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Content based fuzzy search recommender system based on new user preferences

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ABSTRACT

In the ever-expanding e-commerce industry, the continuous influx of data poses a pressing challenge, necessitating the accurate retrieval of long text searches to cater to evolving user preferences and ensure user retention. This research addresses the specific issue of text search retrieval for new user preferences within the realm of recommendation systems. To tackle this challenge, we adopt a design science research approach. Leveraging the Amazon book dataset as our foundation, we formulate a comprehensive solution. The core business logic for our application is implemented in Transact SQL and encapsulated as a stored procedure. The user interface is meticulously crafted using ASP.NET, incorporating HTML, CSS, and JavaScript elements to ensure a seamless user experience. C# serves as the bridge to seamlessly invoke the SQL procedure from Microsoft SQL Server 2019. The resulting system prototype is purpose-built to cater to the unique demands of new user preferences in the book recommendation system domain. Through this research, we aim to contribute valuable insights and practical solutions to enhance the efficacy of recommendation systems, ultimately facilitating better user experiences and improved user retention rates.

1.1 Background Of the study

n today's digital landscape, the World Wide Web is inundated with an overwhelming amount of information, driven by a significant increase in its global user base (Stat, 2021). Consequently, enterprises face a pressing need to navigate this vast information landscape effectively, curate content, and provide personalized recommendations that cater to individual preferences (Shivam, 2015). This surge in dynamic and extensive data across various domains has heightened the importance of big data and, in turn, created a strong demand for robust recommender systems (Saumya, 2019).

Recommender systems have seamlessly integrated into our daily lives, representing one of the most successful applications of machine learning in the business world (Sriram et al., 2020). They excel at predicting user interests, whether it's in literature or product choices, benefiting both businesses and enhancing user experiences (Sriram et al., 2020). From the user's perspective, these systems act as guiding tools through an ever-expanding array of products (Mary et al., 2020), while from a business standpoint, they boost user engagement and provide deeper insights into customer behavior (BuildFire et al., 2020). It's worth noting that these systems have become omnipresent, with a presence on virtually all major cloud platforms.

At their core, recommender systems are instrumental tools and methodologies designed to offer recommendations that align closely with individual user preferences (Michelle et al., 2020). They serve as powerful aids in helping users make informed decisions within a vast sea of available products (Ricci et al., 2015). These systems leverage complex algorithms that take into account a wide range of factors, including user browsing patterns, search histories, purchase behaviors, and stated preferences (Isinkayea et al., 2015). As a result, recommender systems have transformed our interactions with a multitude of services (Saurabh et al., 2014), turning static data delivery into an interactive, personalized experience that empowers users to provide feedback and customize the information they receive (Lumen et al., 2020). Each recommender system tailors information streams for individual users while also considering collective behavioral patterns exhibited by all users within a given service (Wen-Hao et al., 2020).

In recent years, the exponential growth of the internet has intensified the volume and complexity of available information (Liang, 2021). This deluge of data leaves users inundated, making it challenging for them to find content that truly resonates with their specific needs (Wanvimol, 2016). In the e-commerce realm, data continues to grow exponentially, emphasizing the need for e-commerce platforms to understand and accommodate individual user preferences. Failure to do so can result in user attrition, as users may abandon a platform in frustration if their desired items do not surface in initial search results (Nitin et al., 2021). Furthermore, even if the sought-after items are available, their absence in search results can drive users toward alternative platforms, highlighting the critical importance of effective recommendation systems (Nitin et al., 2021; Johnwendy, 2023). While contemporary recommender engines primarily rely on algorithms and data-driven methods to provide users with relevant recommendations, the seamless integration and synergy of search engines and recommender systems remain an unresolved challenge. To draw a parallel, when a customer enters a physical store and looks for a specific product, the store attendant not only guides them to the right aisle but also suggests related items—a dual function similar to the symbiotic operation of a search engine and a recommendation engine. With the increasing popularity of online shopping, individuals are relying more on digital marketplaces, underscoring the importance of seamless search and recommendation functionalities (Nitin et al., 2021).

Given the ongoing proliferation of internet-based information and the expanding user base, the need for online stores to deliver efficient and relevant results has never been more pronounced. In this context, recommender systems play a pivotal role. However, it's essential to acknowledge that recommender systems face challenges in handling continuously evolving data. Edmunds et al. (2021) have highlighted that these systems often exhibit a bias towards older data, struggling to effectively highlight newer content. Newer items may be underrepresented in recommendations due to the dominance of historical data on older items, unintentionally biasing the system toward established content. Collaborative filtering systems, which rely solely on user preferences and ratings, can exacerbate this issue by reinforcing the popularity of already popular items, further complicating the challenge. Additionally, the unpredictable nature of user intent adds complexity to recommendations, as users may seek different items on different occasions (Edmunds et al., 2021).

This research aims to address these challenges through a comprehensive analysis of supervised, unsupervised, and deep reinforcement machine learning algorithms, assessing their performance and efficiency in the context of large-scale information retrieval. The study seeks to identify the most suitable model for deployment, incorporating a fuzzy semantic algorithm to enhance recommendation precision. A prototype system will be developed for deployment testing, utilizing the Amazon books dataset from Kaggle (2017) for evaluation. The primary objectives include designing a content-based fuzzy search book recommendation system using ASP.Net and MSSQL Server 2019.

In a digital environment characterized by an ever-expanding information repository and a growing user base, the role of recommender systems is crucial in providing users with tailored, relevant content. This research aims to advance our understanding of recommender systems and their effective deployment in the evolving data landscape, ultimately contributing to improved user experiences and informed decision-making in online environments.

2.1. Related works of literature

In the realm of information retrieval and recommender systems, researchers have made significant strides in addressing the challenges posed by the intersection of search engines and recommendation systems. In this section, we provide an overview of some notable research efforts aimed at enhancing the synergy between these two domains.

Social-Based Recommendation and Multidimensional Algorithms (Paloma et al., 2010): Paloma and colleagues conducted a web-based study to explore the impact of shifts from characteristic-based to social-based recommendation algorithms. They also investigated the effects of increased dimensions for recommendation algorithms and the challenges posed by products that cannot be assessed for quality before purchase. This study highlights the evolving landscape of recommender systems and their adaptation to social and multidimensional contexts.

Movie User Profiles Analysis (Kleanthi & Nikolaos, 2012): Kleanthi and Nikolaos delved into movie user profiles using a multi-criteria recommendation methodology based on real user data. Their research aimed to uncover hidden aspects of user behavior that could enhance the performance of existing systems. By analyzing user profiles, this study offers insights into improving recommendation accuracy.

Hybrid Content/Collaborative Approach (Ana et al., 2013): Ana, Swapnil, and Doina proposed a content/collaborative hybrid approach, building upon a neighborhood-based method. Their work extends the utility of recommendation systems and underscores the importance of hybrid approaches in achieving more accurate recommendations.

User Profiling with Web Usage Mining (Samane et al., 2014): Samane, Ali, and Vahe introduced a method for user profiling using web usage mining, clustering, and neural networks. Their approach aims to predict user's future requests and enhance the accuracy of recommender systems. This research contributes to the dynamic adaptation of recommendation algorithms.Semantic Understanding in Search Engines (Dharmish et al., 2014): Dharmish, Jheel, and Sindhu proposed a search engine capable of understanding the meaning behind user queries and providing results based on semantic relevance. This approach aims to improve the effectiveness of search engines by returning results that align with user intent beyond keyword matching.

Vietnamese Content-Based News Recommender System (Nguyen et al., 2015): Nguyen, Do, and Viet presented a content-based news recommender system tailored for Vietnamese users. This system leverages short-term and long-term user information to dynamically recommend news articles, demonstrating the adaptability of recommendation systems in diverse cultural contexts.

User Profile Similarity Measurement (Sara et al., 2015): Sara, Seyed, and Hoda proposed a novel model for measuring user profile similarities, departing from traditional approaches by assigning varying weights to items in user profiles. This innovative method contributes to more nuanced similarity assessments.

Keyword-Based User Profiling (Sumit et al., 2016): Sumit, Debajyoti, and Sheetal focused on user profiling by extracting keyword-based information from various web sources. Their research aims to generate structured user profiles and extract knowledge from the profiled information, enhancing the adaptability of recommendation systems.

Collaborative Filtering with Decay Function (Aadhithya & Ela, 2016): Aadhithya and Ela employed a collaborative filtering model that incorporates a decay function to address changing user interests in recommendation systems. Their model provides a dynamic approach to personalized recommendations.

Taxonomy-Based User Knowledge Representation (Wanvimol, 2016): Wanvimol proposed a taxonomy-based method to represent uncertain user knowledge and preferences. This hierarchical structure offers a detailed representation of both user profiles and items, contributing to improved recommendation accuracy.

Mixed-Profiling for Enhanced Recommendations (Siham et al., 2018): Siham, Maryem, and Dalila introduced a Big Data mixed-profiling approach to reduce matrix sparsity and enhance recommendation relevance. This approach integrates explicit and implicit feedback, reflecting user reliability and expertise levels in profiles.

Addressing the Cold Start Problem (Youssouf, 2017): Youssouf tackled the cold start problem in collaborative filtering techniques by incorporating new user demographic data and similarity techniques to identify user 'neighbors.' This approach addresses the challenge of recommending to new or scarcely profiled users.

Recommendation Based on User Publications (Buket, 2018): Buket proposed a method that considers user publications, co-authors, and co-authors' papers to score the user profile based on metadata of articles published by the user. This scoring mechanism enhances the accuracy of user profiles and recommendations in specific subject matters.

Activity and Behavior-Induced Personalized Recommender System (Logesh et al., 2019): Logesh, Subramaniyaswamy, Vijayakumar, and Xiong introduced an activity and behavior-induced personalized recommender system (ABiPRS). This hybrid approach predicts persuasive point-of-interest (POI) recommendations, supporting travelers with effective suggestions for POIs.

User Tag Profiling with Deep Learning (Su et al., 2020): Su, Xin, Ran, Xu, and Leyu developed a user tag profiling model (UTPM) using deep neural networks for multi-label classification. The UTPM model utilizes multi-head attention mechanisms to learn sparse features across different fields, enriching user tag profiles.

Reinforcement Learning-Based Recommender Systems (Debmalya, 2020): Debmalya presented a reinforcement learning-based approach to implement recommender systems. The research highlights interactive, personalized content delivery in a real-life wellness app, showcasing the potential of reinforcement learning in recommendation.

Text Matching Using Deep Learning (Jun et al., 2020): Jun, Xiangnan, and Hang reviewed various machine learning techniques and addressed text matching challenges using deep learning methods. Their work contributes to the advancement of text-based recommendation systems.

Travel Recommender System with Data Mining (Anjali et al., 2021): Anjali, Jasminder, and Deepam explored the potential of travel recommender systems based on user profiles. Their research addresses data sparsity issues and offers personalized content and services to users.

Location-Based Recommender System with Sentiment Analysis (Xiaohui et al., 2021): Xiaohui, Nischal, Patrick, and Aimin proposed a location-based recommender system (LBRS) that combines sentiment analysis and topic modeling to enhance user profiling. This approach improves recommendations for points of interest based on user opinions.

The existing landscape of search engines predominantly relies on keyword-based retrieval, encountering challenges related to synonymy and term matching. Meanwhile, page ranking algorithms remain widely utilized. However, the semantic web offers opportunities to enhance traditional search approaches.

The fuzzy search classifier is mathematically represented as:

cos(θ) = ∑_(i=1)^n (A_1 * B_1) / (√(∑_(i=1)^n (A^2)) * √(∑_(i=1)^n (B^2)))

This mathematical formulation is central to the proposed content-based fuzzy search recommendation system.

In summary, the reviewed literature underscores the evolving landscape of search engines and recommender systems, showcasing diverse methodologies and approaches aimed at improving recommendation

3.1 Research Methodology

For this research project, the Design Science Research will be implemented. Design Science Research can be identified as a paradigm which can be used in problem solving which seeks to enhance human knowledge with the creation of innovative artifacts.

The methodology used for implementing this research is the Design Science Research (DSR). It is seen as a research activity that build new or invents, innovate artifacts for problems solving or improvement attainment such new innovative artifact create a new reality, rather than the existing reality been explain or trying to make sense from it, it creates, and evaluates IT artifact which is intended to solve some identified organizational problems. (Alturki, 2013)

The Design Science Research Methodology is relatively a new approach in the field of Information Systems, and Computer Science because of it prominence rapid growth in the discipline (Alturki, 2013). Design Science Research Methodology basic logic of discovery is deductive, because an unsolved problem is taking and tries to find a justificatory knowledge or a kernel theory which help in solving the problem. (Piirainen, 2014)

3.2 System Analysis

A system is an organized collection of inter related subsystems with a collective responsibility of meeting a goal. Dependent subsystems are regularly interacting while independent group of components forming a unified whole work like standalone in achieving a specified task. A system also defined as an organized or complex unitary whole. The analysis phase answers the questions of who will use the system, what the system will do, and where and when it will be used. During this phase, the project team investigates any current system(s), identifies opportunities for improvement, and develops a concept for the new system. (Dennis, 2015)

System analysis is simply the investigative studies carried out on systems under consideration. These system maybe real and already existing systems or envisioned systems for future development. The primary goal of system analysis is to determine much improved and efficient ways in which systems should function. The analysis are usually based on proper knowledge of the organization and business process for which the system is developed as well as the knowledge of how Information Technology can be exploited to boost processes. (W3C, 2016)

System analysis is the procedure system analysts follow to determine how a system ought to out to work i.e. figuring out the functions, how achievable it is based on the constraints like budget and ensuring that advantages of the system will exceed the expenses incurred in setting up the system.

In the software engineering process, system analysis is one of the primary stages in the requirements engineering phase and it is a major pre-requisite for system design. It is a very important phase that will require both creative and critical thinking for the system developed to optimally provide solutions to the problems for which it was created and ultimately satisfy the needs of the users. Creating the system design specific at an early stage within the system development needs some analysis. The choices made in the analysis and design of the core competencies of the system have a profound impact on whether or not the system will meet crucial necessities such as performance, dependableness and maintainability (Sommerville, 2007).

3.3 Systems Architecture

In any system design, the output is considered first because it is the desired output that will determine both the input and the procedure. All the components of the program (such as different subprogram/modules designed separately) were integrated together to become a single program and then test run. Figure 3.1 below explains the architecture of the system. It shows how various systems interact with each other and the users to create my working book recommendation system.

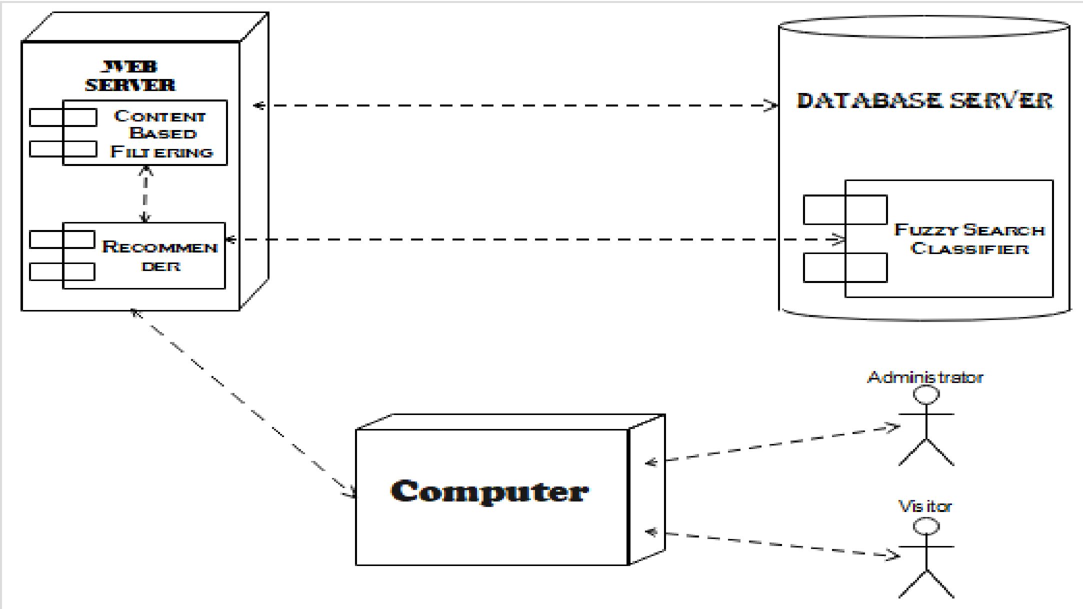

Figure 3.1 System Architecture

3.4 Data Collection Method

Secondary method of data collection was implemented in this research:

Online Research: Online research is a research method that involves the collection of information from the internet. With the advent of the internet, the traditional pen-and-paper research techniques have taken a backseat and made room for online research.

This method was implemented in my research because it is much more impactful than the traditional means, considering the ease of access and cost savings they come with. The response rates received for online research are much higher than the others as the respondents are assured that their identity will be protected.

3.5. Theoretical framework

Table 1: Books Dataset:

BookID	Title	Author	Genre	Description
1	The Catcher in the Rye	J.D. Salinger	Fiction	A classic novel about a teenager in New York City.
2	To Kill a Mockingbird	Harper Lee	Fiction	A powerful story about racism and injustice...
3	1984	George Orwell	Science Fiction	A dystopian tale of a totalitarian society.

4	Pride and Prejudice	Jane Austen	Classic	A timeless love story set in 19th-century...
5	The Great Gatsby	F. Scott Fitzgerald	Fiction	A story of excess and disillusionment...

Table 2: User Preferences Dataset:

UserID	BookID_Rated	Rating
1	1	4.5
2	2	5.0
3	3	3.5
4	4	4.0
5	5	2.0

Mathematical Formulas:

TF-IDF (Term Frequency-Inverse Document Frequency):

Term Frequency (TF) measures how frequently a term (word) appears in a document.

Inverse Document Frequency (IDF) measures the importance of a term across all documents.

Formula for TF-IDF:

$$\text{TF-IDF}(t, d, D) = \text{tf}(t, d) \cdot \text{idf}(t, D)$$

Where:

TF(t, d) = Term Frequency of term 't' in document 'd'

IDF(t, D) = Inverse Document Frequency of term 't' in corpus 'D'

Cosine Similarity:

Cosine Similarity measures the cosine of the angle between two non-zero vectors in an inner product space.

Formula for Cosine Similarity between two vectors A and B:

$$\text{Cosine Similarity}(A, B) = \frac{A \cdot B}{|A| \cdot |B|}$$

Fuzzy String Matching:

Fuzzy String Matching algorithms (e.g., Levenshtein Distance, Jaccard Similarity) can be used to compare strings with variations, such as typos.

Recommendation Score:

The recommendation score for a user-item pair can be calculated using the similarity between the user's preferences (profile) and the item's features (e.g., TF-IDF vectors).

Formula for Recommendation Score (S) for user 'u' and item 'i':

$$S(u, i) = \text{Cosine Similarity}(\text{TF-IDF vector of user profile}, \text{TF-IDF vector of item description})$$

4: Design and implementation

Implementing this recommender system involves designing an MSSQL Server database for storing book/item data and user preferences. In ASP.NET, create a user-friendly web interface to gather new user preferences, preprocess data, implement fuzzy search functionality, and generate recommendations based on content similarity. Ensure security, evaluate system performance, and deploy for real-world usage, with ongoing maintenance and updates for accuracy and scalability.

4.1 System Design Diagram

System modeling is the process of developing abstract models of a system, with each model presenting a different view or perspective of that system. It is about representing a system using some kind of graphical notation, which is now almost always based on notations in the Unified Modeling Language (UML). Models help the analyst to understand the functionality of the system.

USE CASE DIAGRAM

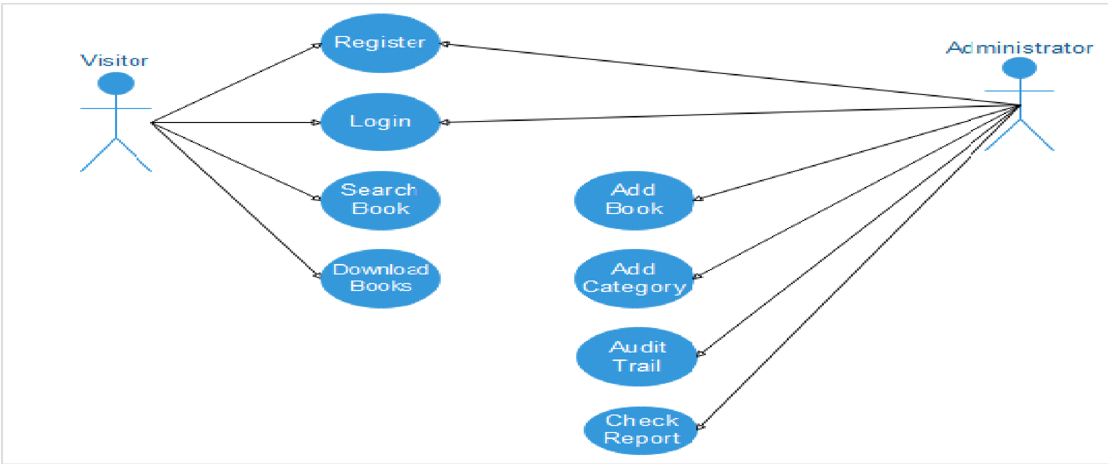

Figure 4.1 User and Admin Use Case Diagram

ACTIVITY DIAGRAM

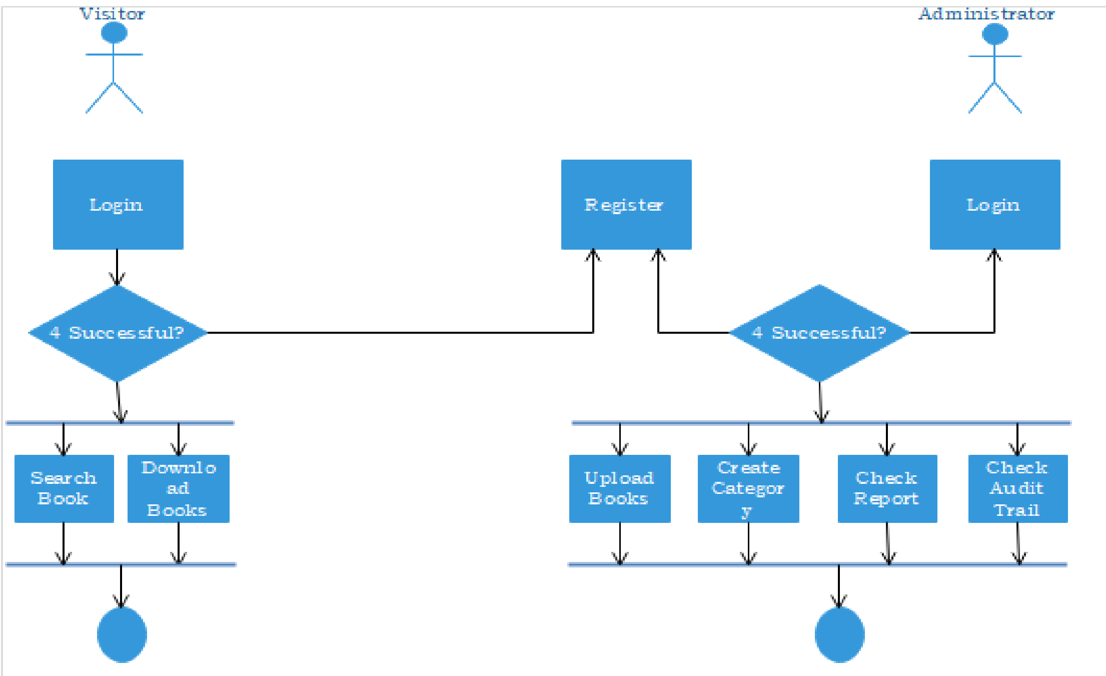

Figure 4.2 User and Admin Activity Diagram

CLASS DIAGRAM

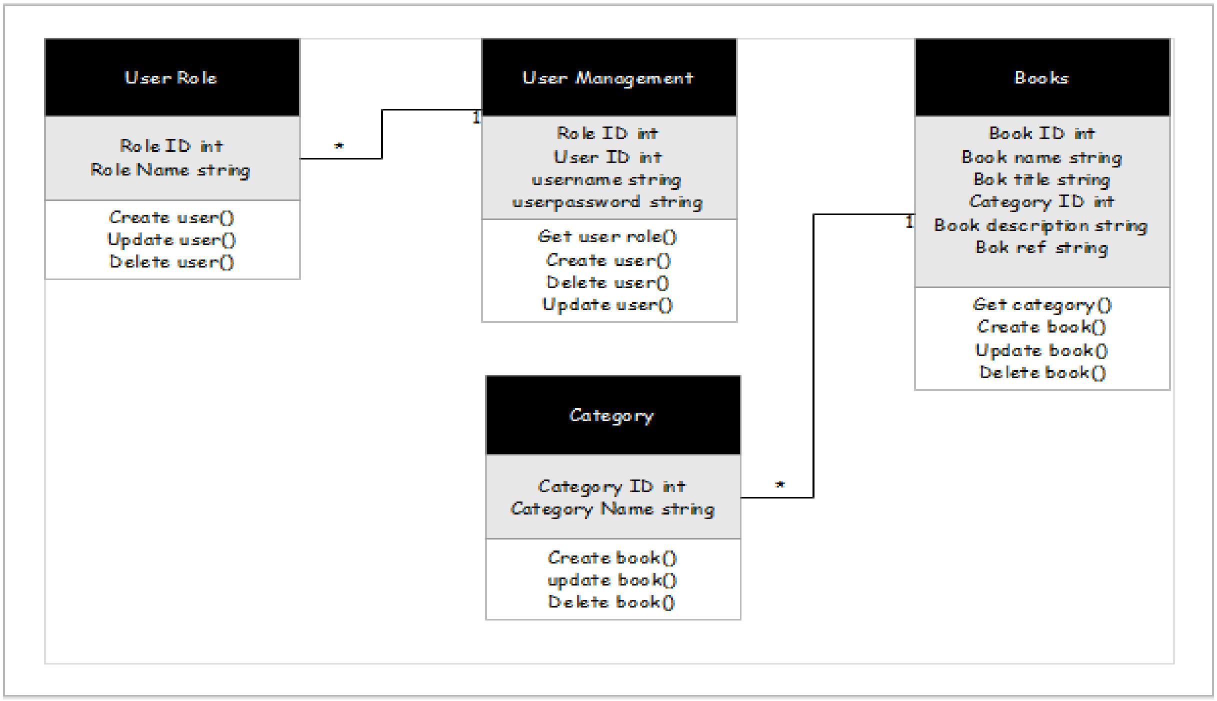

Figure 4.3 Class Diagram of the System

SEQUENCE DIAGRAM

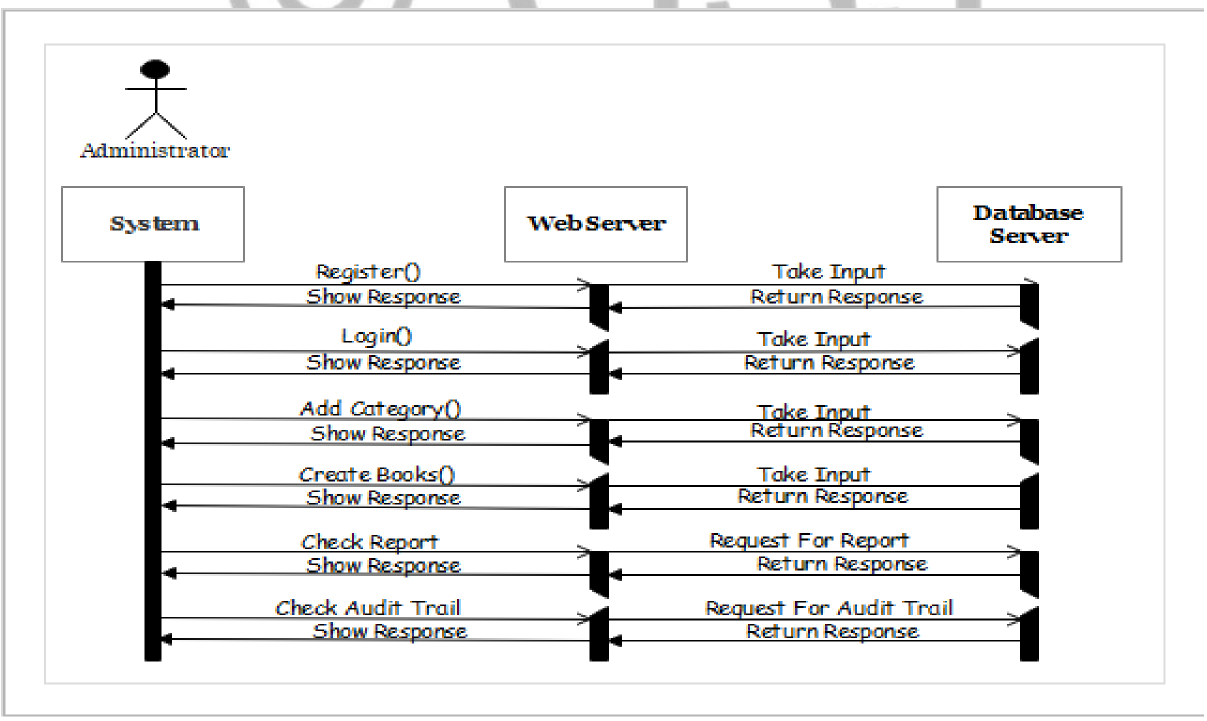

Figure 4.4 Admin Sequence Diagram

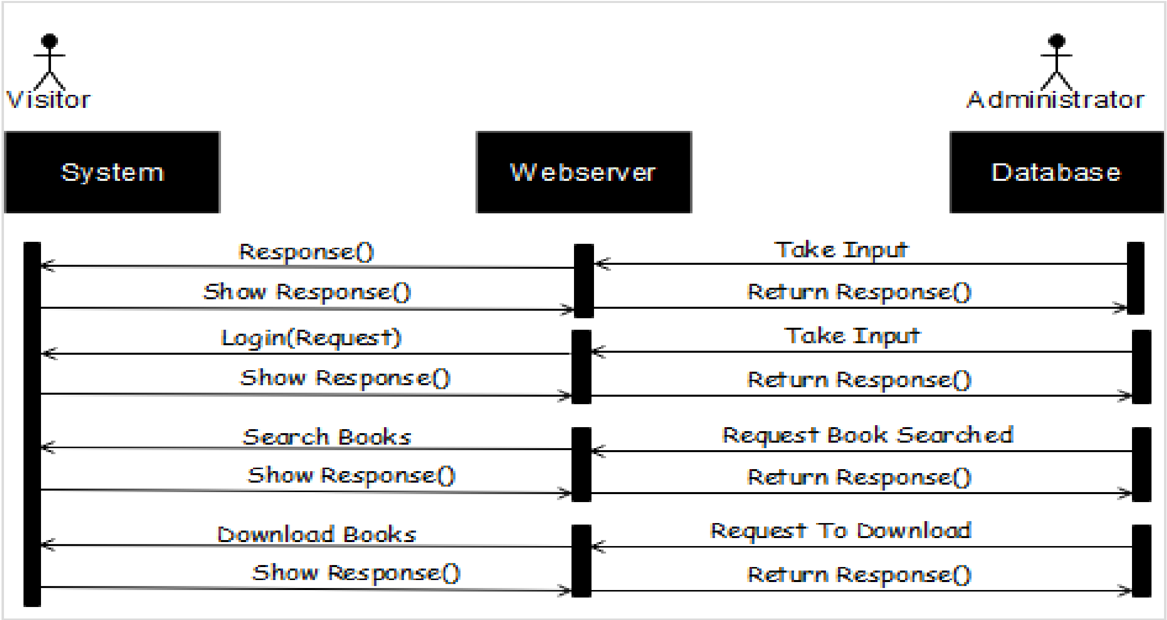

Figure 4.5 User Sequence Diagram

4.2 Web Module

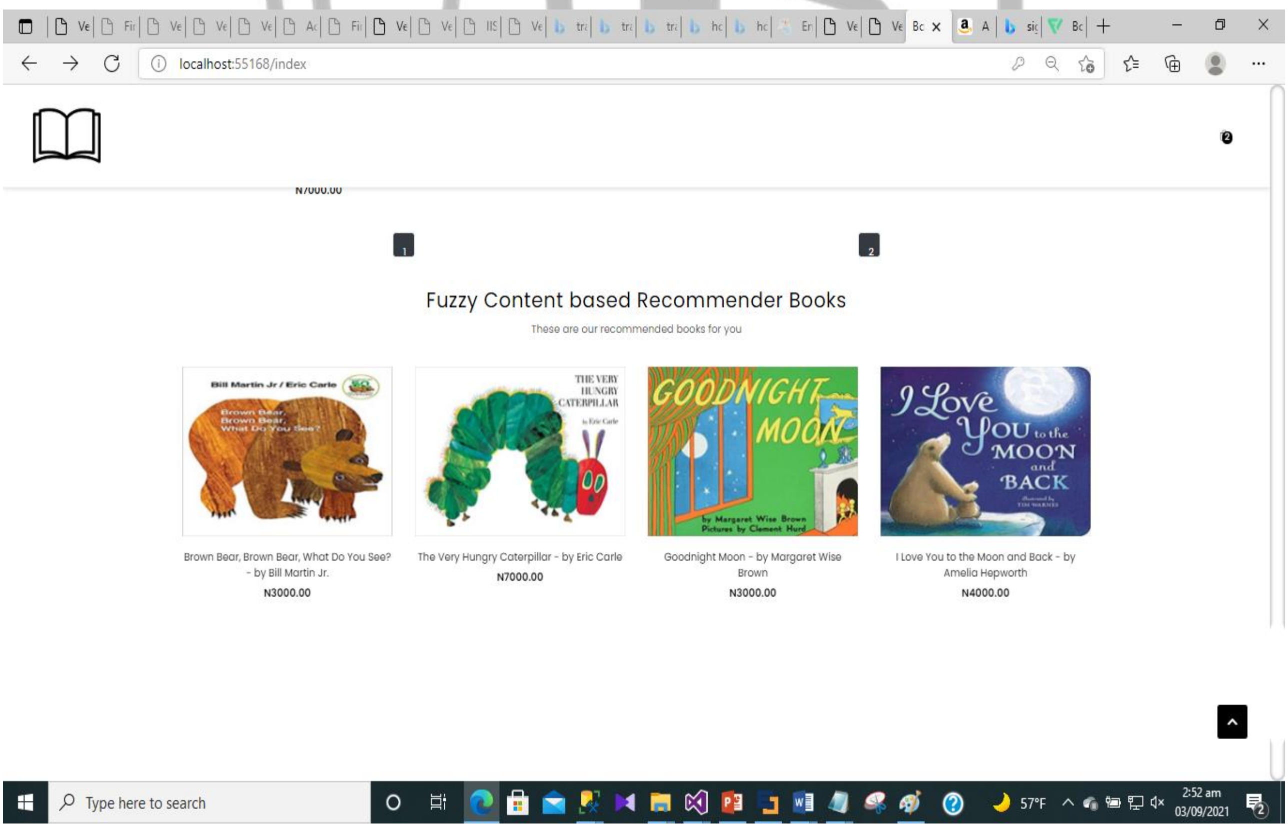

Figure 4.6 Book Recommendation Page

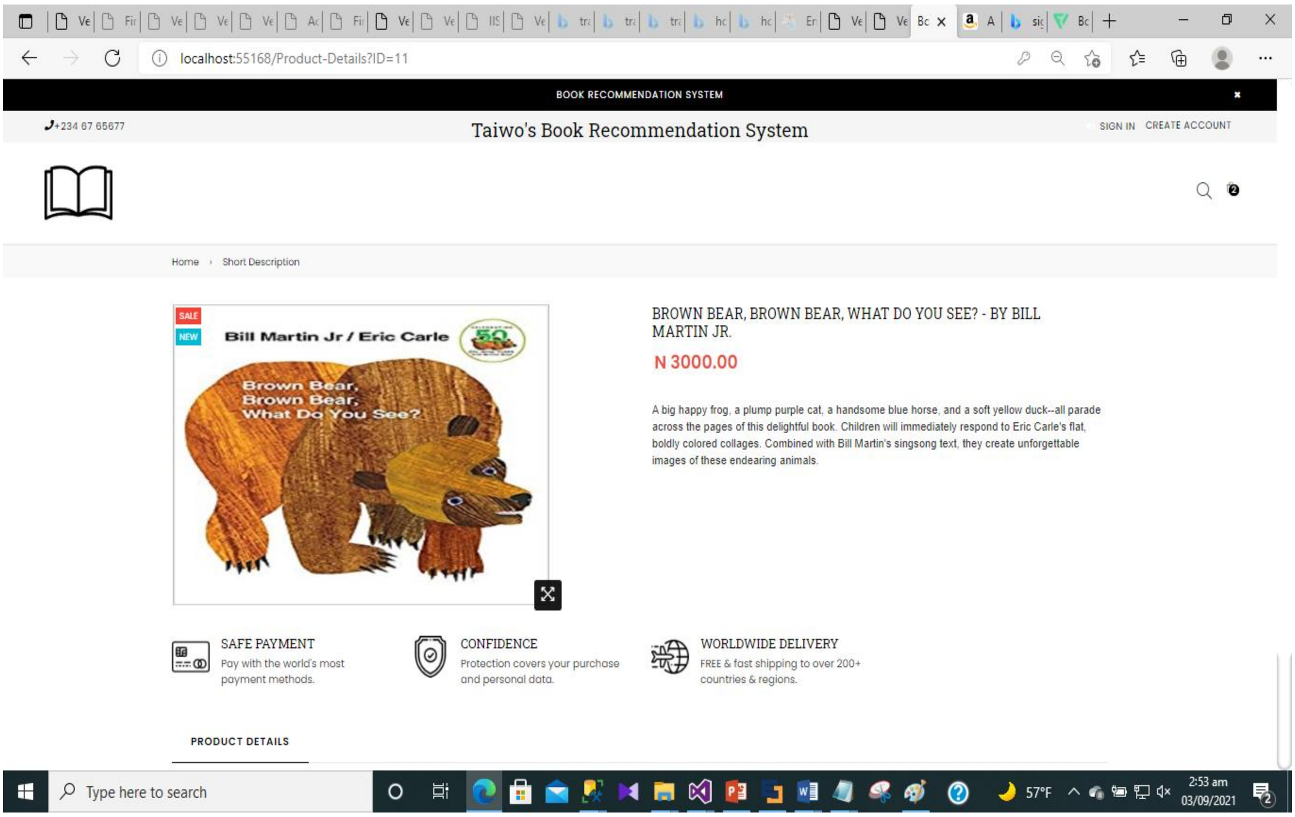

Figure 4.7 Book Details Page

Table 3: User Preferences:

User ID	Genre Preference	Keyword Search
6	Fiction	Mystery

Table 4: System Result:

Book ID	Title	Author	Genre	Description	Content Similarity Score
7	The Da Vinci Code	Dan Brown	Mystery, Thriller	A gripping mystery that unravels the secrets of the past.	0.85
8	Gone Girl	Gillian Flynn	Mystery, Thriller	A psychological thriller that keeps you guessing until the end.	0.81
9	The Girl with the Dragon Tattoo	Stieg Larsson	Mystery, Thriller	An investigative journalist and a hacker team up to solve a decades-old mystery.	0.78
10	In the Woods	Tana French	Mystery, Crime	A detective returns to his hometown to investigate a murder with disturbing ties to his own past.	0.76

The user (User ID 6) has a genre preference for "Fiction" and a keyword search for "Mystery."

The system recommends four books with their respective details, including title, author, genre, and description.

The "Content Similarity Score" represents how closely each recommended book aligns with the user's preferences. Higher scores indicate better matches.

The system ranks and recommends books based on content similarity, providing numerical scores to assist the user in making selections.

5 Findings and Discussions

Throughout this project, our focus has been on designing and implementing a Content-Based Recommender System using the Fuzzy Search Classifier. Our journey involved a comprehensive review of existing literature on the problem domain, the prerequisites for solving it, the tools and resources required, and the suitable areas for deploying our solution. As part of our study, we formulated potential solutions and conducted a rigorous analysis of these models, taking into account constraints such as time, resources, available tools, and expertise. Subsequently, we developed a system aimed at addressing the search retrieval problem effectively.

5.1 Conclusion

This paper introduces the realm of recommender systems, which play a crucial role in the age of information overload. As the volume of available data continues to grow, it becomes increasingly challenging for users to identify relevant information efficiently.Recommender systems have their roots in various research areas, including information retrieval, information filtering, text classification, and more. They employ diverse techniques, such as machine learning and data mining, and encompass concepts like collaborative, content-based, and hybrid approaches. Evaluation methods play a vital role in assessing their effectiveness.The importance of recommender systems cannot be overstated, and their potential applications are vast. They streamline the process of recommending items, making it not only efficient but also time-saving for users. In this era of information abundance, recommender systems offer a valuable solution for guiding users to discover the most relevant content tailored to their preferences and needs.

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