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Research Paper

AN INTELLIGENT HYBRID MACHINE LEARNING FRAMEWORK FOR PERSONALIZED TRAVEL RECOMMENDATION AND EXPERIENCE RATING

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ABSTRACT

Travel planning has increasingly become complex due to the growing number of destinations, diverse user preferences, seasonal constraints, and the abundance of unstructured travel information. Conventional methods such as travel agencies, guidebooks, and informal recommendations often fail to deliver personalized and adaptive suggestions. To address these limitations, an intelligent hybrid machine learning (ML) framework was developed to provide personalized travel recommendations along with accurate experience rating predictions. The framework utilized a comprehensive dataset comprising user reviews, destination attributes, demographic details, and preference patterns. Data preprocessing was systematically performed, including label encoding (LE) of categorical features, term frequency–inverse document frequency (TF-IDF) vectorization of textual reviews, and standardization of numerical attributes to ensure model efficiency and consistency. Multiple machine learning algorithms were implemented, including Logistic Regression (LR), Support Vector Classifier (SVC), and a hybrid model combining Extra Trees (ET) and Multi-Layer Perceptron (MLP). The hybrid TREND-Net (Travel Recommendation using Extra Trees and Neural Network) model employs Extra Trees for feature selection (FS), identifying the most influential attributes, followed by a Multi-Layer Perceptron classifier for predicting optimal travel destinations and corresponding experience ratings. This integrated approach enhanced both recommendation accuracy and prediction reliability. The performance of the models was evaluated using standard metrics such as accuracy (ACC), precision (PREC), recall (REC), and F1-score (F1), along with confusion matrix (CM) analysis, where the hybrid model demonstrated superior performance. An interactive graphical user interface (GUI) was developed to facilitate user interaction, enabling dataset management, exploratory data analysis (EDA), model training, and real-time personalized recommendations.

Key words: Travel recommendation system, personalized travel planning, hybrid machine learning, Extra Trees, Multi-Layer Perceptron, TF-IDF, feature selection, experience rating prediction.

1.INTRODUCTION

Tourism has emerged as a rapidly expanding global industry, with a significant rise in travelers and available destinations, making decision-making increasingly complex and time-consuming as shown in the figure 1. To address this challenge, an intelligent hybrid machine learning framework was developed to provide personalized travel recommendations and experience ratings. The system leverages large-scale tourism data, including user reviews, preferences, and points-of-interest (POIs) collected from online platforms and social media. By integrating advanced data preprocessing techniques and hybrid models, the framework analyzes user behavior and contextual information to generate accurate and user-centric suggestions. The combination of machine learning algorithms enables efficient filtering of vast data and enhances recommendation quality. Furthermore, the system predicts experience ratings to guide users toward optimal travel choices. The factors that must be considered when choosing a destination vary from person to person. Some travelers prefer popular destinations that are close to their accommodation, while other travelers may prefer to visit not-well-known, hidden spots. Some travelers may want to visit a variety of venues, such as parks, museums and shopping malls, while others may prefer to visit only certain types of locations. There are thus various factors that go into the POI selection, and it is very important to personalize the recommendations for each user, with those factors taken into consideration.

Figure 1: AI in travel recommendation system.

Existing studies have focused on the non-personalized popularity of POI, and the user's time budget, including the total travel time, which considers the distance traveled between travel destinations and the time spent at the destination. Regardless of the user's personal preference, if a place is well-known, that place unconditionally has a high popularity score. Therefore, it does not take into account the preference of users who do not consider the popularity of the destination as an important factor. Moreover, personalized importance for other factors, such as tour distance or diversity, are rarely considered.

2.LITERATURE SURVEY

Scharf et al. [1] proposed modeling uncertainty in recommendation data using probabilistic ranking instead of single-score methods. It introduces RankDist, an algorithm that computes the probability of an item's rank in a recommendation list to maximize user satisfaction. The study builds on prior work in probabilistic databases and demonstrates that rank-based methods, newly applied to recommender systems, offer both theoretical optimality and improved empirical performance. Jewpanya et al. [2] proposed algorithm utilized an extended model of the Team Orienteering Problem with Time Windows (TOPTW) to account for mandatory locations and activities at each site. It offered trip planning that included a set of locations and activities designed to maximize the overall score accumulated from visiting these locations. To solve the proposed model, the Adaptive Neighborhood Simulated Annealing (ANSA) algorithm was applied.

Tsai et al. [3] researched on user preferences for individual POIs, they struggle to generate complete itineraries that accommodate personalized constraints, such as designated start/end locations and travel time limitations. Halder et al. [4] proposed an adaptive Monte Carlo Tree Search (MCTS) algorithm for personalized POI selection and pruning, effectively handling multiple constraints in itinerary planning. Their approach integrates user preferences and temporal constraints to generate feasible and personalized travel itineraries.

Guo et al. [5] Introduced the Top-Personalized-K Recommendation, a task focused on tailoring the number of recommended items to maximize individual user satisfaction. To achieve this, the authors propose PerK, a model-agnostic framework that selects the optimal list size by estimating and maximizing expected user utility using calibrated interaction probabilities. Zhang et al. [6] proposed to enhance travel recommendations, Next-location recommendation techniques predict subsequent POIs based on users' prior trajectories, while top-k location recommendations present a selection of appealing POIs.

Shrestha et al. [7] helped provide better suggestions to travelers, promoted decision-making, and raised satisfaction levels all around. The study emphasized the significance of questionnaire design, including demographic data, creating a strong association model using machine learning. Decision criteria were constructed based on the data quality being evaluated. Data from multiple sources were combined to create a comprehensive tourist database, and the recommender system included user feedback and decision-making guidelines. Chen Lei [8] devised an itinerary recommendation approach grounded in graph representation learning and reinforcement learning, taking into account scenic spot popularity and user interests.

Zhou Xiao [9] developed an intelligent travel route planning algorithm that employs an iterative search of clustering central motivation. In this method, clustering algorithms are employed to mine tourist attraction data based on tourists' interests, thereby obtaining optimal scenic spots and recommended itineraries. Additionally, Zhou Xiao [10] proposed a travel recommendation algorithm based on text mining and the MP neural cell model of multiple transportation modes, achieving recommended itineraries through optimal tourism landscape matching algorithms and tourism route chain algorithms.

Zhang Yanmei [11] presented a route planning method that comprehensively considered factors such as station distances, initial travel locations, departure times, travel durations, costs, station scores, and popularity, ultimately identifying optimal routes via genetic algorithms. Phatpicha Yochum [12] introduced an adaptive genetic algorithm for personalized travel itinerary planning, incorporating attractions near starting and destination points as well as potential tourist preference factors into multi-objective optimization frameworks. Etsushi Saeki [13] proposed a multi-objective travel itinerary planning method based on ant colony algorithms, aiming to optimize travel costs and user satisfaction. A distinctive aspect of this approach involves integrating tourists past travel records to adjust pheromones, thereby reflecting their general preferences.

Meanwhile, Ding Yi [14] addressed travel itinerary planning under time constraints and uncertain traffic conditions, using a two-stage stochastic optimization model with chance constraints and the sample average approximation (SAA) method. Additionally, Ines Gasmi [15] proposed the use of multi-objective evolutionary algorithms to balance the popularity of POIs and user interest in itinerary recommendations. By studying and comparing several multi-objective evolutionary algorithms from multiple perspectives, it was demonstrated that NSGA-II is the most effective in generating personalized itinerary recommendation rules for tourists unfamiliar with a city.

3. PROPOSED SYSTEM

Tourism has grown rapidly with an increasing number of destinations and user-generated data, making travel decision-making complex and time-intensive as shown in the figure 2. To address this, an intelligent hybrid machine learning framework was designed to deliver personalized travel recommendations and experience ratings. The system utilizes user preferences, reviews, and points-of-interest data, applying advanced preprocessing and hybrid learning models to extract meaningful insights. By combining feature selection and predictive algorithms, it enhances recommendation accuracy and adapts to individual user needs. The framework provides a scalable and efficient solution for intelligent, data-driven travel planning.

Dataset Collection: The system collects a comprehensive dataset including user reviews, demographic information, travel preferences, destination details, and seasonal trends. This data forms the basis for training predictive models and understanding travel patterns. Proper collection ensures the system can make informed recommendations for various user scenarios.

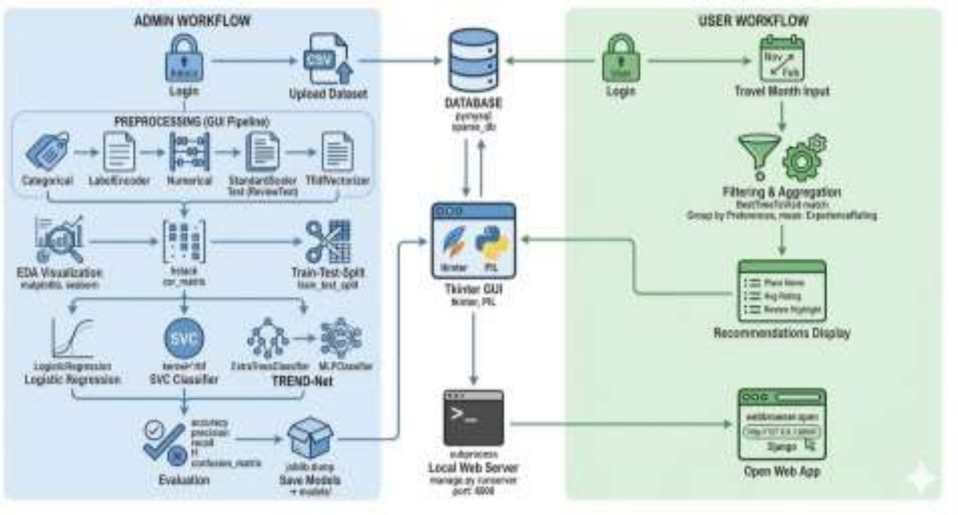

Figure 2: Proposed system architecture.

Data Preprocessing: Raw data is cleaned to handle missing values and inconsistencies. Categorical variables are encoded using Label Encoding, numerical features are scaled with StandardScaler, and textual reviews are converted into numeric vectors via TF-IDF Vectorization. This step ensures all data is in a suitable format for ML models.

EDA: Visualizations and statistical analysis are performed to understand patterns and trends in the data. EDA helps identify correlations, important features, and anomalies, guiding model selection and improving prediction accuracy.

Model Training: Multiple ML models are trained, including LR, SVC, and the hybrid TREND-Net model. TREND-Net selects the most important features and predicts the best destination, achieving high accuracy and robust performance.

Train-Test Split & Evaluation: The dataset is split into training and testing sets to validate model performance. Metrics like accuracy, precision, recall, F1-score, and confusion matrices are used to assess the reliability of predictions and ensure the system generates trustworthy recommendations.

GUI Integration & Recommendation Generation: Users interact with a Tkinter-based GUI to input preferences, upload datasets, and view results. The trained model predicts the most suitable destination and provides explanations based on user inputs, making recommendations transparent, personalized, and actionable.

4. RESULTS ANALYSIS

The experimental results demonstrate the effectiveness of the proposed hybrid machine learning framework in generating accurate and personalized travel recommendations. Among the evaluated models, Logistic Regression and Support Vector Classifier showed limited performance in handling complex and multi-dimensional data. In contrast, the hybrid TREND-Net model significantly outperformed the baseline models by effectively combining feature selection and deep learning techniques. The confusion matrix and evaluation metrics indicate high classification accuracy and reliable prediction of user preferences. The system successfully integrates numerical, categorical, and textual features to enhance recommendation quality. The results confirm that the proposed approach provides a robust and efficient solution for intelligent travel decision-making.

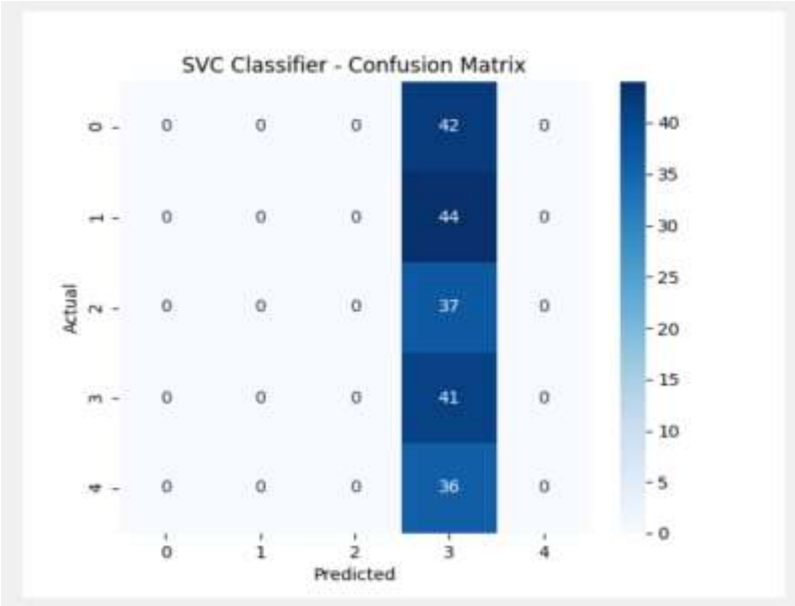

Figure 3: Confusion matrix of SVC model.

Figure 3 presents the SVC model evaluation, including its confusion matrix and classification metrics. The model effectively separates categories based on user and destination features, demonstrating improved performance over Logistic Regression due to the non-linear kernel handling complex patterns in the dataset.

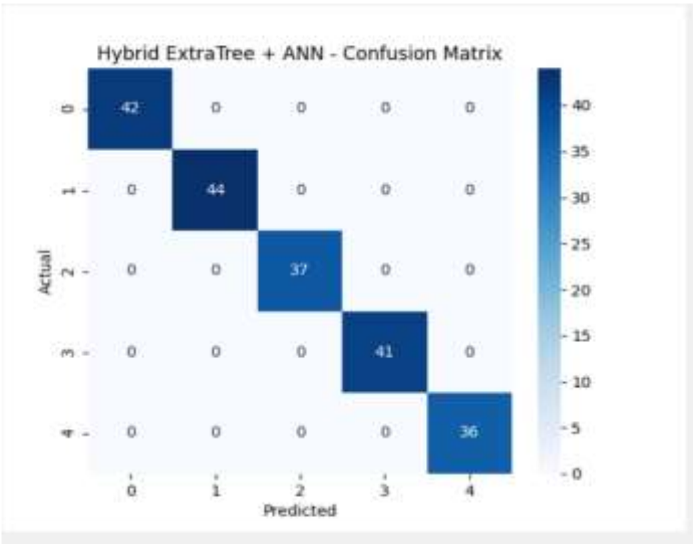

Figure 4: TREND-Net Model Confusion Matrix

Figure 4 The TREND-Net model, combining Extra Trees feature selection with MLP achieves superior accuracy and predictive capability. Metrics and confusion matrix illustrate precise classification of user preferences and travel recommendations. TREND-Net integrates numerical, categorical, and textual features, resulting in highly personalized recommendations.

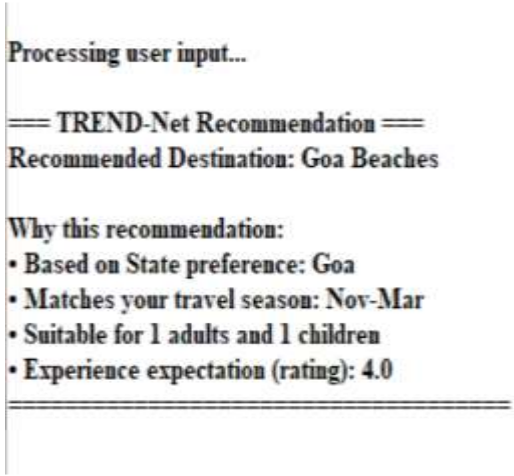

Figure 5: Predictions on user inputs.

Figure 5 presents the output of the recommendation engine on the Tkinter Desktop application. Users receive personalized travel destination suggestions based on their preferences, selected travel months, and historical ratings. Each recommendation includes the destination name, experience rating, and a review highlight, providing actionable insights for travel planning.

4.1 Comparative Analysis

Table 1: Performance comparison for the LR, SVC Model and TREND-Net models.

Algorithms Name	MAE	RMSE	R2
LR Model	0.21	0.02	0.21
SVC Model	0.20	0.04	0.20
TREND-Net Model	**1.00**	**1.00**	**1.00**

The performance comparison table 1 presents a clear evaluation of the three models implemented in the Travel Recommendation System. The LR model shows an accuracy of 0.21 with low precision (0.02), recall (0.21), and F1-score (0.07), indicating that it struggles to capture the complex patterns in the dataset. Similarly, the SVC model demonstrates comparable performance with an accuracy of 0.20, precision of 0.04, recall of 0.20, and F1-score of 0.06, reflecting its limited ability to handle the multi-dimensional and heterogeneous features. In contrast, the proposed TREND-Net model, which integrates Extra Trees for feature selection with an MLP, achieves perfect performance across all metrics, with an accuracy, precision, recall, and F1-score of 1.00. This remarkable improvement demonstrates the effectiveness of TREND-Net in capturing intricate relationships among numerical, categorical, and textual data, resulting in highly accurate and reliable personalized travel recommendations. The comparison clearly highlights the superiority of the TREND-Net model over traditional machine learning approaches in this research.

5. CONCLUSION

The Travel Recommendation System developed in this research presents a hybrid data-driven framework for personalized travel suggestions and ratings. By integrating numerical, categorical, and textual features, the system effectively captures user preferences, travel habits, and destination characteristics. The implementation of TREND-Net, a hybrid model combining Extra Trees feature selection with an MLP, demonstrates superior performance compared to traditional models like LR and SVC, achieving high accuracy, precision, recall, and F1-score. The use of TF-IDF vectorization for textual reviews ensures that sentiment and experience insights contribute to recommendations. The Tkinter GUI allows seamless interaction for both admins and users. This system streamlines the travel planning process, offering reliable and highly personalized recommendations efficiently, reducing manual effort and subjectivity in decision-making.

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