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Adaptive Preference Intelligence for Personalized Tourism Recommendation through Hybrid Computational Reasoning

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Abstract

The increasing availability of digital tourism information has transformed the way travelers plan their journeys, creating a demand for intelligent systems capable of delivering recommendations tailored to individual preferences. Conventional trip planning methods and rule-based recommendation platforms generally provide the same suggestions to a broad range of users, often overlooking personal interests, financial limitations, and available travel time. This research introduces an intelligent tourism recommendation framework designed to generate customised travel options by analysing destination-related information collected from Indonesian tourism resources. To evaluate predictive capability, several machine learning algorithms with Classification and Regression Trees (CART), including Logistic Regression (LR), Support Vector Machine (SVM), and Random Forest (RF), are implemented as benchmark models. The proposed framework incorporates a hybrid architecture named Neuro-Tree-Net (NTN), which combines the feature-learning ability of an Artificial Neural Network with the ensemble decision-making strength of the Extra Trees Classifier (ETC) algorithm. This integration enhances the system's capacity to identify intricate patterns and hidden relationships within tourism datasets, leading to more precise recommendation outcomes. Travelers can specify criteria such as budget, trip duration, and desired destination ratings, allowing the system to generate recommendations that closely match their requirements. Data preprocessing, feature engineering, model development, and performance evaluation are carried out using Python-based libraries such as pandas, scikit-learn, TensorFlow/Keras, and Matplotlib, while an interactive Django-based web application provides seamless access to the recommendation engine. Experimental findings indicate that the proposed hybrid framework consistently achieves superior predictive performance compared with conventional machine learning techniques, offering an efficient and practical solution for personalised travel planning and tourism decision support.

Keywords: Travel Recommendation Systems, Personalized Tourism, Hybrid Learning Models, Neuro-Tree-Net, Tourism Data Analytics.

1. Introduction

The widespread adoption of digital technologies has significantly changed the way people access travel-related information and plan their journeys. Intelligent recommendation systems have become an important component of many online platforms by helping users discover products and services that best match their interests and preferences. Although industries such as e-commerce, online entertainment, and media streaming have successfully integrated advanced recommendation techniques using artificial intelligence, deep learning, and machine learning, several domains, including tourism, healthcare, logistics, and insurance, are still in the early stages of implementing such intelligent solutions. This creates a growing need for advanced recommendation systems capable of providing personalised assistance to users. In the tourism sector, numerous online travel platforms have emerged over the last few decades, offering services such as flight reservations, hotel bookings, and vacation planning. Despite these advancements, many travel platforms continue to provide generalised

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recommendations based mainly on destination popularity or predefined travel packages rather than considering the unique requirements of each traveler. Consequently, many tourists still rely on travel agencies or spend considerable time searching through online resources because they lack sufficient knowledge about suitable destinations and travel opportunities. Although search engines provide access to extensive travel information, the large volume of available content often makes it difficult for users to identify options that best satisfy their individual needs.



Figure. 1: Travel advice

The continuous growth of tourism data generated through websites, travel applications, online reviews, and social media has made travel planning increasingly complex. Travelers are presented with countless alternatives involving destinations, accommodations, transportation, attractions, and activities, making the decision-making process both time-consuming and overwhelming. Recent developments in machine learning, data analytics, and intelligent computing have created new opportunities to build automated recommendation systems capable of processing large-scale tourism information and producing meaningful travel suggestions. Motivated by these technological advancements, this research proposes the design and development of a smart travel recommendation system that utilizes modern machine learning models to generate personalised travel recommendations. Before developing the proposed framework, existing recommendation methods adopted by current travel platforms were carefully analysed to understand their advantages and limitations. Most available systems emphasise fixed travel packages or popularity-driven suggestions, providing limited personalisation despite the availability of rich tourism datasets. However, today's travelers expect recommendations that consider multiple factors, including personal interests, travel budget, available time, preferred activities, destination ratings, and seasonal conditions. Traditional recommendation methods often fail to incorporate these diverse contextual preferences, resulting in recommendations that may not effectively satisfy individual travel expectations.

Recommendation systems represent an important category of intelligent information filtering techniques that analyze user preferences and predict the most relevant items or services for each individual. Organisations that successfully implement recommendation technologies benefit from improved customer satisfaction, greater user engagement, and enhanced service quality through highly personalised experiences. These systems reduce the effort required to search through large collections of travel information while introducing users to destinations and experiences that closely match their interests but might otherwise remain undiscovered. The effectiveness of such systems depends on accurate predictive models capable of learning complex relationships from tourism data and user behavior. Therefore, this research focuses on developing a hybrid machine learning-based travel recommendation system that combines advanced predictive techniques to generate accurate, personalised, and context-aware travel suggestions. The proposed framework aims to improve travel planning, support informed decision-making, and contribute to the continued growth and digital transformation of the tourism industry.

2. Literature Survey

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Zheng et al. [1] introduced a heuristic data mining framework for predicting the next destination of travelers based on their previous movement patterns. The model utilised historical GPS trajectory data collected from visitors at the Summer Palace in Beijing to learn travel behavior and forecast subsequent locations. The proposed approach contributes to location-based services, tourist attraction promotion, crowd management, and personalised travel assistance. Personalised route prediction methods based on machine learning were further reviewed by Sudhanva et al. [2]. Similarly, Xu et al. [3] proposed an enhanced route recommendation model that incorporates real-time traffic congestion and user-preferred destinations to generate an effective recommendation matrix. Scharf et al. [4] presented a probabilistic ranking approach for recommendation systems by introducing RankDist, an algorithm that estimates the probability distribution of an item's position within a recommendation list instead of relying on a single ranking score. The proposed method demonstrated both theoretical effectiveness and improved recommendation quality by maximising expected user satisfaction through uncertainty-aware ranking. Pan et al. [5] proposed a three-stage framework for independent travel route recommendation. Initially, a 0–1 knapsack optimisation model was used to select potential landmarks. These landmarks were subsequently evaluated using an analytic hierarchy process and optimised through simulated annealing. Finally, the selected locations were arranged into an optimal travel route by modeling the problem as a traveling salesman problem.

Halder et al. [6] developed an adaptive Monte Carlo Tree Search (MCTS) approach for personalised itinerary planning. The proposed model effectively selected and pruned points of interest while satisfying multiple travel constraints, including user preferences and temporal limitations, thereby generating feasible and customised travel schedules. Jewpanya et al. [7] presented a travel planning framework based on an extended Team Orienteering Problem with Time Windows (TOPTW). The model incorporated mandatory attractions and activity durations while maximizing the overall travel score. To solve the optimisation problem efficiently, the Adaptive Neighborhood Simulated Annealing (ANSA) algorithm was employed. Chen et al. [8] proposed an intelligent travel recommendation system built on the Hadoop framework to improve the scalability and efficiency of recommendation services. The distributed architecture enabled large-scale processing of tourism information while maintaining recommendation performance for growing datasets. Guo et al. [9] introduced the Top-Personalized-K Recommendation problem, focusing on determining the optimal number of recommendations for each individual user. They proposed the PerK framework, which estimates user utility through calibrated interaction probabilities and dynamically selects the recommendation list size that maximizes user satisfaction.

Worndl et al. [10] proposed a personalized route generation approach where users specify their starting and ending locations through a web interface. The system recommends interesting points of interest along the route, while the Dijkstra algorithm is utilized to compute the shortest travel paths between destinations. Shrestha et al. [11] developed a tourism recommendation framework that combines demographic information, questionnaire responses, and machine learning techniques to improve travel suggestions. The study emphasized high-quality data collection, integration of multiple tourism data sources, user feedback, and decision-support mechanisms to enhance recommendation accuracy and traveler satisfaction. Sun et al. [12] proposed a two-stage personalized route recommendation architecture. Candidate destinations were initially generated using a Support Vector Machine (SVM), followed by

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ranking through a Gradient Boosting Regression Tree model that continuously updated recommendation priorities according to user preferences. Zhang et al. [13] investigated next-location recommendation methods for tourism by predicting future points of interest from traveler's historical trajectories while also generating top-k destination recommendations. Their approach aimed to improve personalized travel planning by accurately identifying locations that align with individual movement patterns.

Tsai et al. [14] observed that although existing recommendation techniques effectively estimate user preferences for individual points of interest, they often struggle to construct complete travel itineraries that satisfy personalized constraints such as travel duration, designated starting locations, and destination sequences. Shen et al. [15] proposed a route recommendation technique based on the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. The method clustered travel routes according to geographical distance and generated recommendations using a weighted tree that considered travel time, distance, vehicle speed, and destination popularity to identify optimal travel paths.

3. Proposed Methodology

The rapid growth of tourism data in Indonesia enables the development of intelligent recommendation platforms capable of delivering customized travel suggestions. In the proposed framework, users upload tourism datasets that undergo several preprocessing stages, including missing value treatment, categorical attribute encoding, TF-IDF transformation of textual reviews, feature selection, normalization, and train-test data partitioning. These preprocessing operations improve data quality and ensure reliable model learning. To evaluate predictive performance, the system employs multiple machine learning algorithms, namely LR, SVM, RF, and the proposed NTN hybrid architecture. The NTN model integrates ETC with an Artificial Neural Network (ANN), enabling the framework to model complex nonlinear relationships within tourism datasets while improving both travel duration prediction and recommendation score estimation. In addition, the platform provides exploratory data analysis (EDA) features that automatically generate visual representations, including histograms, scatter diagrams, box plots, correlation matrices, and pair plots, allowing users to better understand travel behavior and tourism characteristics.

The recommendation platform accepts user-defined inputs such as travel budget, preferred destination, available travel duration, season, and personal interests before producing customized travel recommendations together with estimated trip duration and recommendation scores, as illustrated in Figure 2. Furthermore, the framework incorporates Explainable Artificial Intelligence (XAI) techniques to generate personalized travel suggestions while improving the transparency and interpretability of model predictions.

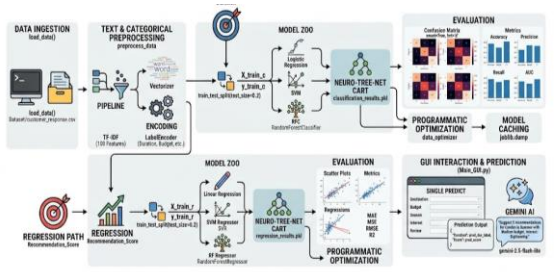


Figure. 2: Proposed system architecture of Hybrid Recommendation Mechanisms for Tourism Personalisation.

3.1 Neuro TreeNet CART Model

The NTN model represents a hybrid predictive framework that combines tree-based ensemble learning with deep neural network architectures. Specifically, it integrates the Extra Trees (ET) algorithm with an Artificial Neural Network (ANN) to exploit the strengths of both techniques. The tree-based component effectively identifies hierarchical decision boundaries, processes heterogeneous attributes,

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and manages incomplete or categorical information, whereas the ANN excels at extracting complex nonlinear feature representations from high-dimensional inputs such as TF-IDF review vectors. By combining these complementary learning strategies, the NTN architecture achieves higher predictive capability than conventional standalone machine learning models.

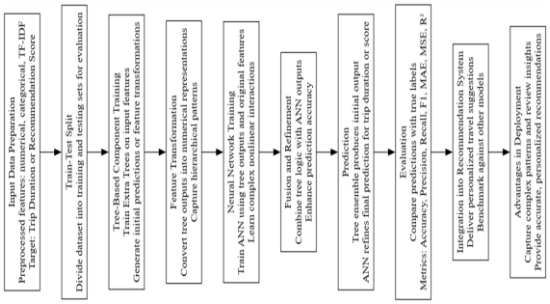


Figure. 3: Internal working of NTN model

Extra Trees Model Construction (ET): Initially, multiple Extra Trees are trained using the processed tourism dataset. Each decision tree identifies optimal feature splits to classify travel categories or estimate regression outputs, producing prediction values and structural representations for every training instance.

Tree Feature Encoding: The outputs generated by the Extra Trees ensemble, including prediction values and leaf-node representations, are transformed into numerical feature vectors. These transformed representations preserve hierarchical decision information that serves as enriched input for the neural network.

Artificial Neural Network Learning: The ANN receives both the transformed tree-based features and the original dataset attributes as inputs. During training, it captures intricate nonlinear relationships and interactions among tourism features that cannot be fully represented by the tree ensemble alone.

Hybrid Prediction Refinement: The neural network further enhances the initial predictions obtained from the tree component by combining hierarchical decision structures with learned nonlinear feature representations. This hybrid learning strategy significantly improves the model's ability to process diverse tourism data.

Recommendation Prediction: For every new traveler request, the Extra Trees component first generates preliminary prediction outputs. These outputs are subsequently processed by the ANN to produce the final prediction, including travel duration classification and personalized recommendation scores.

Performance Assessment: Model effectiveness is evaluated by comparing predicted outputs with actual testing data. Standard evaluation metrics such as Accuracy, Precision, Recall, and F1-Score are calculated for classification tasks, while Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and the coefficient of determination (R^2) are computed for regression performance.

System Integration: The prediction results generated by the Neuro TreeNet framework are incorporated into the intelligent travel recommendation platform. Personalised destination suggestions are delivered according to user preferences, while comparative performance analysis is performed against LLR, SVC, and Random Forest models.

Benefits of the Hybrid Framework: By combining ensemble decision trees with neural network learning, the proposed Neuro TreeNet model effectively captures hierarchical structures, textual review information derived through TF-IDF, and complex nonlinear relationships within tourism datasets. Consequently, the framework produces more accurate and personalized travel recommendations than conventional individual machine learning algorithms.

4. Results description

This section presents the outcomes obtained from the implementation of the Travel AI system developed for tourism prediction and recommendation. The results demonstrate the performance of the ML models used for travel duration classification and recommendation score prediction. Various visualizations and

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evaluation metrics highlight the effectiveness of the implemented algorithms in analysing tourism data. The generated results illustrate the system's ability to process travel attributes, produce accurate predictions, and deliver intelligent travel recommendations through the integrated AI framework.

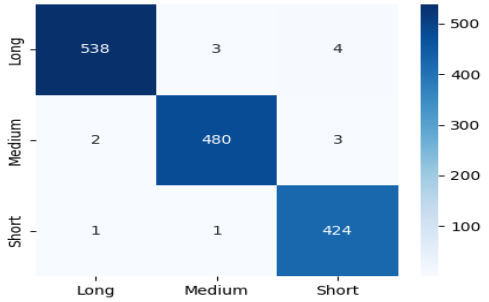


Figure. 4: Obtained confusion matrix of duration attribute from NTN

Figure 4 presents the confusion matrices obtained from Neuro-Tree-Net: The confusion matrix generated by the Neuro-Tree-Net CART model illustrates the classification output obtained from the hybrid tree-based learning approach implemented in the Travel AI system. The matrix shows a strong concentration of values along the diagonal, indicating a high number of correct predictions for travel duration categories. This result demonstrates the effectiveness of the Neuro-Tree-Net CART model in learning relationships between tourism features, textual review representations, and travel duration outcomes within the dataset.

Figure 5 presents scatter plots that illustrate the prediction performance of Neuro-Tree-Net: The scatter plot produced by the Neuro-Tree-Net CART model presents the predicted recommendation scores relative to the actual values in the dataset. The concentration of points near the diagonal reference line reflects strong agreement between predicted and actual scores. This distribution demonstrates the effectiveness of the Neuro-Tree-Net CART approach in modelling relationships between tourism features, review text representations, and recommendation score outcomes within the Travel AI recommendation system.

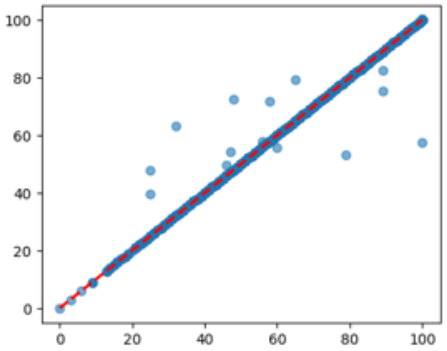


Figure. 5: Obtained scatter plot of recommendation score attribute from Neuro-Tree-Net.

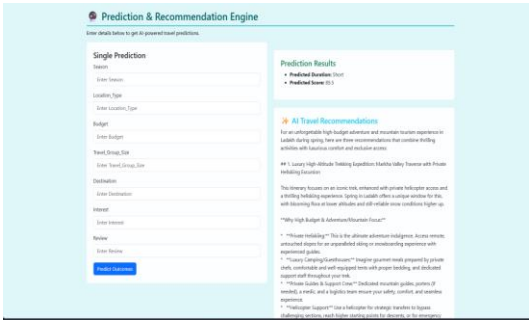


Figure. 6: Prediction on test data

Figure 6 presents the prediction output generated by the Travel AI system when test data is processed through the trained machine learning models. The prediction interface displays the estimated travel duration category and the recommendation score generated from the classification and regression models. The system processes input attributes such as destination, season, budget category, travel interest, and review information. These attributes undergo preprocessing operations including label encoding and TF-IDF transformation before entering the trained models. The Neuro-Tree-Net CART model produces the final predictions, which appear on the interface along with the recommendation score value. The system also generates intelligent travel suggestions through the integrated AI recommendation module, providing personalized tourism guidance based on the predicted results.

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Table 1 presents the classification performance comparison of different machine learning models used for predicting the travel duration attribute in the Travel AI system. The evaluation metrics include Accuracy, Precision, Recall, F1-Score, and AUC. LR and SVM produce moderate classification performance with accuracy values around 0.35. The RF classifier shows improved performance with higher accuracy and balanced precision and recall values. The Neuro-Tree-Net CART model demonstrates the highest performance among all models with an accuracy of 0.99 along with very high precision, recall, and F1-score values. These results indicate that the Neuro-Tree-Net CART model provides highly accurate classification results for predicting travel duration based on tourism features.

Table. 1: Classification performance comparison for travel duration prediction

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
LR model	0.35	0.34	0.35	0.33
SVM model	0.36	0.35	0.36536	0.35
RF model	0.48	0.48	0.48	0.48
Neuro-Tree-Net	0.994	0.99	0.99	0.99

Table 2: regression performance comparison for recommendation score prediction

Model	MAE (%)	MSE (%)	RMSE (%)	R^2 Score (%)
LR model	19.98	552.81	23.51	0.01
SVM model	19.94	553.88	23.53	0.008
RF model	18.46	494.67	22.24	0.11
Neuro-Tree-Net	0.155	3.77	1.94	0.99

Table 2 presents the regression performance comparison of different models used for predicting the recommendation score in the Travel AI system. The evaluation metrics include MAE, MSE, RMSE, and R^2 Score. LR and SVM Regressor produce higher error values and very low R^2 scores, indicating weaker prediction performance. RF Regressor shows better results with reduced error values and an improved R^2 score. The NTN CART model achieves the best regression performance with extremely low MAE, MSE, and RMSE values along with an R^2 score of 0.99. These results demonstrate that the NTN CART model produces highly accurate recommendation score predictions within the Travel AI system.

5. Conclusion

This research offers a smart tourism recommendation platform by combining advanced machine learning algorithms with an interactive web application to estimate trip duration and destination recommendation scores. The system analyses multiple tourism-related features, including destination, travel season, budget, user interests, and textual feedback, to generate personalised recommendations and accurate predictive outcomes. During preprocessing, categorical variables are encoded, textual reviews are transformed using TF-IDF vectorisation, and the processed data are converted into numerical formats suitable for model training and evaluation. Multiple machine learning models for both classification and regression are

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developed and compared to identify the most suitable approach for travel recommendation tasks. Classification algorithms are employed to predict travel duration categories, whereas regression techniques estimate recommendation scores for selected tourist destinations. Experimental evaluation based on Accuracy, Precision, Recall, F1-score, Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and R^2 confirms that the NTN CART framework consistently outperforms the remaining predictive models. The platform further incorporates an AI-assisted recommendation component that delivers customised travel suggestions by combining user preferences with model-generated predictions. Overall, the developed framework serves as a comprehensive solution for tourism data exploration, intelligent prediction, and personalised destination recommendation. The integration of exploratory data analysis, hybrid machine learning techniques, interactive visualisations, and AI-driven recommendations provides an effective decision-support system that simplifies travel planning while enhancing the overall tourist experience.

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