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Hotel Recommendations System Using DL & Dempster - Shafer Theory

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Abstract

The field of context-aware recommender systems, which aims to provide personalized suggestions by considering user circumstances like location and time, has garnered significant attention in research and industry. A notable limitation, however, is the prevalent focus on contextual data at the item level, primarily linking context to overall ratings. This research explores a more nuanced approach by extracting context-specific preferences for individual item features (e.g., a hotel's location, food, and service) from user-generated reviews, employing contextual weighting techniques. These refined preferences are then integrated with context-invariant preferences, also derived from reviews, to capture users' enduring needs.

Keywords: Context-Aware Recommender Systems, Service Recommendation, User Reviews, Contextual Review Analysis, Hotel Recommendation

1. Introduction

In today's fast-evolving travel and hospitality industry, personalized hotel recommendations are crucial for improving customer satisfaction. Traditional recommendation systems rely on collaborative filtering or content-based techniques, but these methods may suffer from limited data and uncertainty in user preferences. This project aims to build a hotel recommendation system that integrates Deep Learning (DL) models with Dempster-Shafer (DS) theory to improve recommendation accuracy under uncertainty. The integration of Deep Learning and Dempster-Shafer theory provides a robust framework for hotel recommendations under uncertainty. This hybrid approach will offer better decision-making, enhancing user satisfaction and trust by addressing the challenges of incomplete and conflicting data.

Hotel recommendations can be challenging due to uncertain and incomplete user information. For instance, users may not always explicitly specify their preferences (e.g., location, amenities, or budget), leading to ambiguity. Traditional approaches struggle to combine multiple factors and deal with conflicting or uncertain data. To address this, the proposed system will leverage **deep learning for feature extraction** and the **Dempster-Shafer theory** to handle uncertainty and aggregate different types of evidence for reliable recommendations.

The proposed Hotel Recommendation System using Deep Learning (DL) and Dempster-Shafer (DS) Theory holds substantial significance for both the hospitality industry and end-users, addressing key challenges in recommendation systems and enhancing user satisfaction. Below are the core reasons that highlight its importance:

- **Enhanced Personalization for Users**

Tailored Experiences: By leveraging deep learning models, the system can analyze user behavior, preferences, and sentiments from reviews to offer highly relevant hotel recommendations.

Dynamic Recommendations: The system adapts to changing preferences, improving personalization as it gathers more data from user interactions.

- **Handling Uncertainty and Incomplete Information**

  Addressing Ambiguity: Users often provide incomplete or conflicting information regarding their preferences. DS theory allows the system to manage such uncertainty effectively by aggregating different types of evidence.

  Reliable Recommendations: Even when data is sparse or noisy, the DS theory ensures the recommendation engine remains reliable by combining multiple belief sources.

- **Competitive Advantage for the Hospitality Industry**

  Improved Customer Satisfaction: Accurate and relevant hotel recommendations result in better user experiences, leading to higher customer retention and loyalty.

  Reduced Churn: Offering reliable recommendations reduces the likelihood of users switching to other booking platforms due to poor suggestions.

2. Literature Review

Badouch et. al. states that accurate hotel recommendations play a crucial role in enhancing the overall travel experience. In re cent years, recommendation systems have gained significant popularity in the tourism industry. These systems use various techniques and algorithms to analyze user preferences and provide personalized hotel recommendations. One of the emerging methods in recommendation systems is deep learning, a branch of machine learning that focuses on training neural networks with multiple layers to make accurate predictions or classifications. Deep learning algorithms have shown great success in various domains such as image processing and natural language processing. This chapter aims to propose a hotel recommendation system that utilizes deep learning techniques for analyzing user preferences and providing personalized recommendations. The proposed hotel recommendation system will leverage user reviews and hotel descriptions to extract meaningful features and train a deep learning model. [1]

Hossen et. al. states that In the age of modern science, everything is based on online and onthe internet. Internet-based shopping has become easier and more popular because of better quality, and fast logistic systems. Internet-based shopping and booking are very comfortable. People can easily make a booking without going outside. The most effective side part of online-based work is that people can give a review. Recognizing reviews allows others to easily understand the emotions of others and obtain the rationality result of different products [2]

Meduri et. al. states that When it comes to creating recommendations for products, recommendation systems are an extremely important factor. They are used to filter information coming from a variety of networks and to forecast the output depending on the preferences of the user. These systems have gained a significant amount of popularity, and one business that might benefit from using recommender systems is the tourism industry. The use of recommendation systems has been shown to increase both the level of happiness and overall experience that customers have in a variety of businesses, including the travel industry. They are generating enormous amounts of income using this method, which is why the vast majority of them are turning to recommendation systems. A subfield of machine learning is called as recommendation engines, and its primary function is to usually rank individuals or items. A recommender system, in its broadest sense, is a system that predicts the ratings that a user would give to a certain item based on their previous interactions with that item. After that, the user will be presented with a rating of these different projections. In order to provide users with product recommendations that are likely to pique their interest, recommender systems make an effort to anticipate the preferences of users. In order to get the The purpose of a hotel recommendation system is to separate the user's selection of a recommended hotel or resort from their other available alternatives. [3]

Ramzan et. al. states presents an intelligent approach to handle heterogeneous and large-sized data using machine learning to generate true recommendations for the future customers. The Collaborative Filtering (CF) approach is one of the most popular techniques of the RS to generate recommendations. We have proposed an ovel CF recommendation approach in which opinion based sentiment analysis is used to achieve hotel feature matrix by polarity identification. Our approach combines lexical analysis, syntax analysis and semantic analysis to understand sentiment towards hotel features and the profiling of guest type (solo, family, couple etc). The proposed system recommends hotels based on the hotel features and guest type as additional information for personalized recommendation. The developed system not only has the ability to handle heterogeneous data using big data Hadoop platform but it also recommend hotel class based on guest type using fuzzy rules. Different experiments are performed over the real world dataset obtained from two hotel websites. Moreover, the values of precision and recall and F-measure have been calculated and results are discussed interms of improved accuracy and response time, significantly better than the traditional approaches. [4]

Abbasi et. al. states that Recommender systems are important tools for users to identify their preferred items and for businesses to improve their products and services. In recent years, the use of online services for selection and reservation of hotels have witnessed a booming growth. Customer' reviews have replaced the word of mouth marketing, but searching hotels based on user priorities is more time consuming. This study is aimed at designing a recommender system based on the explicit and implicit preferences of the customers in order to increase prediction's accuracy. In this study, we have combined sentiment analysis with the Collaborative Filtering (CF) based on deep learning for user groups in order to increase system accuracy. The proposed system uses Natural Language Processing (NLP) and supervised classification approach to analyze sentiments and extract implicit features. In order to design the recommender system, the Singular Value Decomposition (SVD) was used to improve scalability. The results show that our proposed method improves CF performance. [5]

Chih-Hao et. al. states that With a growing number of online reviews, consumers often rely on these reviews to make purchase decisions. However, little is known about managerial responses to online hotel reviews. This paper reports on a framework to integrate visual analytics and machine learning techniques to investigate whether hotel managers respond to positive and negative reviews differently and how to use a deep-learning approach to prioritize responses. In this study, forty 4- and 5-star hotels in London with 91,051 reviews and 70,397 responses were collected and analyzed. Visual analyses and machine learning were conducted. The results indicate most hotels (72.5%) showing no preference to respond to positive and negative reviews. Our proposed deep learning approach outperformed existing algorithms to prioritize responses. [6]

Dowlut, st. al. states that Precise occupancy rate (OR) forecast is essential for the sustainability of hotels in this current complex, rapidly evolving market, restricted by many factors. Failing to identify those factors and the magnitude of their influence leads to wrong perception of the hotel performance and consequently inappropriate business decisions. OR is affected by many factors, such as the availability of safe infrastructures, the pricing strategy [1], political engagement for tourism development the air access [2] among others. Predicting the occupancy of a hotel is vital for the decision-making process of revenue managers. Managers can plan important activities, like stop sales, launch promotional offers or budgeting and even workforce management, with the ultimate goal of improving financial performance - maximise revenue and minimise costs. However, generating forecast reports with an acceptable accuracy is not a simple task and often requires specific data analytics expertise and statistical knowhow. However, generating forecast reports with an acceptable accuracy is not a simple task and often requires specific data analytics expertise and statistical knowhow. For instance, based on the traditional way of exploring historical data, the forecasting exercise carried out by the revenue managers is time consuming and tedious. Data needs to be extracted from numerous sources and the necessary analytical skills are required to come up with results. [7]

Xia st. al. conducts a comprehensive analysis of the evolution and contemporary landscape of recommendation systems, which have been extensively incorporated across a myriad of web applications. It delves into the progression of personalized recommendation methodologies tailored for on line products or services, organizing the array of recommendation techniques into four main categories: content-based, collaborative filtering, knowledge based, and hybrid approaches, each designed to cater to specific contexts. The document provides an in-depth review of both the historical under pinnings and the cutting-edge innovations in the domain of recommendation systems, with a special focus on implementations leveraging big data analytics. The paper also highlights the utilization of prominent datasets such as Movie Lens, Amazon Reviews, Netflix Prize, Last.fm, and Yelp in evaluating recommendation algorithms. It further outlines and explores the predominant challenges encountered in the current generation of recommendation systems, including issues related to data sparsity, scalability, and the imperative for diversified recommendation outputs. [8]

Solano-Barliza et.al. states that the tourism industry generates essential contributions to the world economy and is a valuable resource for developing nations that need to address the industry's requirements by enhancing product diversification and competitiveness in the services they provide tourism, as an economic sector, is vital because it is an essential source of income for many countries and communities, as tourists spend money on accommodation, transport, food, activities, and shopping. It can also help boost the local economy and create jobs in the tourism industry and related sectors, such as hospitality, transport, and commerce. It can also help preserve and promote the culture and heritage of a region as tourists can visit historical sites, museums, and local festivals. [9]

Henriques et. al. explores current state-of-the-art artificial intelligence (AI) methods for forecasting hotel demand. Since revenue management (RM) is crucial for business success in the hotel industry, this study aims to identify state-of-the-art effective AI-based solutions for hotel demand forecasting, including machine learning (ML), deep learning (DP), and artificial neural networks (ANNs). The study conducted an SLR using the PRISMA model and identified 20 papers indexed in Scopus and the Web of Science. It addresses the gaps in the literature on AI-based demand forecasting, highlighting the need for clarity in model specification, understanding the impact of AI on pricing accuracy and financial performance, and the challenges of available data quality and computational expertise. The review concludes that AI technology can significantly improve forecasting accuracy and empower data-driven decisions in hotel management. Additionally, this study discusses the limitations of AI-based demand forecasting, such as the need for high-quality data. It also suggests future research directions for further enhancing AI forecasting techniques in the hospitality industry. [10]

3. Proposed System

The solution integrates Deep Learning (DL) models for accurate feature extraction with Dempster-Shafer (DS) theory to handle uncertainty in user preferences. Below is an overview of the proposed solution:

- **Feature Extraction using DL:**
  Utilize MLPs, CNNs, or LSTMs to extract meaningful insights from user reviews and hotel features (e.g., amenities, location). Collaborative filtering and matrix factorization will address data sparsity issues.
- **Uncertainty Management with DS Theory:**
  Use DS theory to combine conflicting or incomplete data sources, assigning belief masses to different criteria (e.g., reviews, ratings).
  Apply Dempster's rule to aggregate evidence from multiple aspects and produce reliable recommendations.
- **Hybrid Recommendation Model:**
  Combine the outputs from the DL-based models and DS theory to generate personalized hotel recommendations.
  Use multi-criteria optimization to account for various factors, such as price, user preferences, and location relevance.
- **Performance Metrics:**

Evaluate the model using precision, recall, and Mean Reciprocal Rank (MRR) to ensure high-quality recommendations.

4. Methodology

4.1 Steps of execution

Step 1: Data Preparation

- Load Data: Use Pandas for data handling.
- Preprocessing:
- Normalize ratings (e.g., scale between 1 and 5).
- Handle missing values by imputing with the mean or using statistical techniques.
- Split data into training, validation, and test sets (e.g., 80/10/10).
- Libraries: `pandas`, `numpy`, `scikit learn`

Step 2: Embedding Layer

- Apply Matrix Factorization for latent representation of users and items.
- Initialize user and item embeddings (e.g., random vectors).
- Libraries: `scikit learn`, `numpy`, `tensorflow`/`pytorch`

Step 3: Deep Neural Network

- Define a DNN model:
- Input: User and item embeddings concatenated.
- Hidden Layers: Dense layers with ReLU activation.
- Output Layer: Predict multi criteria ratings.
- Libraries: `tensorflow` or `pytorch`

Step 4: Uncertainty Modeling

- Use Dempster Shafer Theory :
- Represent predicted ratings as mass functions.
- Use Gaussian Probability Density Functions for uncertainty quantification.
- Combine evidence using Dempster's Rule
- Libraries: `pyds`, `scipy` (for Gaussian distribution)

Step 5: Training the Model

- Loss Function: Mean Squared Error (MSE) for sub criteria rating predictions.
- Optimizer: Use Stochastic Gradient Descent (SGD) or Adam.
- Batch size, learning rate, and embedding size can be tuned.
- Libraries: `tensorflow`/`pytorch`

Step 6: Evaluation Metrics

- Evaluate performance using: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), Coefficient of Determination (CoD)
- Libraries: `scikit learn`

Step 7: Visualization

- Plot the performance metrics and model comparisons.
- Show the contribution of each sub criterion to the overall rating.
- Libraries: `matplotlib`, `seaborn`

4.2 Working of Algorithm

4.2.1 Data Collection and Preprocessing:

- User Data: Imagine we have data on a user named Alice:
- Past trips: Visited beach destinations twice, once stayed in a family-friendly resort, once in a boutique hotel.
- Stated Preferences: "I like hotels near the beach, with a pool, and preferably with good reviews."
- Budget: Mid-range.
  - Hotel Data: We have data on several hotels:
  - Hotel A: Beachfront, pool, family-friendly, high rating, price: 1000
  - Hotel B: City center, no pool, business-oriented, average rating, price: 2000
  - Hotel C: Beachfront, pool, boutique style, high rating, price: 3000
  - Hotel D: Near the beach, no pool, budget-friendly, good reviews, price: 4000

4.2.2 Deep Learning (DL) for Preference Learning:

- Model: Let's say we use a Recurrent Neural Network (RNN) to analyze Alice's past trips. The RNN learns that Alice prefers beach destinations and has experience with both family-friendly and boutique hotels. We might also use a separate MLP (Multi-Layer Perceptron) to process her stated preferences and budget.
- Input: The RNN takes Alice's past trip data as input (encoded numerically). The MLP takes the stated preferences and budget as input.
- Output: The DL model outputs a "preference score" for each hotel. This score represents how likely the DL model thinks Alice would like the hotel. Let's assume the scores are:
  - Hotel A: 0.8 (High due to beachfront, family-friendly aspect)
  - Hotel B: 0.2 (Low due to city center, no pool)
  - Hotel C: 0.9 (Very high due to beachfront, pool, boutique style)
  - Hotel D: 0.6 (Moderate due to beachfront, good reviews, but no pool and budget-friendly, which might be a change for Alice)

4.2.3 Dempster-Shafer (DS) Theory for Evidence Combination:

Sources of Evidence:

- DL Model Score: The preference scores from the DL model.
- Stated Preferences: Alice's explicit preferences.
- Similar User Ratings (Optional): We could also include ratings from other users with

similar profiles, but we'll keep it simpler for this example.

- Hypotheses: We define hypotheses about each hotel:
  - H1: "Alice will like this hotel."
  - H2: "Alice will not like this hotel."
- Basic Probability Assignment (BPA): For each source of evidence, we assign BPAs to the hypotheses. This reflects our belief (and uncertainty) based on that evidence.
- DL Model: Let's say we convert the DL scores into BPAs. Higher scores mean more belief in H1 (Alice will like the hotel). We also have some uncertainty:
  - Hotel A: m(H1) = 0.7, m(H2) = 0.1, m(Uncertain) = 0.2 (Relatively high belief in H1, some uncertainty)
  - Hotel B: m(H1) = 0.2, m(H2) = 0.6, m(Uncertain) = 0.2 (Stronger belief in H2)
  - Hotel C: m(H1) = 0.8, m(H2) = 0.05, m(Uncertain) = 0.15 (Very high belief in H1)
  - Hotel D: m(H1) = 0.5, m(H2) = 0.3, m(Uncertain) = 0.2 (Moderate belief in H1)
- Stated Preferences: We translate Alice's stated preferences into BPAs. Since she likes beach, pool, and good reviews, this strongly supports Hotel A and C, moderately supports D, and disfavors B:
  - Hotel A: m(H1) = 0.8, m(H2) = 0.1, m(Uncertain) = 0.1
  - Hotel B: m(H1) = 0.1, m(H2) = 0.8, m(Uncertain) = 0.1
  - Hotel C: m(H1) = 0.9, m(H2) = 0.05, m(Uncertain) = 0.05
  - Hotel D: m(H1) = 0.6, m(H2) = 0.2, m(Uncertain) = 0.2
- Dempster's Combination Rule: We use Dempster's rule to combine the BPAs from the DL model and the stated preferences. This rule mathematically combines the belief masses, taking into account the uncertainty. (The actual calculation is a bit complex, but there are online calculators and libraries that can do it).
- Result: The combined BPAs will likely show a very strong belief in H1 for Hotel C, a strong belief in H1 for Hotel A, a moderate belief in H1 for Hotel D, and a strong belief in H2 for Hotel B.

4.3 System Architecture

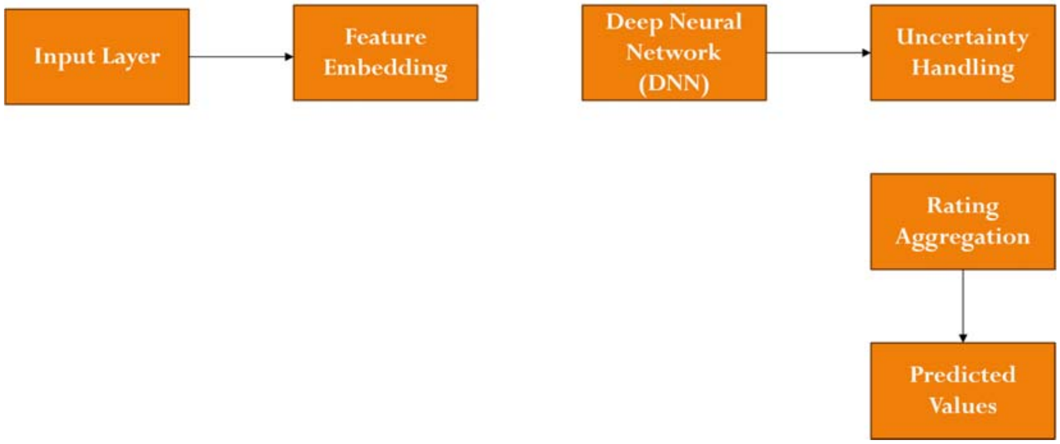

Fig. 4.1 System Architecture

- **Module 1: Input Layer**
  - Users, items, and multi criteria rating data.
- **Module 2: Feature Embedding**
  - Use Matrix Factorization (SVD) for embedding users and items.
- **Module 3: Deep Neural Network (DNN)**
  - A multilayer perceptron to process embeddings and predict sub criteria ratings.
- **Module 4: Uncertainty Handling**
  - Model uncertainty in predictions using Dempster Shafer Theory
- **Module 5: Rating Aggregation**
  - Combine sub criteria ratings into an overall rating using evidence combination
- **Module 6: Output**
  - Predicted overall rating with uncertainty assessment.
  - The Developed Model will be deployed on WSGI Server.
  - Developing a flask web application that uses API deployed on the local host through WSGI server

5. Result

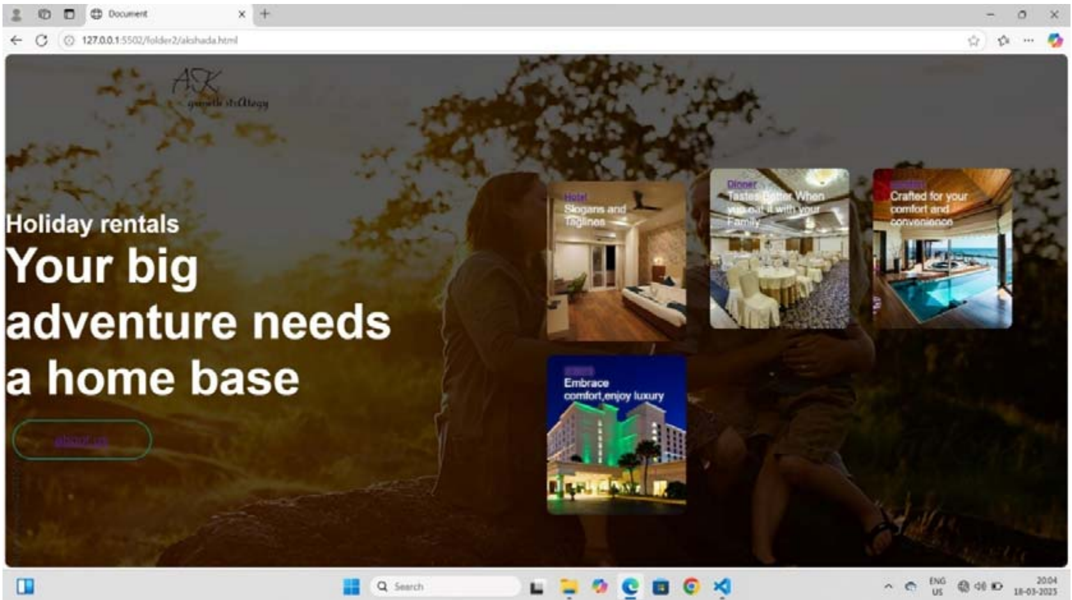

Fig. 5.1 Homepage of the hotel recommendation system

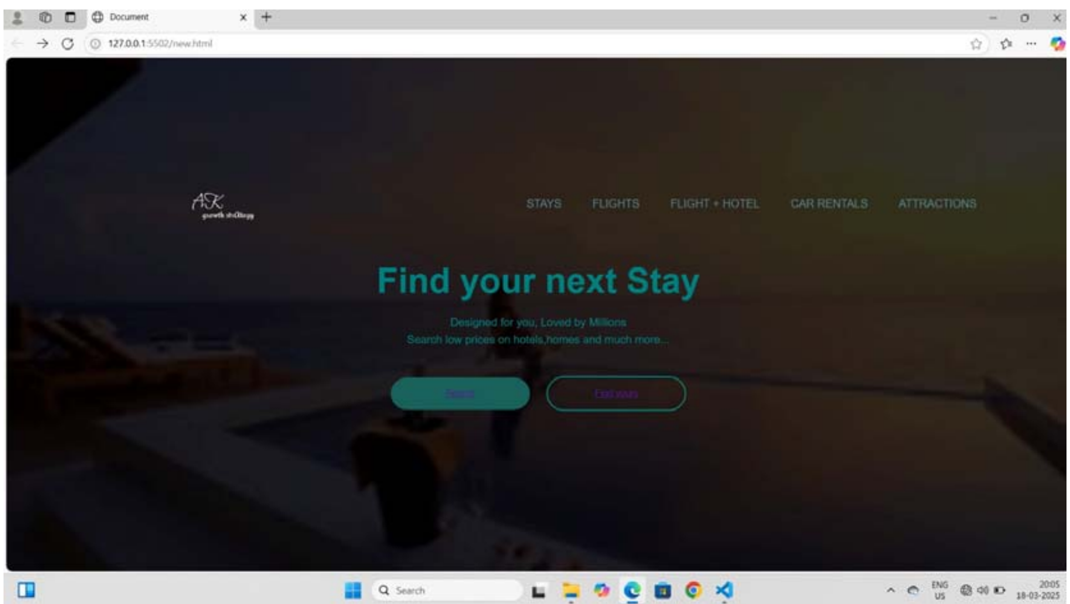

Fig. 5.2 Button Link to hotel recommendation system

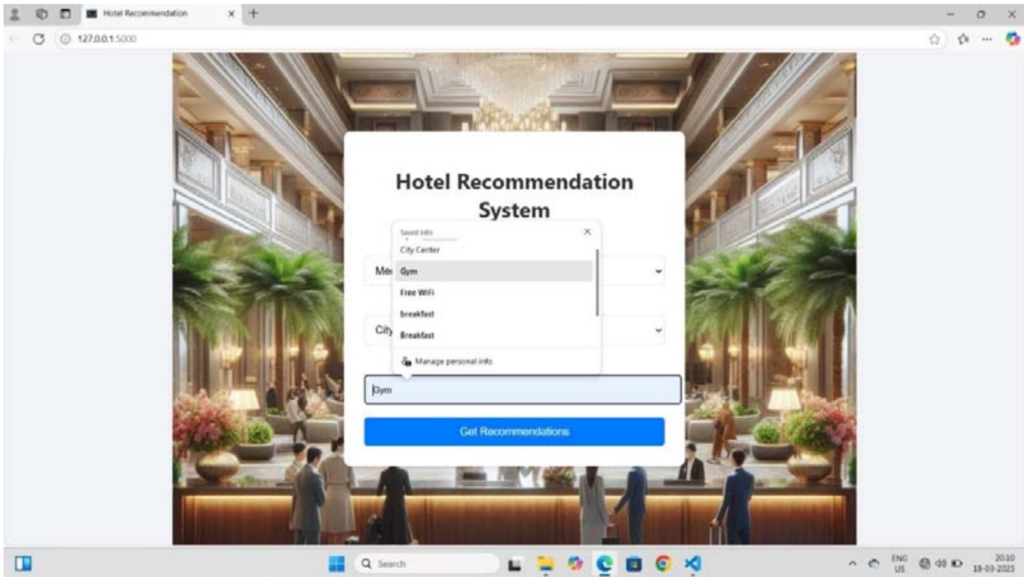

Fig. 5.3 Field selection for Hotel Recommendation system

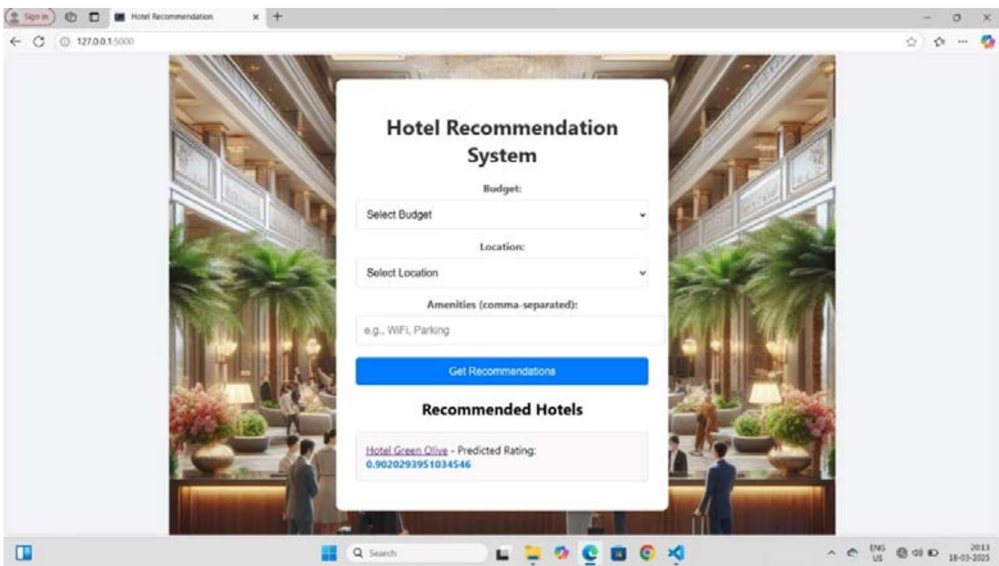

Fig. 5.4 Hotel recommended after applying DL-Shaper Algorithm

6. Conclusion

To effectively address the challenges of uncertain user preferences in hotel recommendations, a powerful strategy involves merging deep learning and Dempster-Shafer theory. Deep learning facilitates the discovery of pertinent patterns and inclinations from expansive and intricate datasets, whereas Dempster-Shafer theory offers a structured mathematical approach to synthesize evidence from diverse origins and manage ambiguities in user desires. This integrated approach leads to more precise and tailored recommendations, thereby elevating user contentment by aligning suggestions with individual requirements. Furthermore, this technological confluence strengthens the system's ability to adjust to shifting user behaviours and diverse contextual variables. Future development should prioritize refining data preparation, integrating supplementary contextual information, and optimizing computational efficiency. Ultimately, the collaborative application of deep learning and Dempster-Shafer theory establishes a robust groundwork for intelligent, user-focused recommendation systems within the hospitality sector, stimulating continued advancements in this area.

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