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Research Article

Personalized Travel Recommendations System Using Hybrid Filtering and Deep Learning

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ABSTRACT

Personalized recommendations are provided by recommender systems, which help users cope with the issue of information overload. The primary objective of this research paper is to address the issue of information overload by offering personalized tourism recommendations to users. The study proposes using multi-criteria recommendation algorithms that consider many attributes rather than depending exclusively on overall user ratings, as is common in traditional recommender systems. The fundamental concept of this strategy relies on a hybrid filtering technique. In addition, the system employs a bi-directional autoencoder (BDA) model to personalize recommendations based on various visitor profiles. The proposed methodology has evaluated various real-world data obtained from several travel websites. The experimental evaluations have demonstrated its outstanding efficacy in enhancing prediction accuracy when compared to existing algorithms. The proposed approach not only addresses the challenges associated with vast and diverse data but also offers personalized travel plans according to the unique preferences of each visitor, thus enhancing the user experience in tourist recommendation systems.

Keywords: *personalized recommendation system, hybrid filtering, bi-directional autoencoder, travel plan, tourism recommendation.*

INTRODUCTION

Recommendation systems (RSs) have gained immense popularity among both businesses and consumers in recent years. These systems are designed to enhance e-commerce by providing relevant and valuable recommendations to customers. Essentially, RSs analyze customer data, such as purchase history, browsing history, and product reviews, to generate customized recommendations that are tailored to each customer's unique preferences and needs. This personalized approach has led to high levels of customer satisfaction and has become a crucial factor in building long-term client loyalty. In today's highly competitive e-commerce environment, customer satisfaction is more critical than ever. Businesses that fail to meet or exceed customer expectations risk losing customers to competitors. As such, RSs have become an essential tool for businesses seeking to enhance their customer service and build long-term client loyalty.

Development in information technology exposes consumers to vast quantities of data. However, the task of acquiring the most suitable data sources might be perplexing and tiring. Consequently, every person has the potential to encounter the issue of information overload. RSs offer effective methods for addressing this issue by selectively selecting appropriate material. Recommender systems enable customers to efficiently obtain relevant information about their desired product or service, such as films, books, holiday plans, or online searches.Moreover, internet booking and reservation systems play a vital role in the tourism industry. According to Mariani et al. [1], the tourism sector is the most significant contributor to the global economy's gross domestic product (GDP). In recent years, tourists worldwide have been increasingly relying on RSs to book accommodations and transportation online. These systems provide a proactive approach that helps them avoid any potential obstacles upon arriving at their destinations [2]. With RSs, tourists can easily access reviews, photos, and other relevant information about their desired destinations, making it easier for them to plan their trips and make informed decisions [3] [4]. The RSs have become an essential tool for businesses seeking to enhance customer satisfaction and build long-term client loyalty. In the tourism industry, RSs play a critical role in ensuring that tourists can book accommodations and transportation with ease, contributing significantly to the sector's growth and overall economic success. The ability of RSs to provide personalized recommendations based on customer data has made them a powerful tool for businesses seeking to stay ahead of the competition and meet the evolving needs of their customers.

The tourism industry has experienced significant growth in recent years. The growth has resulted in the industry becoming more dynamic and driven by user input. As new technology emerges, it is crucial to integrate it with existing systems in order to develop improved and more effective solutions for these ever-changing issues. The user's capabilities and proficiency significantly influence the complexity and usefulness of any technology. The tourism industry has become diverse due to several factors, such as the emergence of online businesses, advancements in global positioning systems, and the widespread use of social media [5] [6]. However, with the rising use of RSs, user expectations have become more diverse. Customers should evaluate items based on many criteria. Hence, relying on aggregate ratings when making predictions about a user's satisfaction with a product or service may not be sufficient. When planning a trip, a user may take into account several factors, such as place, traveling, pricing, stay, and so on, in order to form a comprehensive assessment.

Hybrid techniques can be used to improve the performance of recommender systems, especially with the growing popularity of social networking [7]. Previous studies have applied hybrid techniques to recommender systems, but there is still a need for more advanced methodologies and data fusion [8] [9] [10]. This paper introduces a new hybrid method for combining personalized recommendations from multiple recommendation systems. The objective is to provide accurate and compelling recommendations for points of interest (POI). The novelty of the recommendation results is enhanced by modifying the parameters of the hybrid recommendation system, which allows for the combination and prioritization of each approach. Additionally, a fusion technique is used to merge demographic and contextual data, creating a catalog of POIs that perfectly match the user's interests and preferences.

To address the limitations of previous methods, our framework uses a hybrid approach which provides a selection of tourist destinations and itineraries that are suitable based on the evolving preferences of tourists. The study addresses the problem of cold starts by utilizing users' demographic information. An asymmetric schema is employed to address symmetric user similarity issues and improve algorithm performance. The development of effective recommendation systems can be a complex task, particularly when employing a hybrid approach. This is due to the diverse range of recommendation methodologies, the heterogeneous nature of tourist data, and the need to integrate multiple information sources. The proposed framework has the potential to improve the efficiency and accuracy of tourist recommendation systems, thereby benefiting both businesses and consumers in the tourism industry. It evaluates varied reviews of tourist destinations and generates a personalized list of recommendations based on the user's preferences. Furthermore, the system utilizes a bi-directional autoencoder (BDA) model to customize suggestions according to different visitor characteristics.

Additionally, the system provides a search feature to enable the user to gather more information about different tourist destinations. Consequently, customers may obtain more tailored suggestions by articulating their preferences regarding products and services from various perspectives. Furthermore, the precision of recommendation systems (RSs) is enhanced by using supplementary data since it allows for the extraction of user relationships based on various features of items. The user can further explore these recommendations and access relevant resources to plan their itinerary.

The subsequent sections of the paper are structured as follows: Section 2 offers a concise overview of contemporary recommendation techniques. In Section 3, the proposed methodology and dataset used are explained. Section 4 details the experimental setup, including the performance metrics used to evaluate the model, results, and comparisons. Finally, Section 5 summarizes the research findings and outlines future work.

LITERATURE REVIEW

Over the years, numerous studies have delved into the concepts associated with recommenders, which include information filtering and recommendation algorithms. These ideas have played a key role in the development of recommender systems [11]. Information filtering involves the analysis of user preferences and the automatic classification of information sources to provide personalized recommendations to users. Recommendation algorithms, on the other hand, involve the use of various techniques, such as collaborative filtering, content-based filtering, and hybrid filtering, to provide recommendations to users. These concepts have highlighted the importance of recommenders in the current era of web technologies, where users are constantly inundated with vast amounts of information and require personalized recommendations to make informed decisions.

In their research, Koren et al. [12] have focused on the importance of providing excellent recommendations. The author suggests that when processing a large number of user ratings and reviews, the quality of recommendations is crucial for ensuring efficient and accurate results. The paper [13] explores the use of Twitter data to provide personalized travel recommendations. It evaluates the accuracy of the model and suggests ways to enhance it. By matching the predictions with user preferences and adjusting for tweet sources (friends and followers), the model achieved a prediction accuracy of 68%. To improve its accuracy, the study recommends curating more travel tweets for the training dataset and enhancing the categorization of places in machine learning. The study also suggests using Twitter data to personalize travel recommendations and proposes ways to enhance the model. It compares user choices in a survey to the model's performance and recommends improvements.

The study [14] focuses on the hybridization of collaborative filtering and content-based recommendation systems. The researchers have employed the IMDB dataset to propose a movie recommendation system based on a collection of 13 different features. The analysis focuses on determining the most effective feature weights and presents a framework for recommendation. According to the authors [15], the field of recommendation algorithms encompasses two primary techniques: collaborative filtering (CF) and content-based filtering (CBF). The CF involves analyzing the behavior and preferences of multiple users to generate recommendations, while the CBF focuses on analyzing the features and attributes of individual items to make recommendations. A hybrid approach, which combines the strengths of both CF and CBF, is known as a hybrid. By leveraging the complementary nature of these algorithms, a hybrid system can often provide more accurate and diverse recommendations.

The research paper [16] highlights the importance of user reviews, sentiment analysis utilizing state-of-the-art machine learning algorithms, and personalized tourist recommendations. It introduces a tailored tour plan recommendation system aimed at simplifying user decision-making. To generate a sentiment analysis-based list of recommendations, the system harnesses machine learning and deep learning algorithms, including Multinomial Naïve Bayes, Random Forest Classifier, Bernoulli's Naïve Bayes, Convolutional Neural Networks, and Recurrent Neural Networks, trained on Amazon Product Reviews and tourist reviews. The main objective of the recommendation system is to align users' interests with the top-rated tourist destinations and devise a customized itinerary based on various criteria, such as ratings, atmosphere, cleanliness, must-see status, nightlife, parking, and tranquility. This is achieved by analyzing user reviews to generate personalized suggestions.

In [17] this paper, a tourism recommendation system that utilizes collaborative filtering, user preference data, and city similarities is explored as an effective means of providing travel recommendations. The study includes potential improvements and future applications of the system, as well as a successful implementation and testing of its effectiveness on a group of 188 participants. The methodology involved gathering users' travel preferences through questionnaires, utilizing ridge regression to weigh the importance of different features, measuring city similarity based on these weights, and implementing an urban heat optimization model to suggest cities. The results of the study indicated that the top tourist cities recommended were highly regarded by the survey's 188 valid respondents. [18] This paper introduces a new algorithm for travel route recommendations that uses interest themes and distance matching. The algorithm was found to perform better than traditional algorithms in real web server log data analysis from tourism enterprises. The proposed methodology involves the acquisition of historical travel footprints, formulation of user preferences, development of a travel route calculation algorithm, utilization of actual web server log data, construction of a recommendation engine, examination of relevant literature, and presentation of experimental findings.

A recommender system was introduced in [19] to reduce information overload, a multi-criteria collaborative filtering algorithm based on autoencoders, AE-MCCF algorithm to improve prediction accuracy. The proposed multi-criteria collaborative filtering algorithm based on autoencoders improves prediction accuracy, AE-MCCF decomposes multi-criteria recommendation problems into single-rating problems, and accuracy improves with more layers. Van Canneyt et al. recommended utilizing social media as a means to discover points of interest [20]. The demonstration illustrated the potential of utilizing geographically annotated social media data to enhance and supplement existing place databases. However, their research does not prioritize the customization of the recommendation system through social media. Previous studies have utilized user-uploaded photographs to identify user preferences and interests.

The authors in [21] present a social media-based personalized travel recommendation system that outperforms existing models with 75.23% accuracy, user customization, and adaptability to different scenarios and social media platforms. It outperformed the proposed model in personalized place of interest recommendation, adaptability to changing travel behaviors during pandemics, and potential extension to include Facebook and Instagram content. Extracting travel-relevant tweet attributes, categorizing travel tweets, sentiment analysis, recency bias, and model accuracy are the steps. The study measured user perception of products/services inferred from social media activity features like URL count, hash-tag count, favorite count, etc., travel tweet sentiment measured using TextBlob, and prediction accuracy with recency weight across all four categories (69.2%).

Numerous recommender systems have been developed by researchers and developers using hybrid filtering algorithms and techniques [22-27] to provide recommendation services. Collaborative and content-based filtering involves the use of user knowledge to determine correlation with other users and make deductions in the feature space [28-31]. This paper presents a highly efficient hotel recommender system that narrows the gap by analyzing natural language opinions to extract hotel features. Collaborative filtering and sentiment analysis are used to efficiently handle large heterogeneous data and generate true recommendations [32]. It emphasizes the recommender systems' role in decision-making, proposes an intelligent approach for true recommendations based on heterogeneous data, and highlights the system's efficiency in data storage and recommendation. Sentiment analysis, collaborative filtering, a big data Hadoop platform, experiments, customer preferences, and big heterogeneous web data processing and analysis are used to recommend hotels based on features and guest type.

METHODOLOGY

The proposed approach aims to streamline the trip planning process for users, as illustrated in Figure 1. By analyzing multiple user reviews and inputs, to provide a list of personalized recommendations. The deep learning system evaluates the polarity of each place's evaluation to determine its degree of positivity or negativity, which is used to rank locations. Favorable outcomes increase a place's chances of being suggested, while unfavorable outcomes lower the ranking and reduce the probability of it being recommended. Each location is classified based on its offerings, such as the India Gate being categorized as a historical site due to its significance. To tailor the recommendations to individual preferences, users provide their desired type of destination (adventurous, historical, architectural, etc.), the number of travelers, including children, and the trip duration. The proposed model incorporates user evaluations for each place and creates a customized itinerary based on each customer's specific requirements. This eliminates the need to settle for generic plans typically provided by corporations.

The primary feature of the proposed system is its personalized recommendation list, which utilizes user interests and ratings derived from reviews. The recommendation list is generated by considering various factors such as ambiance, cleanliness, must-visit status, nightlife options, parking availability, and quietness. Each of these attributes is assigned a score out of 5, and the maximum possible total score for any area is 4. Users tend to place high value on factors such as ambiance, cleanliness, must-visit status, and ratings, which carry the most weight in the final score. The importance of other characteristics is determined based on the user's preferences. By calculating these scores, the model provides a comprehensive ranking of each tourist destination, and the list of recommendations is generated by arranging these scores in decreasing order. It enables tourists to make informed decisions when selecting destinations that align with their preferences. As such, it provides invaluable assistance to individuals seeking to optimize their travel experiences.

A. Dataset Description

To gather data for this study, the popular photo-sharing social network Flickr was utilized. With its vast library of images and metadata, including photo and photographer IDs, shooting time, location, title, tags, and user information, Flickr proved to be an excellent resource. The study specifically acquired geotagged Flickr photos and their corresponding attribute data using the Flickr Application Programming Interface (API). While access to Flickr's vast collection of photos and videos is possible without an account, sharing data requires one. For this study, the researchers made use of the Yahoo Flickr dataset, which is stored at Webscope Yahoo Labs. The methodology was evaluated using Flickr's image metadata, and API techniques were employed to retrieve picture data from 2015 to 2019.

B. Preprocessing

In order to conduct proper data analysis, it is necessary to preprocess the data source in order to clean it. This is because the data contains ambiguous and inappropriate information that can lead to inaccurate results. The process involves removing data that does not meet the required criteria, including photos that are not adequate. It is important to note that when visiting a point of interest (POI), people tend to take multiple photographs of it. If the time difference between the first and subsequent shots is less than a specific threshold, those photos are considered to be taken at the same location. This process ensures that the data is accurate and reliable for subsequent analysis.

a. Time and Weather Context Matching: The dataset's image elements were associated with contextual data, such as the timestamp and geographical location, for each uploaded photograph. The climate application was used to determine the present climate, as shown in Table 1. The database contains other date-related data, including contextual information such as temperature and season.

Table 1: Time and weather context matching

Context	Condition	Description
Time Context	Season	Winter (December to February)
		Spring (March to May)
		Summer (June to August)
		Fall (September to November)
	Day	Working (Monday to Friday)
		Weekend (Saturday & Sunday)
	Time	Morning (6:00 to 12:00)
		Afternoon (12:00 to 18:00)
		Night (18:00 to 6:00)
Weather Context	Temperature	Cold (< 18°C)
		Warm (18-34°C)
		Hot (>34°C)
	Weather	Snowy (snowfall)
		Cloudy (Cloudy)
		Rainy (Rain and fog)
		Sunny (Clear sky and sunny)

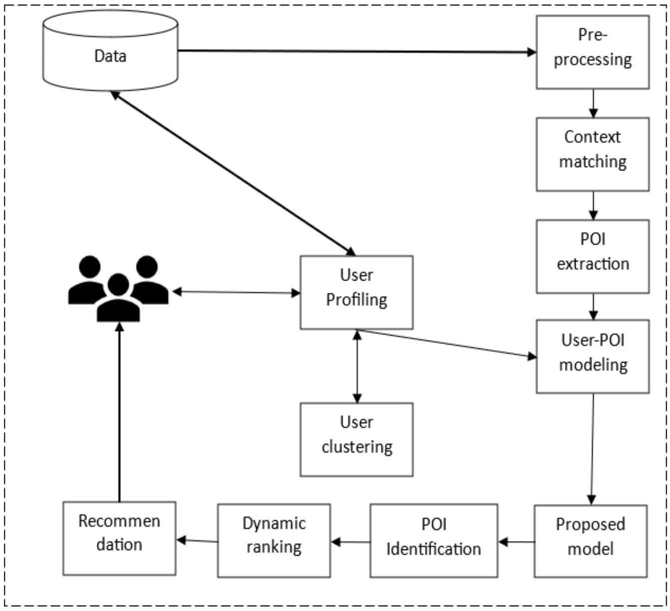

Figure 1: Proposed flow diagram for travel recommendation.

b. Identifying POIs:

POIs are identified in the proposed model using Self Organizing Maps (SOMs). The term "Points of Interest" (POIs) refers to data points that possess unique characteristics that aid in determining their type. Examples of such characteristics include geographical coordinates (latitude, longitude), categorization by type (e.g., restaurant, museum, park), user ratings or reviews, and social media check-ins (if applicable). In SOMs, initially, data points are organized in a grid of interconnected nodes, typically in a two-dimensional format to facilitate visualization. Each node represents a potential cluster. To construct these clusters, a POI data point is randomly selected, and the distance between the data point and every node on the grid is calculated. The node that is in closest proximity to the data point is dubbed the "winning node." The winning node and its neighboring nodes on the grid are then adjusted (drawn closer) to the data point. This adjustment process gradually creates clusters of comparable POIs on the grid. This process is repeated for every POI data point.

During the training phase, the self-organizing map (SOM) generates a "feature map" that reflects comparable POIs among nodes that are close to one another. This map partially preserves the geographic connections among the original data points. By examining the winning nodes for each POI and their adjacent nodes, clusters of POIs with similar attributes become discernable. Upon completion of the training phase, a recently introduced POI can be classified by identifying the node on the Self-Organizing Map (SOM) grid with the highest score. The node's location and the nodes in its vicinity provide valuable information about the most probable cluster (type) for the new POI. As a result, a collection of POIs and a database of key tourist destinations are created.

c. User Profiling:

The proposed tourism system is designed to provide customized travel recommendations that provide to the unique interests, preferences, and requirements of its users. By analyzing location-based social network data, the system collects pertinent information on the user's social activities and behaviors to create a personalized user profile. This data enables the system to gain a deeper understanding of the user's preferences. User profiles are created based on demographic factors such as age, gender, and work status, as well as preferences like previous check-ins, reviews, feedback, comments, postings, and requests. Various factors, such as weather conditions, season of the year, travel time, travel companions, personal interests, and budget, influence users' preferences for points of interest (POI). Typically, tourists prefer to sightsee in the morning and evening while taking a break for meals at midday. Therefore, the system utilizes location-based social network data to identify key characteristics of the users.

A multilayer approach is used to create user profiles that are tailored to their unique preferences. These profiles are built using information from internet reviews and ratings, with each layer representing the user's preferences for specific features like weather, cost estimation, companions, trip frequency, and time. To ensure that the recommendations are highly suitable, only positive ratings are considered. Ratings below 3 are regarded as negative reviews and are not included, while ratings above 3 are considered favorable. By utilizing the traditional five-star rating system commonly used by travellers, we can anticipate ratings for unknown points of interest. A statistical approach is used to create the multilayer user profile, which is defined as follows:

$$UP = \frac{\sum_{r_{i \in R_f}} P(w|r_i)}{|R_f|} \qquad \text{Eqn.1}$$

R_f represents the collective combination of all favorable reviews for the specific feature. The influencing word is represented by $(w|r_i)$. The conditional probability denoted as $P(w|r_i)$, is computed as follows:

$$P(w|r_i) = \frac{F_w^{r_i} + \mu^{F_w^{R_f}} / \sum_w F_w^{R_f}}{\sum_w F_w^{r_i} + \mu} \qquad \text{Eqn.2}$$

μ represents the smoothing parameter, F_w^{ri} represents the influential word, w represents the frequency of r_i, and $F_w^{R_f}$ represents the influential word's frequency of R_f.

d. User Clustering:

The proposed dynamic travel recommendation model, a Bi-directional Autoencoder (BDA), is a neural network architecture pivotal in shaping dynamic travel recommendation systems through its ability to cluster users based on their travel preferences and behaviors. Unlike conventional methods, BDA offers a potent approach to user clustering that adjusts to evolving user preferences and a changing landscape of Points of Interest (POIs). They bridge the gap between users and POIs by establishing a two-way connection rather than solely focusing on user profiles. The core of a BDA comprises interconnected encoder and decoder networks for both users and POIs. The user encoder takes a user profile, encapsulating their travel interests, and compresses it into a latent representation that captures the essence of their preferences. Simultaneously, the decoder endeavors to reconstruct the original profile from this latent vector.

Similarly, the POI encoder condenses a POI's features, such as category, location, and ratings, into a latent representation, while the decoder aims to recreate the original POI details. Following the training of the BDA, the latent space representations of users can be clustered using a direct clustering approach in the latent space using density-based or partition-based techniques. This clustering method amalgamates users with similar travel preferences and behaviors into clusters, allowing the recommendation system to personalize travel recommendations for various user segments. Moreover, the BDA can undergo periodic updates to adapt to changes in users' preferences, behaviors, or the availability of new data, ensuring that the clustering of users remains pertinent and effective over time. The bi-directional autoencoder emerges as a potent tool for user clustering in dynamic travel recommendation systems, facilitating personalized and targeted recommendations tailored to the preferences of different user segments and thereby augmenting the overall user experience in travel planning and decision-making.

- BDA Model Architecture: The proposed model comprises two interconnected models, as illustrated in Figure 2.
  - User Encoder-Decoder Model:
    - Encoder: An encoder function (φ) is used to take a user profile (u) that contains their trip preferences (such as preferred places, activities, and budget) and compress it into a latent representation (z). This latent vector encapsulates the fundamental nature of the user's travel preferences.

      $$z = \varphi(u) = h(W_e * u + b_e) \qquad \text{Eqn.3}$$

      W_e represents encoder weight matrix, $b_e$encoder bias and h represent the activation function.
    - Decoder: The decoder (ψ) takes the latent representation (z) as input and aims to rebuild the original user profile (u_rec).

      $$\text{u\_rec} = \psi(\text{z}) = \text{h}'(W_d * z + b_d) \qquad \text{Eqn.4}$$

      W_d represents decoder weight matrix, b_d decoder bias and h' represents the activation function.
  - POIs Encoder-Decoder Model:
    - Encoder: The encoder (φ') is a function that takes a feature vector (p) of a point of interest (POI), which contains information such as the category (museum, restaurant), location, user ratings, and amenities, and converts it into a compressed representation (z').

      $$z' = \varphi'(p) = h(W'_e * p + b'_e) \qquad \text{Eqn.5}$$

    - Decoder: The decoder (ψ') aims to recover the original characteristics of the point of interest (p_rec) using the latent representation (z').

      $$p\_rec = \psi'(z') = h(W'_d * z' + b'_d) \qquad \text{Eqn.6}$$

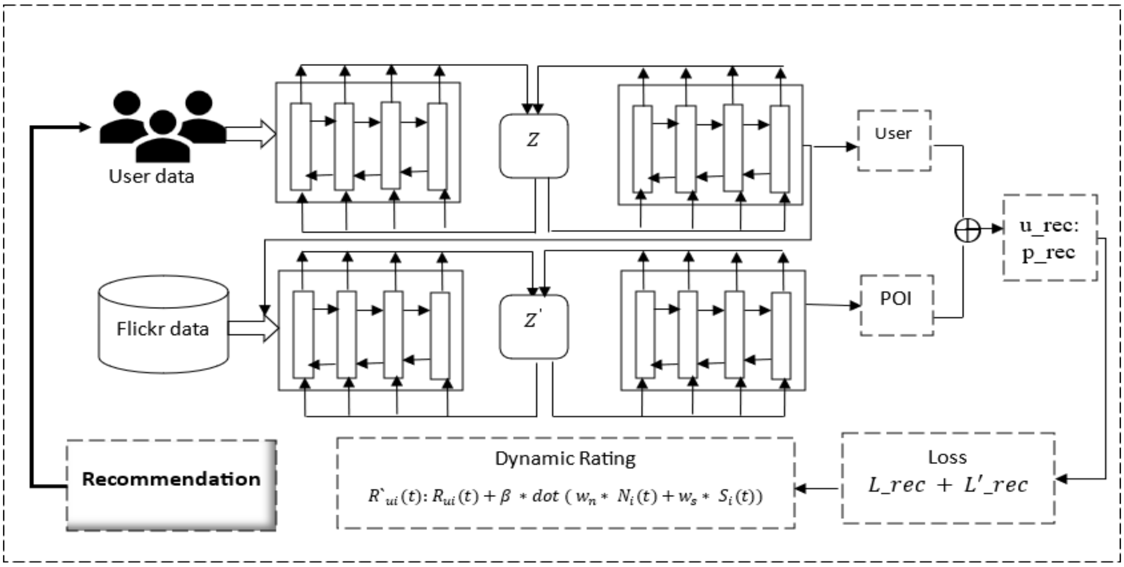

Figure 2: Proposed dynamic model architecture for personalized travel recommendation using hybrid and deep learning approach.

e. Model Training and Optimization:

After developing the model framework, the training process begins with the collection of user profiles that accurately represent their preferences. In addition, Point of Interest (POI) data is gathered, which includes comprehensive information about each POI. The collection of user-POI interaction data is crucial as it provides valuable insights into the POIs that users have engaged with. The model takes a user profile (u) and the related interacting POI as input. The user encoder (φ) generates a latent representation (z) of the user profile, while the POI encoder (φ') generates a latent representation, referred to as z', of the POI. The user decoder (ψ) aims to rebuild the user profile (u_rec) using z, while the POI decoder (ψ') aims to reconstruct the POI characteristics, represented as p_rec, from the input z'.

The total loss is computed by combining two components of reconstruction loss. User profile reconstruction loss (L_rec) quantifies the difference between the initial user profile (u) and its rebuilt counterpart (u_rec). In contrast, the POI feature reconstruction loss (L'_rec) quantifies the difference between the initial POI features (p) and their rebuilt counterpart (p_rec).

$$Total\_loss = L\_rec + L'\_rec \qquad \text{Eqn.7}$$

The weights of the encoder and decoder networks for both users and POIs are adjusted using the backpropagation technique to minimize the overall loss. Optimizers such as Adam are commonly used to explore the weight space and achieve convergence effectively.

f. Dynamic Rating:

Dynamic Rating Adjustment (DRA) is a crucial feature of travel recommendation systems that improves suggestion accuracy by dynamically adjusting item ratings. DRA takes into account user preferences, item popularity, and contextual factors to provide personalized suggestions that reflect the current state of user preferences and travel patterns. During peak seasons, popular items are rated higher, and less relevant items are rated lower. The system continuously monitors user behavior and contextual information to enhance recommendations and maximize user satisfaction and engagement. Travel recommendation systems depend on user ratings to propose POIs, but fixed ratings might become obsolete when user preferences and POIs themselves change over time. Dynamic Rating Adjustment addresses this issue by constantly improving the perceived value of a point of interest (POI) for a particular user. The notation $R_{ui}(t)$ denotes the modified rating assigned by user u to the point of interest i at time t. Past ratings influence the adjusted rating $R_{ui}(t-\delta)$, but the impact of these ratings diminishes with time through the use of a decay factor α. Adjusted Rating Influence α: $\alpha(t)$ is calculated using the exponential function $e^{(-\lambda*(t-t_0))}$.

$$\alpha: \alpha(t) = e^{(-\lambda*(t-t_0))} \qquad \text{Eqn.8}$$

The decay rate, denoted by λ, determines the speed at which previous ratings lose their impact t_0. The above equation guarantees that more recent ratings will have a more significant influence on the adjusted rating.

Integrating User Preferences: Let $P_{ui}(t)$ denote a vector that represents the preferences of user u at time t. These considerations encompass preferences such as the desired category (museums or nightlife) or the range of money. The adjusted rating can be enhanced by taking into account the extent to which the POI corresponds with the user's present preferences, and ratings are adjusted with preferences.

$$R`_{ui}(t): R_{ui}(t) + w * dot\ (P_u(t), POI_i(t)) \quad \text{Eqn.9}$$

The weighting factor w determines the level of effect that preferences have. The dot product $dot\ (P_u(t), POI_i(t))$ measures the alignment between the user's preferences and the features of a POI.

External data sources, such as news stories $N_i(t)$ or social media trends $S_i(t)$, might provide insight into the current popularity of a POI. These can be combined using a weighting factor β.

$$R`_{ui}(t): R_{ui}(t) + \beta * dot\ (w_n * N_i(t) + w_s * S_i(t)) \quad \text{Eqn.10}$$

w_n and w_s represents the weights for news and social media. By integrating these adaptable modifications, the travel recommendation system may provide consumers with the most pertinent and current ideas for POI, guaranteeing a more personalized and pleasurable travel experience.

EXPERIMENTAL EVALUATION AND RESULTS

A. Evaluation Metrics

The current study aims to evaluate the efficacy of the proposed dynamic recommendation system in providing personalized recommendations of POIs for the target user. The evaluation process is based on the most commonly used performance metrics, such as Recall, Precision, F1-score, coverage, Mean Average Precision (MAP), and Root Mean Squared Error (RMSE). Table 2 represents the mathematical formulation for the metrics mentioned above.

Table 2: Performance metrics used to evaluate the proposed model performance.

Evaluation metric	Formula
Precision	$\frac{\lvert Recommended\_POI(user) \cap Relevant\_POI(user)\rvert}{\lvert Recommended\_POI(user)\rvert}$
Recall	$\frac{\lvert Recommended\_POI(user) \cap Relevant\_POI(user)\rvert}{\lvert Relevant\_POI(user)\rvert}$
F1-score	$2 \times \frac{Precision \times Recall}{Precision + Recall}$
Coverage	$\frac{Number\ of\ predicted\ ratings}{Total\ number\ of\ ratings\ in\ the\ test\ set}$
MAP	$\frac{1}{N_{users}} \sum_{user=1}^{N_{users}} \lvert AP_{user}$
RMSE	$\sqrt{\frac{\sum_{user\ POI} (Actual_{ratings(POI\ user)} - Predicted_{ratings(POI\ user)})^2}{N}}$

B. Results and comparison

The study was carried out by proposing 6 and 12 POIs from all the recommendations made by the proposed model, resulting in group sizes ranging from 2 to 16 individuals. When making travel plans, it is commonly observed that travelers prefer visiting no more than six places within a single region. In order to provide personalized recommendations, it is reasonable to recommend anywhere from two to six POIs. It is observed that the addition of POIs significantly decreased the accuracy of recommendation results when using Mean Average Precision (MAP) once the number of suggestions exceeded six, as illustrated in Figure 3 and Figure 4, respectively, for 6 and 12 POIs, where the x-axis represents the recommendations 2 to 16 (each unit represents 2 individuals) and the y-axis represents the model comparison.

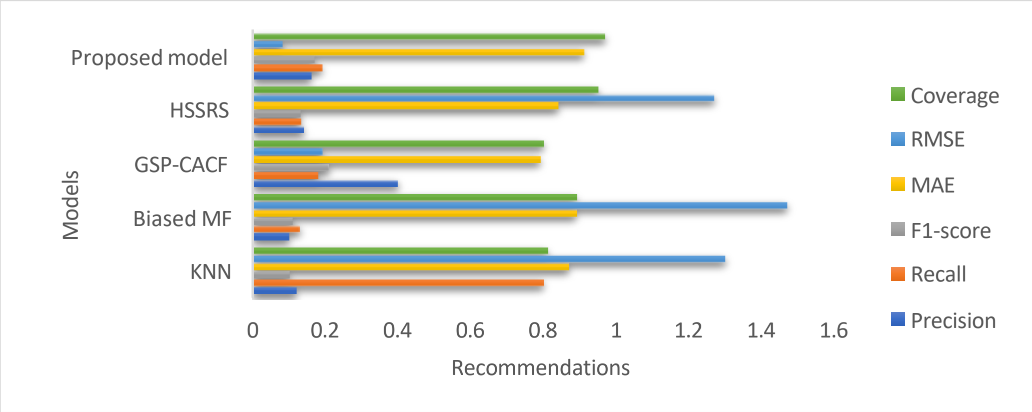

Figure 3: The list of recommendations obtained and compared with existing models for 6 POIs and 16 individuals.

Figures 3 and 4 illustrate that as the number of suggestions increases, the recall also increases, respectively, for 6 and 12 POIs. This is because a greater number of accurate POIs are included in the top-N recommendations. The analysis presented in Figure 5 indicates that the precision of recommendations decreases as the number of suggested POIs increases as the primary recommendations are comprised of increasingly detailed and specific POIs. It is noteworthy that tourists may face difficulty in visiting all the suggested locations due to a lack of adequate information on their preferences and itinerary.

According to the outcome of the F1-score, the proposed model has demonstrated superior effectiveness when compared to other techniques. The proposed approach successfully addressed the challenges of cold start and data sparsity, as seen in Figures 3 and 4. The notable results achieved can be attributed to its ability to leverage user-profiles and utilize an asymmetric schema technique to estimate the best matches for the desired individual. Moreover, the demographic data of users can be analyzed to predict their preferences for future visits, helping to address the issue of a cold start. To overcome the challenge of sparse data, a clustering approach is applied, avoiding the reliance on a single website to identify POIs.The Root Mean Square Error (RMSE) measure is a widely used method to quantify the difference between expected and actual ratings in recommender systems. It is particularly useful in determining the disparity between an item's predicted ratings and its actual ratings. The accuracy of the prediction can be improved by employing context-aware techniques. In previous research, contextual approaches were proposed but the recommended technique outperforms them and exhibits a lower error rate compared to non-contextual approaches. One of the major challenges in recommender systems is the cold start issue, where there is insufficient user or item data available for the system to make accurate recommendations. To address this issue, the proposed dynamic model outperforms other techniques by incorporating demographic data and user subject distribution. Incorporating these factors minimizes the cold start issue and improves the overall accuracy of the system.

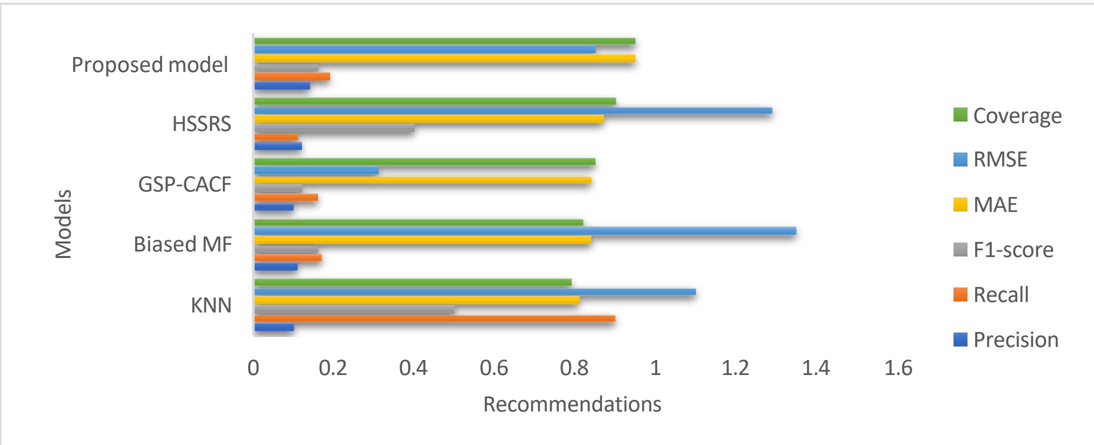

Figure 4: The list of recommendations obtained and compared with existing models for 12 POIs and 16 individuals.

CONCLUSION AND FUTURE ENHANCEMENT

This article presents a novel approach to generate tailored travel recommendations for tourists. By leveraging contextual and demographic information along with geotagged social media images, this method offers more precise and personalized recommendations than existing techniques. The system employs hybrid modeling to generate personalised travel ideas based on trip records' topic distribution, taking into account tourists' preferences and current location data. Additionally, the system incorporates a bi-directional autoencoder (BDA) model to enhance its recommendation accuracy further. Empirical evaluations conducted using actual data from a range of travel websites demonstrate the efficacy of this approach in providing customized travel itineraries that cater to individual visitors' unique tastes. Furthermore, this research contributes to the evolution of personalized dynamic tourist recommendation systems, which can enhance the user experience and satisfaction in planning and making travel decisions.

The potential for future advancements is to enhance the data collection process by integrating real-time data from wearable technology and smart environments. By doing so, it would be possible to provide personalized recommendations that are highly dynamic and can adapt to a traveler's current experiences and preferences. This would result in a continuous feedback loop that can offer an exceptionally customized travel experience.

REFRENCES

[1] Mariani, M. M., Buhalis, D., Longhi, C., & Vitouladiti, O. (2014). Managing change in tourism destinations: Key issues and current trends. Journal of Destination Marketing & Management, 2(4), 269-272.

[2] Ko, H., Lee, S., Park, Y., & Choi, A. (2022). A survey of recommendation systems: recommendation models, techniques, and application fields. Electronics, 11(1), 141.

[3] Cao, L., Luo, J., Gallagher, A., Jin, X., Han, J., & Huang, T. S. (2010, March). A worldwide tourism recommendation system based on geo tagged web photos. In 2010 IEEE international conference on acoustics, speech and signal processing (pp. 2274-2277). IEEE.

[4] Abbasi-Moud, Z., Vahdat-Nejad, H., & Sadri, J. (2021). Tourism recommendation system based on semantic clustering and sentiment analysis. Expert Systems with Applications, 167, 114324.

[5] Shih, D. H., Yen, D. C., Lin, H. C., & Shih, M. H. (2011). An implementation and evaluation of recommender systems for traveling abroad. Expert Systems with Applications, 38(12), 15344-15355.

[6] Jiao, X., Xiao, Y., Zheng, W., Wang, H., & Hsu, C. H. (2019). A novel next new point-of-interest recommendation system based on simulated user travel decision-making process. Future generation computer systems, 100, 982-993.

[7] Li, M., Li, Y., Lou, W., & Chen, L. (2020). A hybrid recommendation system for Q&A documents. Expert systems with applications, 144, 113088.

[8] Çano, E., & Morisio, M. (2017). Hybrid recommender systems: A systematic literature review. Intelligent data analysis, 21(6), 1487-1524.

[9] Chen, J. H., Chao, K. M., & Shah, N. (2013, September). Hybrid recommendation system for tourism. In 2013 IEEE 10th International Conference on e-Business Engineering (pp. 156-161). IEEE.

[10] Al Fararni, K., Nafis, F., Aghoutane, B., Yahyaouy, A., Riffi, J., & Sabri, A. (2021). Hybrid recommender system for tourism based on big data and AI: A conceptual framework. Big Data Mining and Analytics, 4(1), 47-55.

[11] Kabassi, K. (2010). Personalizing recommendations for tourists. Telematics and Informatics, 27(1), 51-66.

[12]Koren, Y., Bell, R., & Volinsky, C. (2009). Matrix factorization techniques for recommender systems. Computer, 42(8), 30-37.

[13]Coelho, J., Nitu, P., & Madiraju, P. (2018, July). A personalized travel recommendation system using social media analysis. In 2018 IEEE International Congress on Big Data (BigData Congress) (pp. 260-263). IEEE.

[14]Debnath, S., Ganguly, N., & Mitra, P. (2008, April). Feature weighting in content based recommendation system using social network analysis. In Proceedings of the 17th international conference on World Wide Web (pp. 1041-1042).

[15] Burke, R. (2002). Hybrid recommender systems: Survey and experiments. User modeling and user-adapted interaction, 12, 331-370.

[16] Kulkarni, A., Barve, P., & Phade, A. (2019). A machine learning approach to building a tourism recommendation system using sentiment analysis. International Journal of Computer Applications, 178(19), 48-51.

[17] Pu, Z., Du, H., Yu, S., & Feng, D. (2020, February). Improved tourism recommendation system. In Proceedings of the 2020 12th international conference on machine learning and computing (pp. 121-126).

[18] Cheng, X. (2021). A travel route recommendation algorithm based on interest theme and distance matching. EURASIP Journal on Advances in Signal Processing, 2021(1), 57.

[19] Batmaz, Z., & Kaleli, C. (2019). AE-MCCF: an autoencoder-based multi-criteria recommendation algorithm.

Arabian Journal for Science and Engineering, 44, 9235-9247.

[20] Van Canneyt, S., Van Laere, O., Schockaert, S., & Dhoedt, B. (2012, November). Using social media to find places of interest: a case study. In Proceedings of the 1st ACM SIGSPATIAL International Workshop on Crowdsourced and Volunteered Geographic Information (pp. 2-8).

[21] Nitu, P., Coelho, J., & Madiraju, P. (2021). Improvising personalized travel recommendation system with recency effects. Big Data Mining and Analytics, 4(3), 139-154.

[22] Geetha, G., Safa, M., Fancy, C., & Saranya, D. (2018, April). A hybrid approach using collaborative filtering and content based filtering for recommender system. In Journal of Physics: Conference Series (Vol. 1000, p. 012101). IOP Publishing.

[23] Dong, X., Yu, L., Wu, Z., Sun, Y., Yuan, L., & Zhang, F. (2017, February). A hybrid collaborative filtering model with deep structure for recommender systems. In Proceedings of the AAAI Conference on artificial intelligence (Vol. 31, No. 1).

[24] Chen, R., Hua, Q., Chang, Y. S., Wang, B., Zhang, L., & Kong, X. (2018). A survey of collaborative filtering-based recommender systems: From traditional methods to hybrid methods based on social networks. IEEE access, 6, 64301-64320.

[25] Kouki, P., Schaffer, J., Pujara, J., O'Donovan, J., & Getoor, L. (2019, March). Personalized explanations for hybrid recommender systems. In Proceedings of the 24th International Conference on Intelligent User Interfaces (pp. 379-390).

[26] Paradarami, T. K., Bastian, N. D., & Wightman, J. L. (2017). A hybrid recommender system using artificial neural networks. Expert Systems with Applications, 83, 300-313.

[27] Walek, B., & Fojtik, V. (2020). A hybrid recommender system for recommending relevant movies using an expert system. Expert Systems with Applications, 158, 113452.

[28] Cui, G., Luo, J., & Wang, X. (2018). Personalized travel route recommendation using collaborative filtering based on GPS trajectories. International journal of digital earth, 11(3), 284-307.

[29] Logesh, R., & Subramaniyaswamy, V. (2019). Exploring hybrid recommender systems for personalized travel applications. In Cognitive Informatics and Soft Computing: Proceeding of CISC 2017 (pp. 535-544). Springer Singapore.

[30] Nilashi, M., bin Ibrahim, O., Ithnin, N., & Sarmin, N. H. (2015). A multi-criteria collaborative filtering recommender system for the tourism domain using Expectation Maximization (EM) and PCA– ANFIS. Electronic Commerce Research and Applications, 14(6), 542-562.

[31] Sun, Y., Fan, H., Bakillah, M., & Zipf, A. (2015). Road-based travel recommendation using geotagged images. Computers, Environment and Urban Systems, 53, 110-122.

[32] Ramzan, B., Bajwa, I. S., Jamil, N., Amin, R. U., Ramzan, S., Mirza, F., & Sarwar, N. (2019). An intelligent data analysis for recommendation systems using machine learning. Scientific Programming, 2019, 1-20.