 0.99), outperforming SVM, LDA, and Decision Trees. These findings confirm that advanced machine learning techniques can improve data security, efficiency, and resilience in smart grid operations, paving the way for more secure and sustainable energy systems.

In addition, Bourday et al. [24] proposed a Transformer-XGBoost model for Bitcoin price prediction and find that it achieves the highest accuracy in Bitcoin price forecasting, outperforming other hybrid models. However, it lacks sentiment analysis integration.

While AI-based sentiment analysis models are commonly used in customer service, their potential for recommending destinations tailored to tourists with diverse preferences remains underexplored. This research aims to evaluate the effectiveness of a deep learning model employing Neural Collaborative Filtering (NCF), which utilizes deep neural networks to capture complex, non-linear patterns between users and destinations, surpassing the limitations of traditional matrix factorization methods. It also analyzes tourist data by considering key factors such as distance, travel convenience, and destination popularity, with the goal of delivering precise tourist destination recommendations.

2. Theoretical Framework

The theoretical framework comprises the following steps (see Figure 1):

User Input: The input of essential data is crucial for generating personalized recommendations tailored to each individual user such as attraction and metro data.

Data Collection: This stage involves gathering tourism-related data from multiple sources, such as user-generated reviews, social media activity, historical travel logs, and demographic information. The collected data may include textual descriptions, ratings, and user preferences. Additionally, transportation data (such as metro stations, visit, and accessibility information) can be integrated to enhance recommendation accuracy.

Data Preprocessing: Data preprocessing in a tourism recommendation system involves cleaning and integrating information from various sources, such as attractions, metro routes, and user profiles. This process also includes extracting key features (e.g., attraction category) and transforming data through normalization and encoding to prepare it for deep learning models.

Model Selection: At this stage, a deep learning algorithm processes the collected data to analyze patterns and extract meaningful insights. The system leverages machine learning techniques such as Collaborative Filtering, Content-Based Filtering, Recurrent Neural Networks (RNNs), Graph Neural Networks (GNNs), or Transformer-based models to personalize recommendations. The model incorporates factors like user preferences, travel behavior, and sentiment analysis from reviews to generate optimal recommendations.

Recommendation Generation: After processing the input data, the deep learning model generates personalized travel suggestions based on the user's interests and location. The recommendations are ranked according to relevance and popularity and presented through a user-friendly interface to help travelers make informed decisions.

Model Update: This stage involves improving the model by incorporating new data, such as recent user behavior or feedback from previous recommendations. It may include retraining the model or fine-tuning its parameters to enhance accuracy and ensure the system continues to deliver relevant and up-to-date suggestions.

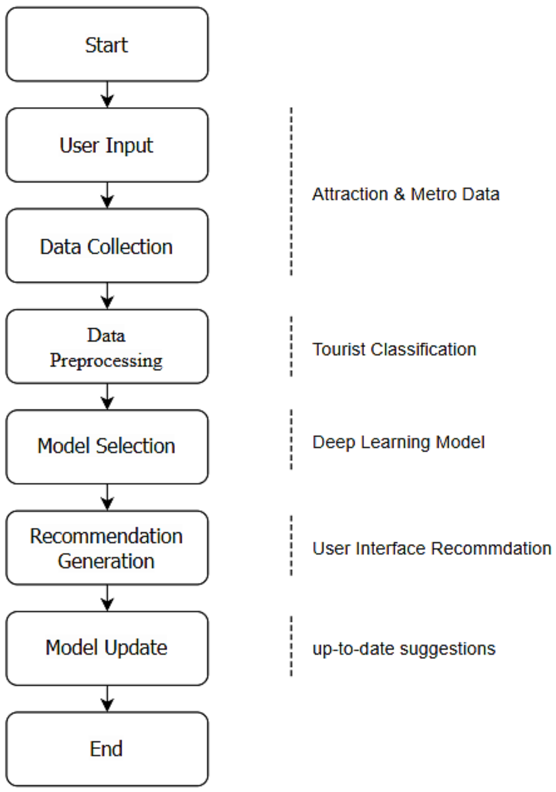

Figure 1. Process recommendation

Deep learning algorithms for tourist attraction recommendations often rely on neural networks. A popular approach is to use Collaborative Filtering (CF) enhanced by deep learning techniques, such as Neural Collaborative Filtering (NCF). Below is a step-by-step explanation of how a deep learning algorithm works for this problem, including relevant formulas.

2.1. Problem Definition

Initial Set of user $U = \{u_1, u_2, \dots, u_n\}$.

Initial set of tourist attractions $A = \{a_1, a_2, \dots, a_m\}$.

User-Item $R \in \mathbb{R}^{n \times m}$ where r_{ij} represents the rating or interaction of user u_i with attraction a_j.

2.2. Input Representation

User Embedding E_u Represent each user u_i as a dense vector $e_{u_i} \in \mathbb{R}^d$.

Attraction Embedding E_a Represent each attraction a_j as a dense vector $e_{a_j} \in \mathbb{R}^d$.

2.3. Neural Collaborative Filtering Architecture

- Embedding Layers

  For each user u_i and attraction a_j retrieve their embedding vectors:

$$e_{u_i} = E_u[i]\,,\; e_{a_j} = E_a[j] \tag{1}$$

- Interaction Layer The user and attraction embeddings are combined to model their interaction. Common methods include:

Concatenation:

$$Z = \left[e_{u_i}, e_{a_j}\right] \tag{2}$$

Element-wise Product

$$Z = e_{u_i} \odot e_{a_j} \tag{3}$$

where: Z is the interaction vector used as input to the next layers.

- Hidden Layers Feed the interaction vector Z into a series of fully connected layers:

$$h_1 = \sigma(W_1 Z + b_1) \tag{4}$$

$$h_2 = \sigma(W_{21} Z + b_2) \tag{5}$$

where: W_l and b_l are weights and biases for layer l; $\sigma(\cdot)$ is the activation function.

- Output Layer The output layer predicts the interaction score:

$$\hat{r}_{ij} = f(h_L) \tag{6}$$

where: $f(\cdot)$ is a suitable activation function for the output; For rating prediction: $f(x) = x$.

2.4. Loss Function

The loss function measures the error between predicted and actual interactions. Common choices include Mean Squared Error (MSE) for rating predictions.

$$MSE = \frac{1}{|R|} \sum_{(i,j) \epsilon R} (r_{ij} - \hat{r}_{ij})^2 \tag{7}$$

where: $|R|$ is the number of user-attraction interactions in the dataset; r_i□ is the actual interaction; $\hat{r}_i$□ is the predicted interaction.

2.5. Training Process

The algorithm is trained using a gradient descent optimizer.

Forward Pass: Compute $\hat{r}_{ij}$ for each user-attraction pair.

Compute Loss: Calculate $\mathcal{L}$ using the chosen loss function.

Backward Pass: Compute gradients of $\mathcal{L}$ w.r.t model parameters.

Update Parameters:

$$\theta \leftarrow \theta - \eta \nabla_\theta \mathcal{L} \tag{8}$$

where: η is the learning rate; θ is Model parameters (weights and biases).

2.6. Performance

To evaluate the performance of the prediction model, this paper uses several evaluation metrics, including Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). These metrics predict value x_i and the actual value x as follows:

$$x_i = \{x_{i1}, x_{i2}, \dots, x_{in}\} \tag{9}$$

$$x = \{x_1, x_2, \dots, x_n\} \tag{10}$$

2.7. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a commonly used metric for evaluating the accuracy of predictive models, especially in regression tasks. It measures the average absolute difference between predicted and actual values.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| x_{ij} - x_j \right| \tag{11}$$

where: n is the number of observations; x_{ij} is the actual value; $x_j$is the predicted value.

3. Material and Methods

In this study, the researcher selected popular and significant tourist attractions that serve as key destinations for tourists, in relation to the stations along the Pink Line of the mass transit system. The tourist attraction selection was made with consideration to travel convenience, based on the assumption that the closer a tourist attraction is to a transit station, the easier it is to access thereby increasing the likelihood of visitation. Moreover, the tourist attractions along the Pink Line vary in nature and type, appealing to a wide range of tourists and helping distribute knowledge and tourism activity more evenly across different areas. Therefore, the inclusion of 30 transit stations and 31 tourist attractions is considered sufficient for the current prototype model developed in this research. The study primarily focuses on qualitative analysis, such as identifying trends and exploring preliminary spatial relationships. The dataset also covers all stations along the Pink Line and includes attractions distributed across the route, allowing for an adequate level of spatial analysis.

3.1. Data Collection

This study integrates both user-related data, such as tourists' opinions on destinations, and location-based data from the attractions themselves. Data was collected from 31 tourist destinations, including cultural and significant attractions near the 30 stations along the Metro Pink Line (Figure 2), ensuring that each station is linked to a notable cultural or recreational site. Table 1 presents information about each station and its nearby attractions.

Table 1. Stations along the Metro Pink Line and their nearby attractions

Station	Attraction(s)
PK01 Nonthaburi Civic Center	Makutromsaran Park
PK02 Khae Rai	Wat Khema Phirataram Ratchaworawihan
PK03 Sanambin Nam	Khae Nok Temple
PK04 Samakkhi	Mumtas Thai cuisine
PK05 Royal Irrigation Department	Wat Chonprathan Rangsarit Phra Aram Luang
PK06 Yaek Pak Kret	Pakkret Old waterfront Market
PK07 Pak Kret Bypass	The Church of Jesus Christ of Latter-Day Saints
PK08 Chaeng Watthana-Pak Kret 28	Central Chaengwattana
PK09 Si Rat	Wat Phasuk Maneechak
PK10 Mueang Thong Thani	IMPACT Arena, Exhibition and Convention Center, Muang Thong Thani
PK11 Chaeng Watthana 14	Good Thingz Happen, Lifestyle Café
PK12 Government Complex	Chaengwattana Horse Club
PK13 National Telecom	The Administrative Court Museum
PK14 Lak Si	Wat Lak Si
PK15 Rajabhat Phranakhon	Thai Teacher Training Museum
PK16 Wat Phra Sri Mahathat	Bangkhen Camp Food
PK17 Ram Inthra 3	Ramintra sport center
PK18 Lat Pla Khao	Wat Lat Pla Khao
PK19 Ram Inthra Kor Mor 4	Wat Trai Rattanaram
PK20 Maiyalap	Ease Park
PK21 Vacharaphol	Plearnary Mall
PK22 Ram Inthra Kor Mor 6	9 Salads Restaurant
PK23 Khu Bon	Wat Khubon
PK24 Ram Inthra Kor Mor 9	The Alley Ramindra
PK25 Outer Ring Road - Ram Inthra	Fo Guang Shan Temple, and Fashion Island
PK26 Nopparat	Siam Amazing Park
PK27 Bang Chan	Wat Rat Satthatham (Bangchan)
PK28 Setthabutbamphen	Kwan-Riam Floating Market
PK29 Min Buri Market	Min Buri Local Museum
PK30 Min Buri	Minoburi

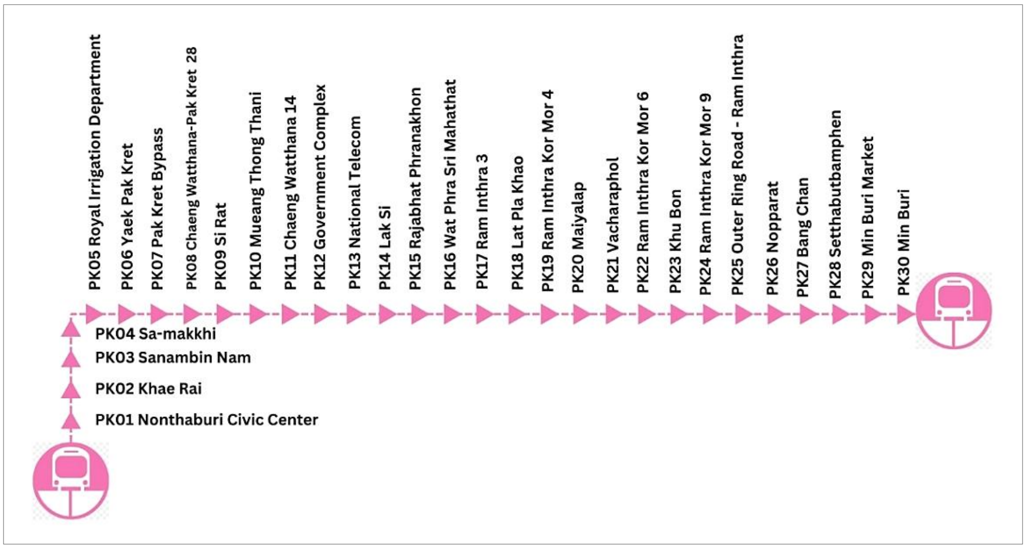

Figure 2. The Metro Pink Line route map

3.2. Tourist Attractions

Classifying tourists can help facilitate personalized recommendations, enhance travel experiences, and support tourists in making well-informed decisions. This study classifies tourists into distinct categories based on their characteristics and behaviors as follows. ***Nature Tourists*** travel to destinations known for their natural beauty, outdoor adventures, and ecological experiences. ***Cultural Tourists*** are drawn to local traditions, arts, customs, and heritage. They explore museums, temples, historic towns, cultural festivals, and traditional markets, engaging in activities such as attending performances, sampling local cuisine, and immersing themselves in history. ***Historical Tourists*** visit historical landmarks, ancient ruins, and significant sites such as castles, battlefields, historic cities, and UNESCO World Heritage Sites, seeking to connect with the past. ***Industrial Tourists*** are fascinated by factories, industrial sites, and technological advancements. They explore manufacturing plants, power stations, mining sites, and industrial museums to gain insight into production processes and industrial heritage. ***Shopping Tourists*** primarily travel for retail experiences and unique purchases. They visit luxury malls, traditional markets, fashion districts, and duty-free shopping zones in search of exclusive products and cultural souvenirs.

Based on different tourist categories, 31 notable attractions have been recommended. The values of Dep-t, Stay-t, Influencers, and Like for each attraction have been analyzed. Table 2 presents information showcasing all tourist attractions, for which the values of the Dep-t, Stay-t, Influencers, and Like factors have been analysed.

Table 2. The collection of information on tourist attractions

Attraction	Picture	Dep-t	Stay-t	Influencers	Like
Makutromsaran Park		0.34	0.31	0.77	0.91
Wat Khema Phirataram Ratchaworawihan		0.12	0.41	0.17	0.41
. . .	. . .	. . .	. . .	. . .	. . .

Siam Amazing Park		0.84	0.21	0.27	0.81

The information in Table 3 (below) is gathered from users or tourists, reflecting their connection to key tourist attractions. They rate their satisfaction across various aspects of each location, with the results presented as average scores.

Table 3. The values gathered from users expressing their opinions on tourist attractions

Tourist (User)	Attraction 1	Attraction 2	…	Attraction 31
U_1	0.652	0.552		0.233
U_2	0.542	0.765		0.134
.				
.				
U_n	0.326	0.432		0.652

Neural Collaborative Filtering (NCF) is a deep learning approach well-suited for tourist destination recommendations. It captures complex relationships between users and attractions more effectively than traditional methods. By utilizing deep neural networks with multiple layers, NCF learns intricate patterns that go beyond the linear interactions modeled by conventional matrix factorization techniques.

This adaptability makes Neural Collaborative Filtering (NCF) particularly suitable for handling diverse and complex tourism behaviors, such as individual preferences and various types of attractions. Consequently, the researchers select NCF for this study, as it is specifically designed to recommend items based on actual user behavior, aligning directly with the research objectives.

Pseudocode

```
# Tourist Destination Recommendation Using Deep Learning (Short Pseudocode)
# Initialize model
InitModel()
# Define deep learning model
Function NCF(user, attraction):
    z ← Combine(Embed(user), Embed(attraction))
    z ← DeepLayers(z)
    Return Predict(z)
# Training process
Function Train():
    For epoch in Epochs:
        For (u, a, y) in TrainingData:
            Update(Backward(ComputeLoss(NCF(u, a), y)))
        Print(Evaluate(ValidationData))
# Recommendation function
Function Recommend(user, k):
    Return TopK(SortByScore([NCF(user, a) for a in A]), k)
# Execute recommendation system
Function Main():
    Train()
    Print({u: Recommend(u, k) for u in U})
```

4. Results and Discussion

4.1. The Effectiveness of the Deep Learning Model

Regarding the effectiveness of the deep learning model employing Neural Collaborative Filtering (NCF), this study utilizes deep neural networks to capture complex, non-linear patterns between users and destinations, surpassing the limitations of traditional matrix factorization methods. Table 4 presents the classification performance results of a deep learning model for various categories of tourists. It reveals the correct classifications, misclassifications, and error rates for each category. The Nature Tourists category has an error rate of 0.0938, with most misclassifications occurring as Historical Tourists. The Cultural Tourists category exhibits the highest error rate of 0.3871, frequently being misclassified as the Historical Tourists category, suggesting feature similarities. The Historical Tourists category is well-classified, with an error rate of just 0.0469. The Industrial Tourists category is classified perfectly, with an error rate of 0.000, indicating strong feature distinctiveness. Meanwhile, the Shopping Tourists category has an error rate of 1.0000, likely due to the small sample size, making the model ineffective for this category.

Table 4. Classification performance results of a deep learning model for various types of tourists

Category of tourists	Nature tourists	Cultural tourists	Historical tourists	Industrial tourists	Shopping tourists	Error	Rate
Nature Tourists	58	0	5	1	0	0.0938	6/64
Cultural Tourists	5	9	7	0	0	0.3871	12/31
Historical Tourists	2	1	61	0	0	0.0469	3/64
Industrial Tourists	0	0	0	7	0	0.0000	0/7
Shopping Tourists	1	0	0	0	0	1.0000	1/1
Total	**66**	**20**	**73**	**8**	**0**	**0.1317**	**22/167**

The proposed deep learning model in Table 5 presents key statistics from each layer of the neural network, including activation type, regularization terms (L1, L2), learning rate metrics (Mean Rate, Rate RMS), as well as statistics on weights and biases (Mean, RMS).

Table 5. Results of the deep learning model

Layer	Unit	Type	L1	L2	Mean Rate	Rate RMS	Mean Weight	Weight RMS	Mean Bias	Bias RMS
1	154	Input	-	-	-	-	-	-	-	-
2	10	Rectifier	0.000010	0.000000	0.001388	0.001515	0.005923	0.109397	0.461116	0.051089
3	10	Rectifier	0.000010	0.000000	0.000761	0.000445	-0.023553	0.304096	0.987405	0.060852
4	5	SoftMax	0.000010	0.000000	0.002156	0.002152	-0.240704	0.940678	-0.011935	0.090679

The architecture of the model consists of four layers: an input layer with 154 units, two hidden layers using the Rectifier (ReLU) activation function with 10 units each, and an output layer using the SoftMax function with 5 units to correspond to the five tourist categories. The use of minimal L1 and L2 regularization values (0.00001 and 0.00000, respectively) across all trainable layers indicates a very light constraint on the model weights, allowing for flexible learning while still preventing overfitting to some degree. The learning rates (Mean Rate and Rate RMS) are low across all layers, showing that the model updates parameters cautiously, which may contribute to training stability and generalization.

In the first hidden layer (Layer 2), the Mean Weight is relatively small (0.0059) with a moderate Weight RMS of 0.1094, indicating initial feature extraction with limited complexity. The Mean Bias in this layer is positive (0.4611), suggesting an initial push in the activation function toward positive outputs. Layer 3, the second hidden layer, shows an increase in complexity, as reflected by a higher Weight RMS (0.3041) and a significantly higher Mean Bias (0.9874), suggesting stronger signal propagation before reaching the output layer. Interestingly, the Mean Weight is slightly negative (-0.0236), which may indicate that inhibitory relationships being learned between certain features. In the output layer (Layer 4), the SoftMax function is used to transform the output into probability distributions over the five classes. The Weight RMS in this layer is the highest (0.9407), reflecting the model's confidence in classification. The Mean Bias in this layer is near zero (-0.0119), which helps maintain output balance across classes, and ensures that no single class is inherently favored before activation.

Overall, the structure and parameter statistics indicate a well-formed model capable of learning complex representations. The distribution of weights and biases suggests effective feature learning and differentiation between tourist categories. The design also maintains numerical stability, making it suitable for scalable recommendation systems. The performance of the proposed deep learning model was evaluated based on four key metrics: Accuracy, Time, Mean Absolute Error (MAE), and Precision. The results for each tourist category are presented in Table 6.

Table 6. Performance of the deep learning model

Category of tourists	Accuracy (%)	Time	MAE	Precision (%)
Nature Tourists	96.26	0.023	4.6	90
Cultural Tourists	80.59	0.054	5.8	80
Historical Tourist	93.78	0.067	5.4	98
Industrial Tourists	70.35	0.044	7.3	95
Shopping Tourists	97.66	0.065	8.2	95

The model demonstrates high classification performance overall, particularly for the Nature Tourists and Shopping Tourists categories, achieving accuracy rates of 96.26% and 97.66%, respectively. Both categories also report high precision scores, indicating strong model confidence and correct classification outcomes. The relatively low MAE values (4.6 and 8.2, respectively) suggest minimal prediction error in user preference estimation. In contrast, the Cultural Tourists and Industrial Tourists categories yield lower accuracy scores of 80.59% and 70.35%, respectively. The higher MAE values (5.8 and 7.3, respectively) indicate greater deviation between predicted and actual values, which may stem from less distinctive user behavior patterns or overlapping preferences within these categories. Nonetheless, the precision for the Industrial Tourists category remains high at 95%, reflecting the model's ability to make reliable positive predictions, even if overall classification is more challenging. The Historical Tourists category achieves a strong balance of performance across all metrics, with 93.78% accuracy, a moderate MAE of 5.4, and the highest precision at 98%. This suggests that the model effectively captures unique behavioral traits within this category. In terms of computational efficiency, the model exhibits fast processing times, ranging from 0.023 to 0.067 seconds per prediction, making it suitable for real-time recommendation systems. These results affirm the effectiveness of the proposed deep learning approach in accurately profiling tourist types and generating personalized travel recommendations. However, further refinement, such as incorporating more diverse user data or applying attention mechanisms, may improve performance in categories with lower accuracy.

4.2. Tourist Destination Recommendations

By categorizing tourists based on their interests, the model provides personalized destination recommendations that support informed travel decision-making. Specifically, this study proposes three optimal routes for cultural tourists. Route 1 is designed for both nature and cultural enthusiasts, beginning at Alley Ramindra, which serves as the primary reference location. At the second level, visitors can stop at Mumtas Thai Cuisine for a food-related experience, or at Fo Guang Shan Temple, a religious and cultural site. From Fo Guang Shan Temple, travelers can continue to the third level with two options: Siam Amazing Park, a theme park offering entertainment, or Fashion Island, a shopping mall serving as a commercial attraction. For the fourth level, visitors choosing Siam Amazing Park can explore Kwan-Riam Floating Market, a popular destination accessible from multiple locations, and Khae Nok Temple, a religious site. Alternatively, those who visit Fashion Island can proceed to Kwan-Riam Floating Market for more cultural experiences. Route 1, tailored for nature and cultural tourists, is illustrated in Figure 3.

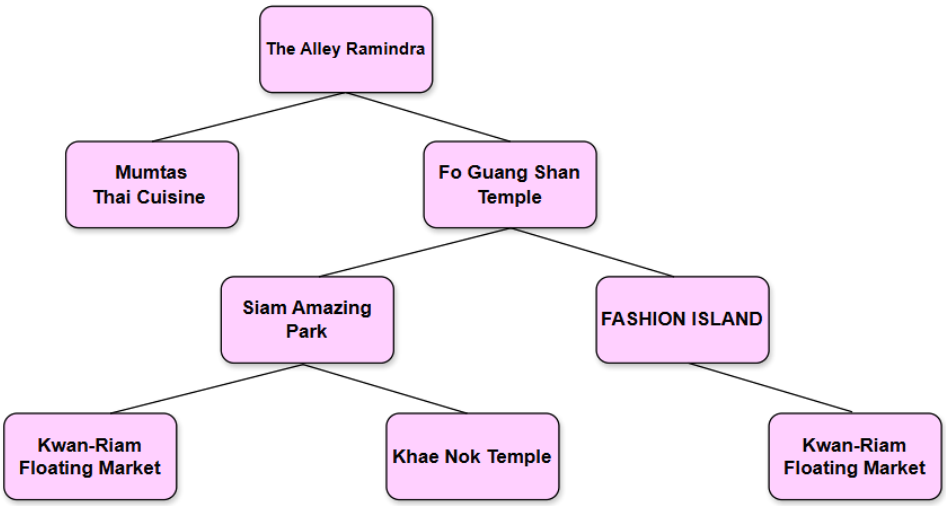

Figure 3. Route 1 recommended for nature and cultural tourists

This study also proposes Route 2 as an optimal itinerary for nature and cultural tourists, incorporating multiple temples and a natural park. The journey unfolds as follows: Travelers begin at Wat Khae Nok. From this temple, travelers have two diverging paths. One path leads to Wat Trai Rattanaram, and from there, they can continue to Wat Rat Satthatham (Bangchan) or proceed to Makutrosara Park. The other path leads to Fo Guang Shan Temple, after which travelers can explore either Wat Trai Rattanaram or Wat Laksi. Route 2 is depicted in Figure 4.

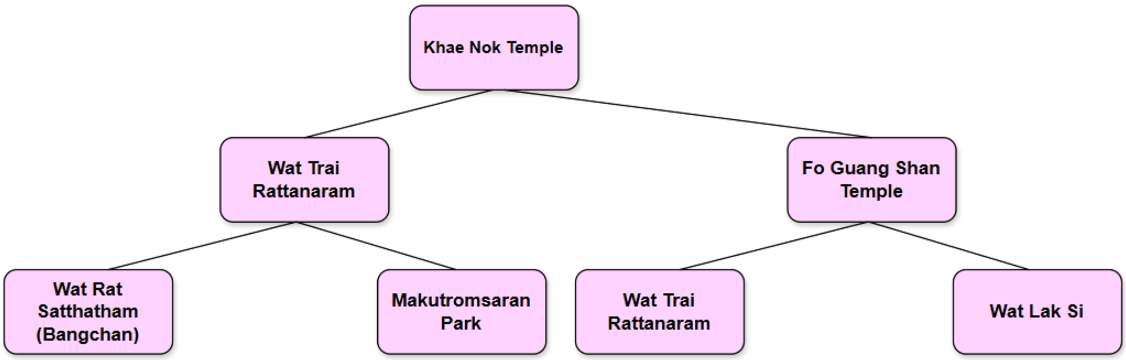

Figure 4. Route 2 recommended route for cultural tourists

Furthermore, this study introduces Route 3 for historical and cultural tourists. This route starts at Min Buri Local Museum, serving as the primary reference point. From here, travelers can choose between two paths: one leading to cultural institutions and the other to recreational facilities. For the cultural institutions path, travelers can proceed from Min Buri Local Museum to the Thai Teacher Training Museum to explore educational heritage. Afterwards, they can visit either the Administrative Court Museum to learn about legal and governance history or the Church of Jesus Christ of Latter-Day Saints to experience a unique cultural and spiritual perspective. For the recreational facilities path, travelers can move from the primary reference point to Ramintra Sport Center, a hub for sports and fitness activities. From there, they can continue to Chaengwattana Horse Club for horse-riding experiences—an ideal destination for adventure seekers. Alternatively, those who prefer a calm atmosphere can visit Makutromsaran Park, a tranquil natural retreat perfect for relaxation, picnics, and outdoor activities. Route 3 is illustrated in Figure 5

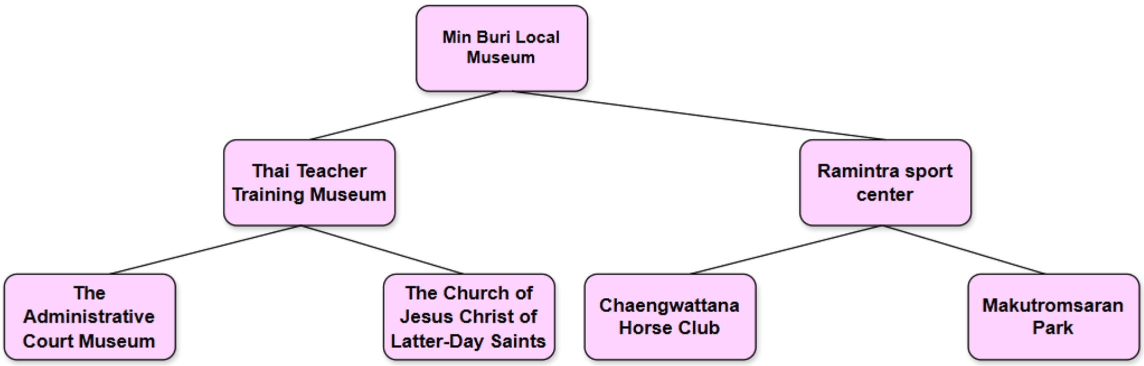

Figure 5. Route 3 recommended for historical and cultural tourists

Despite the achievements of the proposed deep learning-based model in this study, some limitations are worth mentioning. For example, it does not consider external factors such as time period, seasonal changes, and economic conditions, which may influence the popularity of tourist destinations. It assumes that travel convenience is a key factor influencing tourists' decision-making. Moreover, it does not address people outside the urban area, focusing only on initial patterns and spatial relationships. Although the proposed model is well-suited for developing a prototype to understand tourist behavior within the context of urban transportation infrastructure, it may not be applicable to people outside this context. In recognition of these limitations, the study suggests that future research should incorporate these factors or explore other contexts to enhance the model's flexibility and predictive accuracy.

5. Conclusion

The proposed deep learning model, which employs Neural Collaborative Filtering (NCF) and utilizes deep neural networks to capture complex, non-linear patterns between users and destinations, demonstrates strong performance in classifying various tourist categories. It achieves particularly high accuracy for Shopping, Nature, and Historical Tourists. While challenges remain in accurately classifying Industrial Tourists, the model shows promise, with low processing times and solid precision across the board. Its predictive accuracy, as reflected in the low MAE values for most categories, further reinforces its effectiveness. Additionally, this research provides a comprehensive guide to cultural attractions accessible via the Metro Pink Line, with the aim of enhancing tourism planning and promoting cultural exploration. The study proposes tourist destination recommendations for different types of tourists, suggesting three routes: Route 1 for Nature and Cultural Tourists, Route 2 for Cultural Tourists, and Route 3 for Historical and Cultural Tourists. Although still in the prototype phase, the model holds significant potential for future applications, particularly in addressing public transportation challenges. Expanding it into mobile applications and integrating it with GPS systems could further enhance its practicality, making it an effective tool for providing accurate and convenient tourist destination recommendations.

6. Declarations

6.1. Author Contributions

A.R. and C.L. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available in the article.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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