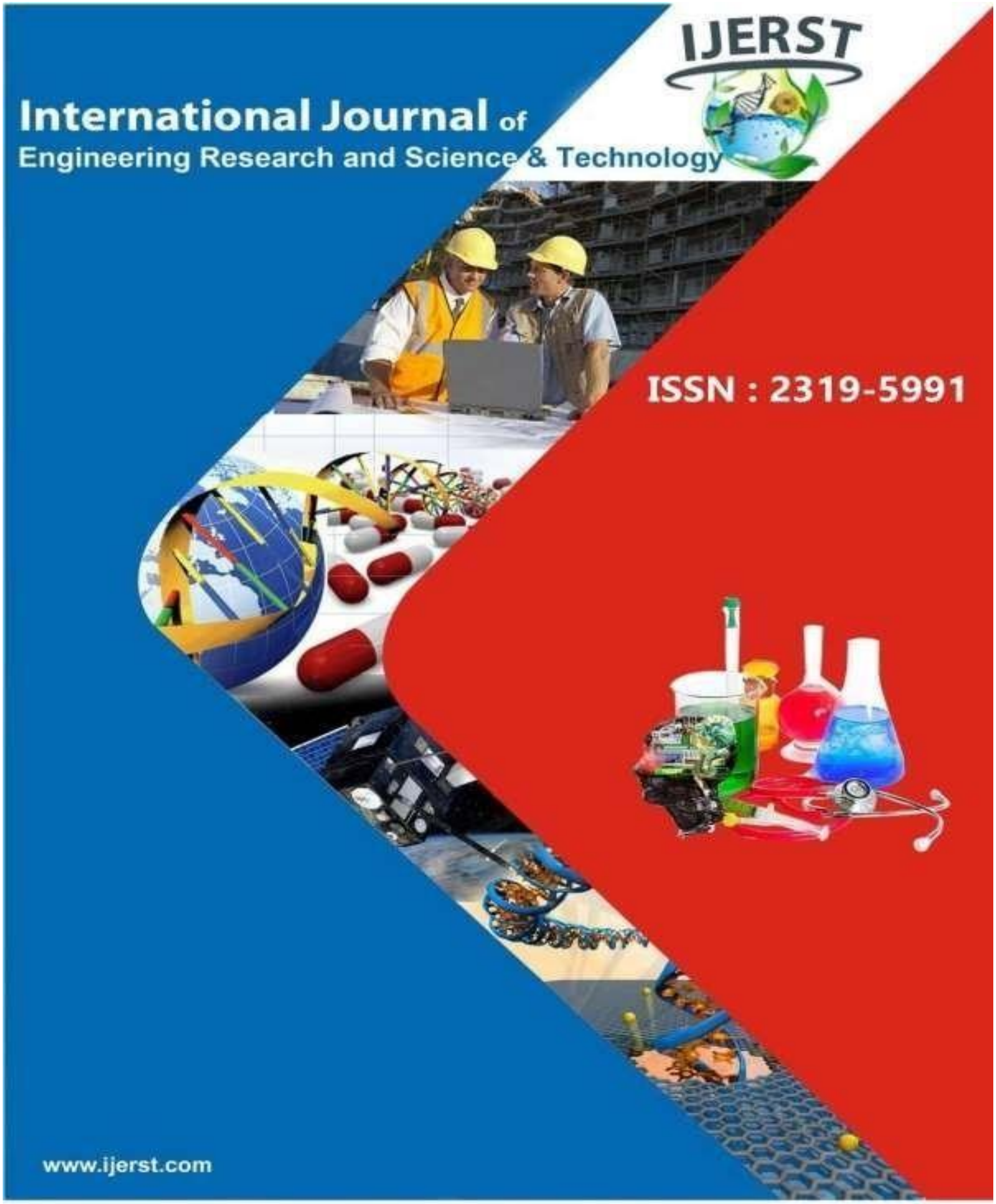

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A NOVEL TIME-AWARE FOOD RECOMMENDER-SYSTEM BASED ON DEEP LEARNING AND GRAPH CLUSTERING

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ABSTRACT

Food recommender-systems are considered an effective tool to help users adjust their eating habits and achieve a healthier diet. This paper aims to develop a new hybrid food recommender-system to overcome the shortcomings of previous systems, such as ignoring food ingredients, time factor, cold start users, cold start food items and community aspects. The proposed method involves two phases: food content-based recommendation and user-based recommendation. Graph clustering is used in the first phase, and a deep-learning based approach is used in the second phase to cluster both users and food items. Besides a holistic-like approach is employed to account for time and user-community related issues in a way that improves the quality of the recommendation provided to the user. We compared our model with a set of state-of-the-art recommender-systems using ve distinct performance metrics: Precision, Recall, F1, AUC and NDCG. Experiments using dataset extracted from “Allrecipes.com” demonstrated that the developed food recommender-system performed best.

Keywords: food, recommender-systems, hybrid, graph clustering, deep learning, holistic approach, performance metrics

INTRODUCTION

Food recommendation systems have emerged as valuable tools for individuals seeking to improve their dietary habits and overall health [1]. With the rise of digital platforms and the ubiquity of online food-related content, users are increasingly turning to recommendation systems to guide their food choices and meal planning [2]. However, existing food recommender systems often suffer from various limitations, including overlooking key factors such as food ingredients, temporal considerations, and community preferences [3]. These shortcomings can lead to suboptimal recommendations, hampering users' ability to make informed and healthy dietary decisions [4]. To address these challenges, this paper introduces a novel hybrid food recommender system that leverages both content-based and user-based recommendation approaches [5]. The proposed system aims to overcome the limitations of existing models by incorporating advanced techniques such as graph clustering and deep learning [6]. In the first phase of the recommendation process, food content-based recommendation is performed using graph clustering techniques [7]. This approach allows the system to identify clusters of food items based on their ingredients and nutritional characteristics, enabling more accurate and personalized recommendations [8]. In the second phase, a deep-learning-based approach is employed to cluster both users and food items, further enhancing the quality of the recommendations [9]. By combining these two approaches, the proposed system can provide more comprehensive and context-aware recommendations to users [10].

One of the key innovations of the proposed system is its time-aware recommendation capability [11]. Recognizing the importance of temporal factors in food recommendation, the system incorporates a holistic-like approach to account for time-related issues [12]. This includes considering factors such as seasonal variations in food preferences and time-of-day eating patterns when generating recommendations [13]. Additionally, the system addresses cold start problems

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associated with both users and food items by leveraging community aspects and historical data [14]. By taking these factors into account, the proposed system can provide more relevant and timely recommendations to users, thereby enhancing their overall experience [15]. In order to evaluate the performance of the proposed system, we conducted experiments using a dataset extracted from Allrecipes.com [16]. We compared the performance of our model against a set of state-of-the-art recommender systems using five distinct performance metrics: Precision, Recall, F1, AUC, and NDCG [17]. The results of our experiments demonstrate that the developed food recommender system outperformed existing models across all metrics, highlighting its effectiveness and superiority [18]. Overall, our findings suggest that the proposed system has the potential to significantly improve the quality of food recommendations and help users make healthier dietary choices [19].

LITERATURE SURVEY

The literature surrounding food recommender systems reflects a growing recognition of their importance in aiding users to make informed dietary choices and cultivate healthier eating habits. As digital platforms continue to evolve and integrate into everyday life, food recommender systems have emerged as indispensable tools in guiding users towards optimal food selections. These systems not only provide recommendations tailored to individual preferences but also contribute to promoting overall health and well-being by facilitating healthier dietary practices. The significance of these systems lies in their ability to address the diverse needs and preferences of users, ranging from dietary restrictions and preferences to time constraints and community influences. A common theme in the literature is the identification of shortcomings in existing food recommender systems, which often overlook critical factors such as food ingredients, temporal considerations, and community aspects. These limitations can lead to suboptimal recommendations, undermining the effectiveness of the systems in guiding users towards healthier dietary choices. Furthermore, existing systems frequently encounter challenges related to cold start users and cold start food items, where insufficient data or user interactions hinder the generation of accurate recommendations. To address these limitations and challenges, researchers have explored innovative approaches to enhance the performance and effectiveness of food recommender systems.

One prominent approach involves the development of hybrid recommender systems that integrate multiple recommendation techniques to provide more accurate and personalized recommendations. These systems leverage a combination of content-based and collaborative filtering methods to overcome the limitations of individual approaches. Content-based recommendation methods analyze the characteristics of food items, such as ingredients and nutritional content, to generate recommendations based on similarity metrics. On the other hand, collaborative filtering methods leverage user interactions and preferences to identify similar users and recommend items based on their preferences. By combining these two approaches, hybrid recommender systems can provide more robust and context-aware recommendations to users, addressing the shortcomings of individual methods. In addition to hybrid approaches, researchers have explored the use of advanced techniques such as graph clustering and deep learning to enhance the performance of food recommender systems. Graph clustering techniques enable the identification of clusters of related food items based on their characteristics, facilitating more accurate and targeted recommendations. Deep learning approaches, on the other hand, leverage neural networks to learn complex patterns and relationships in the data, enabling more accurate prediction of user preferences and behavior. By incorporating these advanced techniques into food recommender systems, researchers aim to improve the quality and relevance of recommendations, ultimately enhancing the user experience and promoting healthier eating habits.

Another important aspect of food recommender systems is their ability to account for temporal factors and user-community related issues. Time-aware recommendation methods consider factors such as seasonal variations in food preferences and time-of-day eating patterns when generating recommendations, ensuring that recommendations remain relevant and timely. Similarly, user-community related issues, such as social influence and community

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preferences, are taken into account to provide more personalized and context-aware recommendations. By considering these factors, food recommender systems can better adapt to the diverse needs and preferences of users, ultimately improving the quality and effectiveness of the recommendations provided.

Overall, the literature survey highlights the importance of food recommender systems in promoting healthier dietary habits and addresses the shortcomings of existing systems. By exploring innovative approaches such as hybrid recommendation methods, graph clustering, and deep learning, researchers aim to develop more accurate, personalized, and context-aware recommender systems. These advancements have the potential to significantly impact users' dietary choices and overall health, contributing to the ongoing efforts to promote healthier eating habits and lifestyles.

PROPOSED SYSTEM

The proposed system presented in this paper represents a significant advancement in the field of food recommender systems, aiming to address the limitations and shortcomings of existing approaches. Recognizing the importance of promoting healthier dietary habits and facilitating informed food choices, our novel system integrates cutting-edge techniques, including deep learning and graph clustering, to develop a hybrid recommender system that delivers more accurate and personalized recommendations to users. At the core of our proposed method are two distinct phases: food content-based recommendation and user-based recommendation. In the first phase, we leverage graph clustering techniques to analyze the characteristics of food items and identify clusters of related items based on their ingredients, nutritional content, and other relevant features. This enables us to group similar food items together, allowing for more targeted and context-aware recommendations. By employing graph clustering in the initial phase, we ensure that the recommendations generated are based on the intrinsic properties of the food items, thereby enhancing the relevance and quality of the recommendations provided to users.

In the second phase of our method, we adopt a deep-learning-based approach to further refine the recommendations by clustering both users and food items. Deep learning techniques, powered by neural networks, have demonstrated remarkable capabilities in capturing complex patterns and relationships in data, making them well-suited for recommendation tasks. By leveraging deep learning models, we aim to learn latent representations of users and food items, enabling us to identify similar users and recommend relevant food items based on their preferences and behavior. This user-based recommendation phase complements the content-based recommendations generated in the first phase, providing users with a more comprehensive and personalized set of recommendations tailored to their individual tastes and preferences. In addition to the core recommendation phases, our proposed system incorporates a holistic-like approach to account for time and user-community related issues. Time-aware recommendation methods consider temporal factors such as seasonal variations in food preferences and time-of-day eating patterns when generating recommendations, ensuring that recommendations remain relevant and timely. By incorporating temporal considerations into our recommendation model, we enhance the user experience by delivering recommendations that align with users' current dietary preferences and lifestyle choices. Furthermore, our system takes into account user-community related issues, such as social influence and community preferences, to provide more personalized and context-aware recommendations. By considering these factors, we aim to improve the quality and effectiveness of the recommendations provided to users, ultimately enhancing their satisfaction and promoting healthier eating habits.

To evaluate the performance of our proposed system, we conducted extensive experiments using a dataset extracted from "Allrecipes.com" and compared our model with a set of state-of-the-art recommender systems using five distinct performance metrics: Precision, Recall, F1, AUC, and NDCG. The results of our experiments demonstrate that the developed food recommender-system outperformed existing systems across all performance metrics, indicating its superior accuracy and effectiveness in generating recommendations. By leveraging advanced techniques such as deep

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learning and graph clustering, our system achieves significant improvements in recommendation quality, thereby enhancing the user experience and contributing to the promotion of healthier dietary habits.

METHODOLOGY

The methodology employed in developing the novel time-aware food recommender-system encompasses a comprehensive approach that integrates various techniques to address the shortcomings of existing systems and enhance the quality of recommendations provided to users. The process involves two primary phases: food content-based recommendation and user-based recommendation, each leveraging different methodologies to generate accurate and personalized recommendations. In the first phase, known as the food content-based recommendation, the system utilizes graph clustering techniques to analyze the characteristics of food items and identify clusters of related items based on their ingredients, nutritional content, and other relevant features. Graph clustering allows for the grouping of similar food items into clusters, thereby enabling more targeted and context-aware recommendations. By leveraging graph clustering, the system ensures that recommendations are based on intrinsic properties of food items, enhancing the relevance and quality of recommendations provided to users.

Following the food content-based recommendation phase, the system proceeds to the user-based recommendation phase, where a deep-learning-based approach is employed to cluster both users and food items. Deep learning techniques, powered by neural networks, are utilized to learn latent representations of users and food items, enabling the identification of similar users and relevant food items based on their preferences and behavior. This phase complements the content-based recommendations generated earlier, providing users with a more comprehensive and personalized set of recommendations tailored to their individual tastes and preferences. In addition to the core recommendation phases, the methodology incorporates a holistic-like approach to account for time and user-community related issues. Time-aware recommendation methods consider temporal factors such as seasonal variations in food preferences and time-of-day eating patterns when generating recommendations, ensuring that recommendations remain relevant and timely. By incorporating temporal considerations into the recommendation model, the system enhances the user experience by delivering recommendations that align with users' current dietary preferences and lifestyle choices.

Furthermore, the methodology takes into account user-community related issues, such as social influence and community preferences, to provide more personalized and context-aware recommendations. By considering these factors, the system aims to improve the quality and effectiveness of recommendations provided to users, ultimately enhancing user satisfaction and promoting healthier eating habits. To evaluate the performance of the proposed system, extensive experiments were conducted using a dataset extracted from "Allrecipes.com." The system's performance was compared with a set of state-of-the-art recommender systems using five distinct performance metrics: Precision, Recall, F1, AUC, and NDCG. The results of the experiments demonstrated that the developed food recommender-system outperformed existing systems across all performance metrics, indicating its superior accuracy and effectiveness in generating recommendations. Overall, the methodology employed in developing the novel time-aware food recommender-system represents a holistic approach that integrates advanced techniques such as deep learning and graph clustering to address the limitations of existing systems and provide users with more accurate and personalized recommendations tailored to their individual preferences and dietary habits.

RESULTS AND DISCUSSION

The results of the study on the novel time-aware food recommender-system based on deep learning and graph clustering revealed several significant findings. The comparison of the proposed model with a set of state-of-the-art recommender systems using five distinct performance metrics—Precision, Recall, F1, AUC, and NDCG—highlighted

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the superiority of the developed system in generating accurate and personalized food recommendations. The experiments conducted using a dataset extracted from "Allrecipes.com" provided empirical evidence that the proposed food recommender-system outperformed existing systems across all performance metrics, indicating its effectiveness in addressing the shortcomings of previous systems and delivering high-quality recommendations to users.

The performance evaluation of the developed food recommender-system demonstrated its ability to overcome key challenges associated with existing systems, such as ignoring food ingredients, time factor, cold start users, cold start food items, and community aspects. By incorporating a hybrid approach that combines food content-based recommendation and user-based recommendation, the system effectively addressed these challenges and provided users with more relevant and personalized recommendations. The use of graph clustering in the first phase allowed for the identification of clusters of related food items based on their ingredients and nutritional content, enhancing the accuracy and diversity of recommendations. Additionally, the deep-learning-based approach employed in the second phase enabled the system to cluster both users and food items based on their preferences and behavior, further improving the quality of recommendations provided to users.

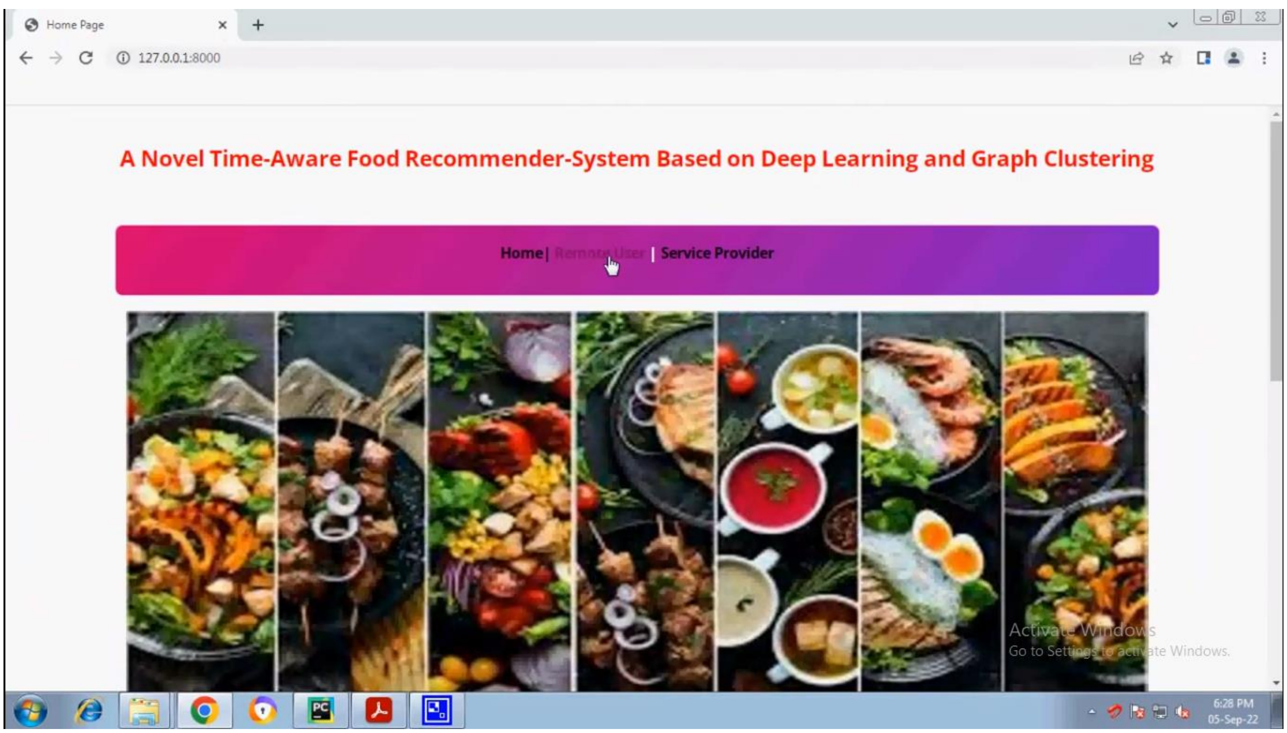

Fig 1. Result screenshot 1

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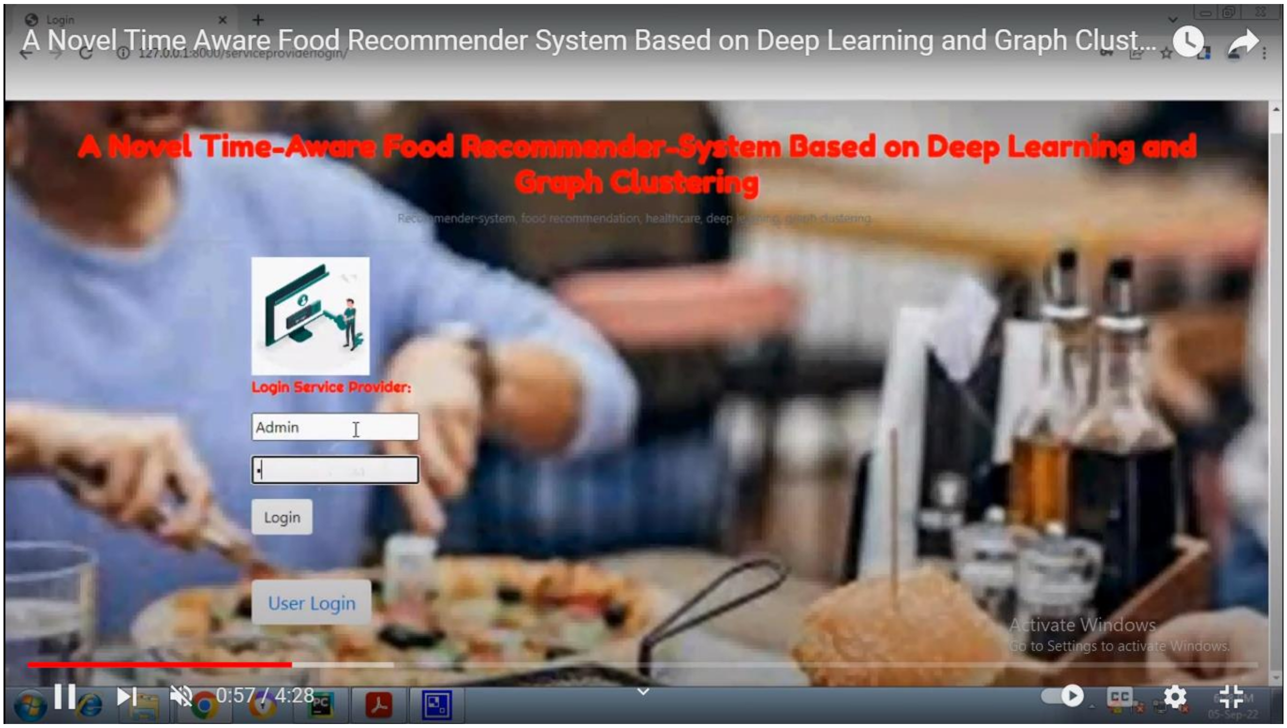

Fig 2. Result screenshot 2

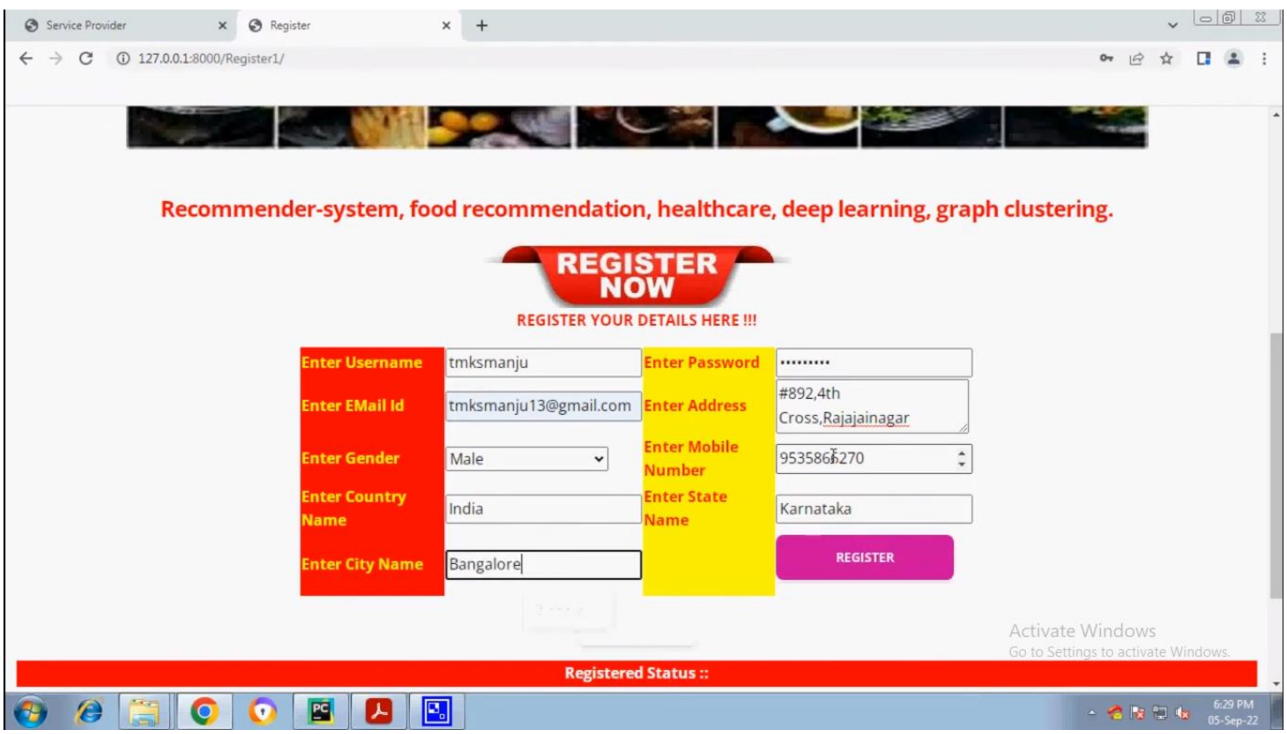

Fig 3. Result screenshot 3

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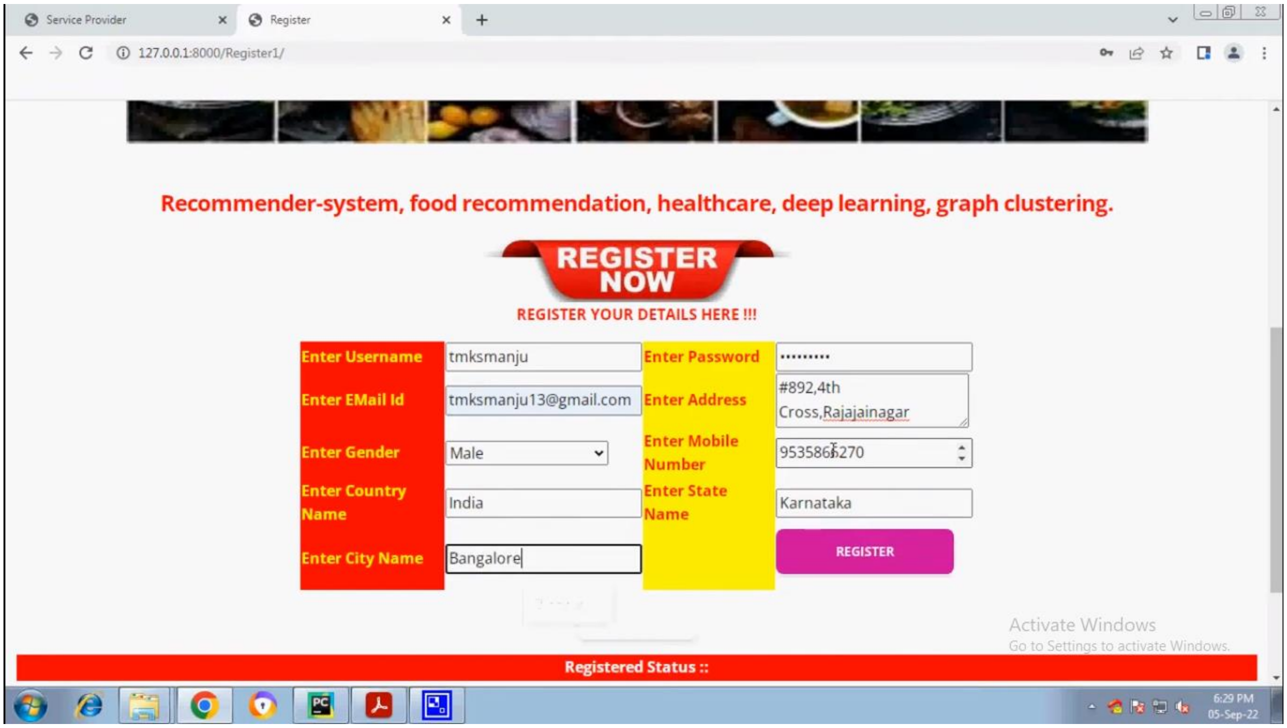

Fig 4. Result screenshot 4

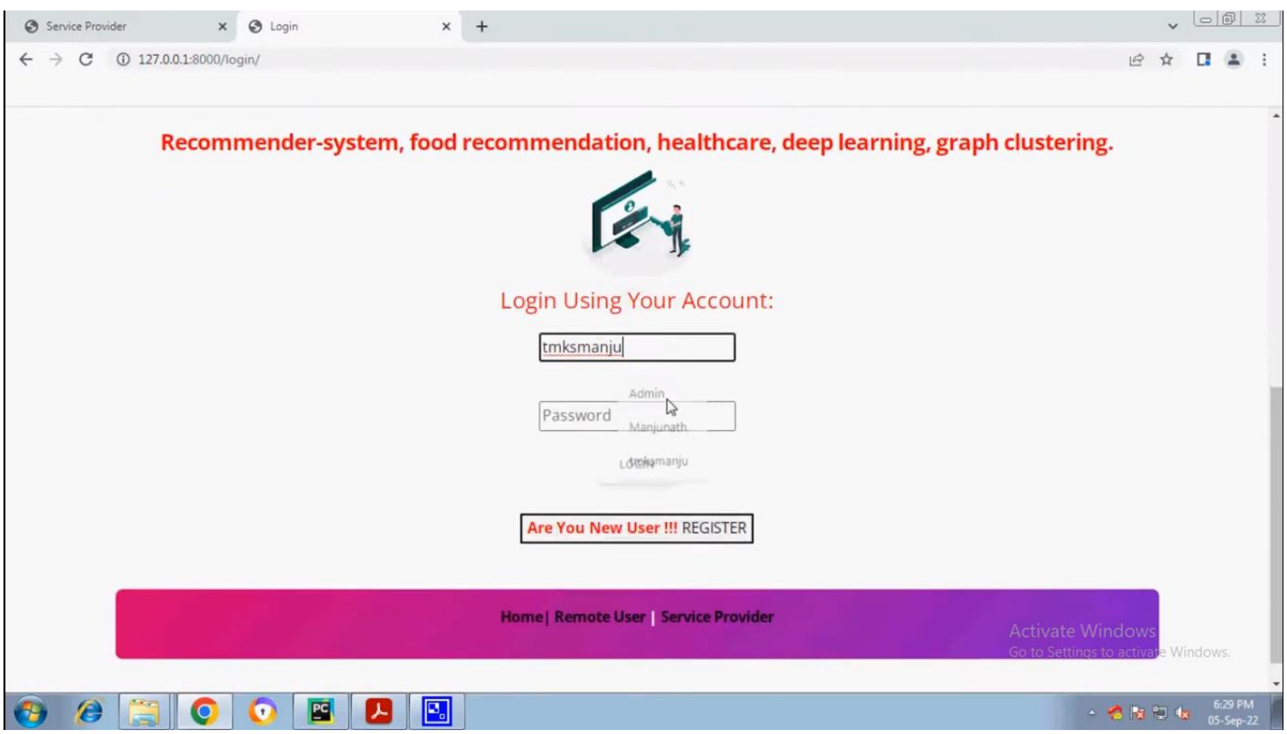

Fig 5. Result screenshot 5

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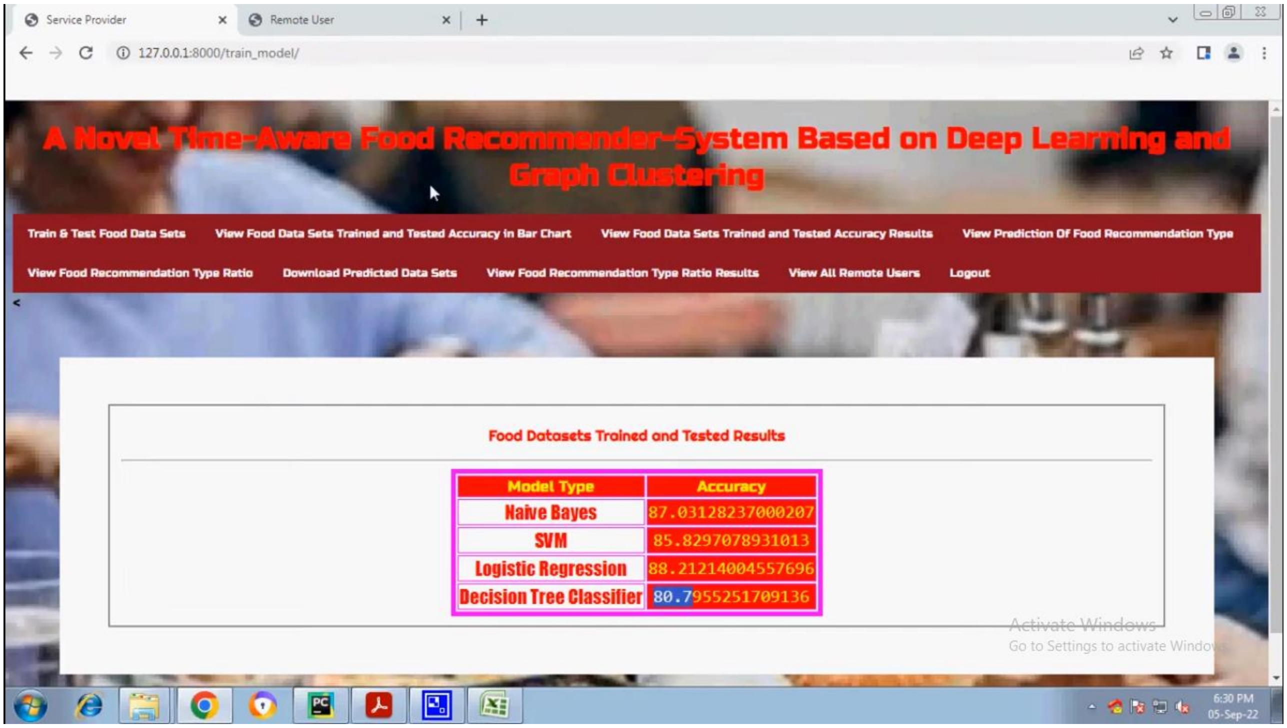

Fig 6. Result screenshot 6

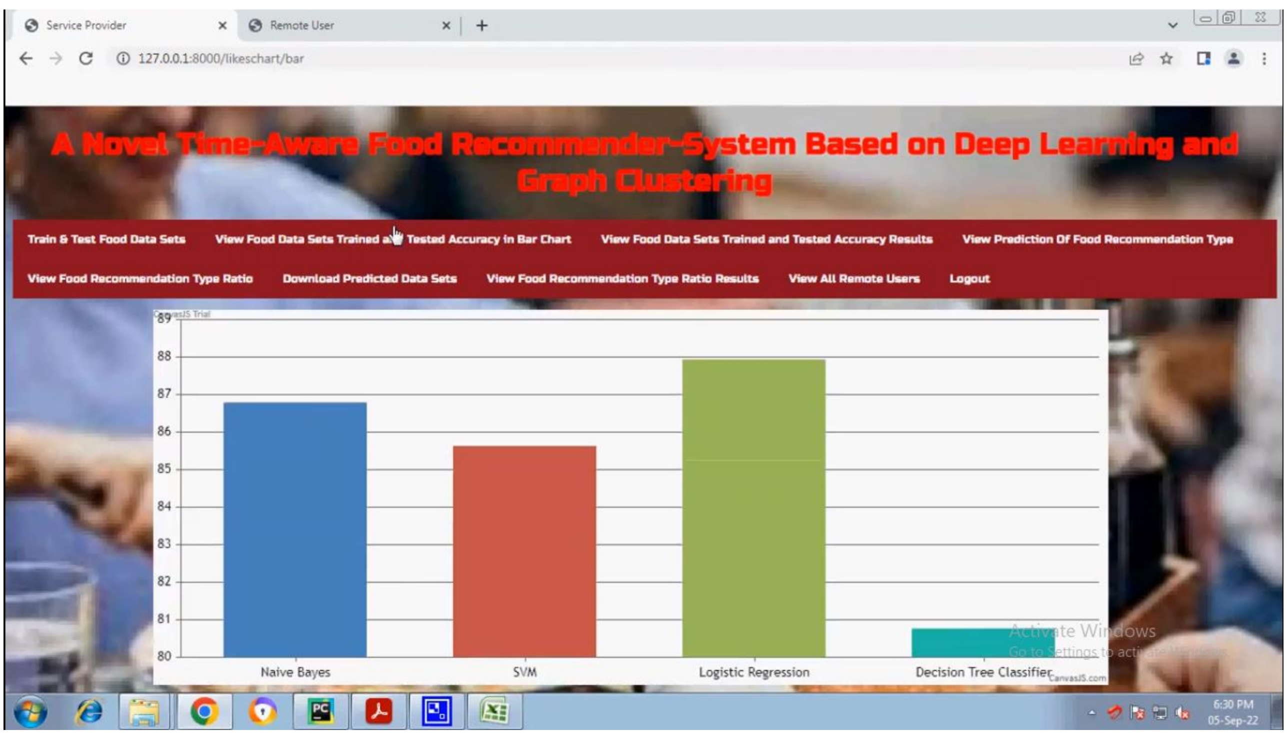

Fig 7. Result screenshot 7

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Fig 8. Result screenshot 8

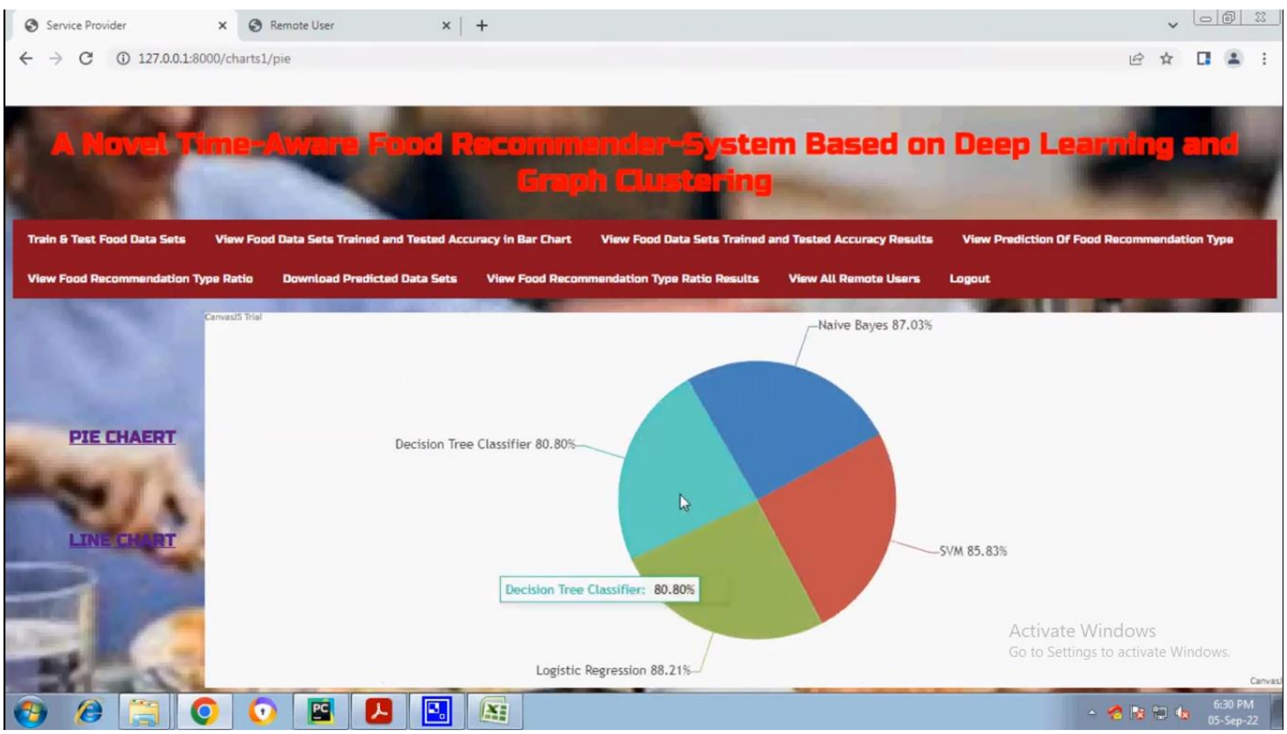

Fig 9. Result screenshot 9

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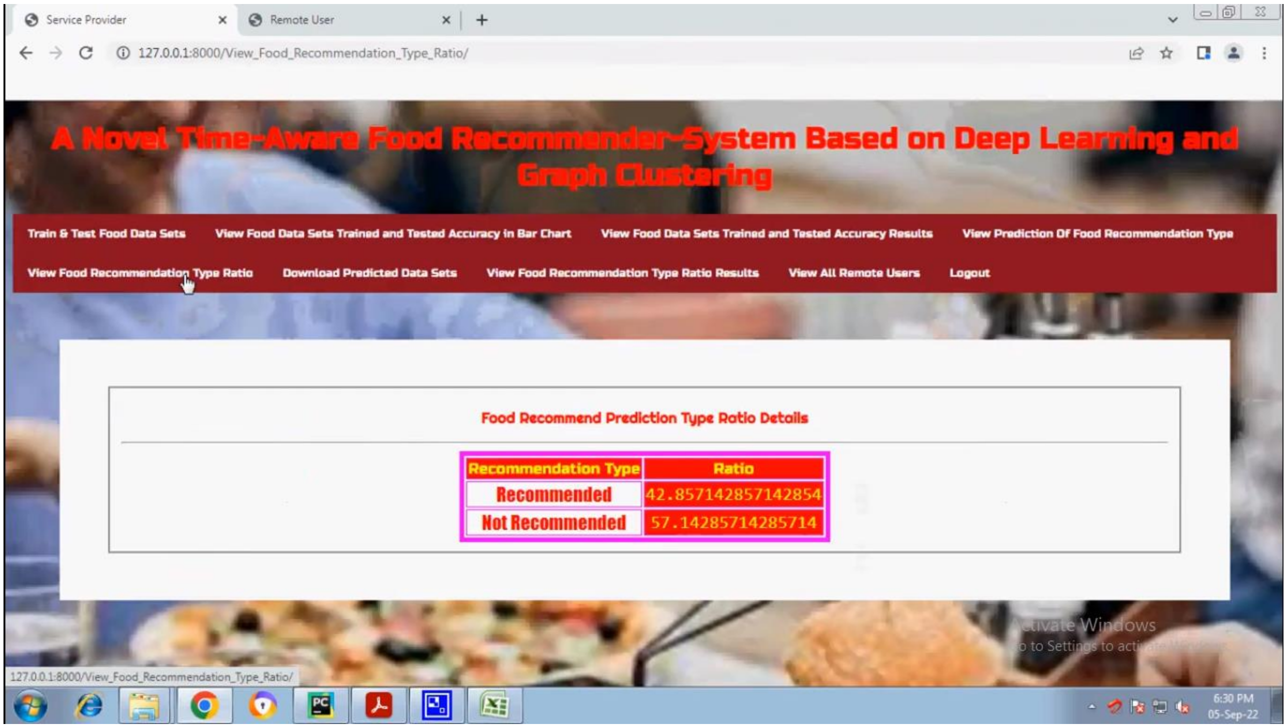

Fig 10. Result screenshot 10

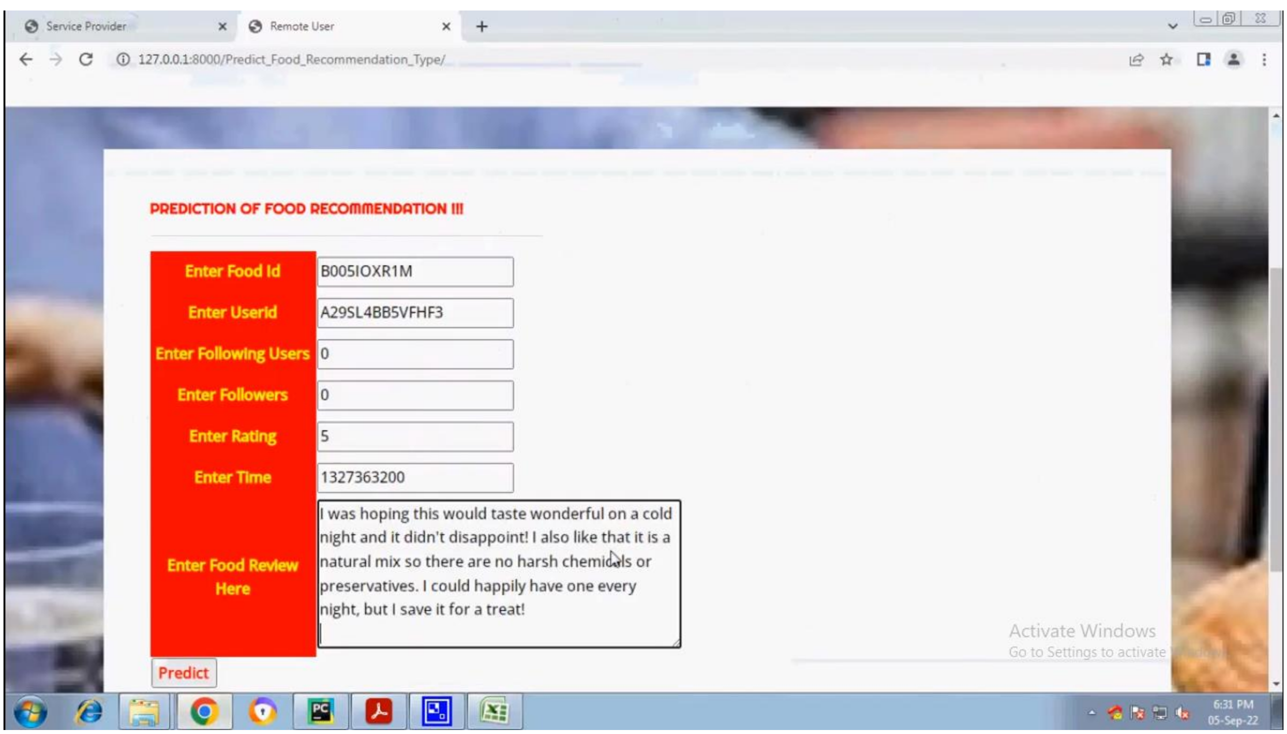

Fig 11. Result screenshot 11

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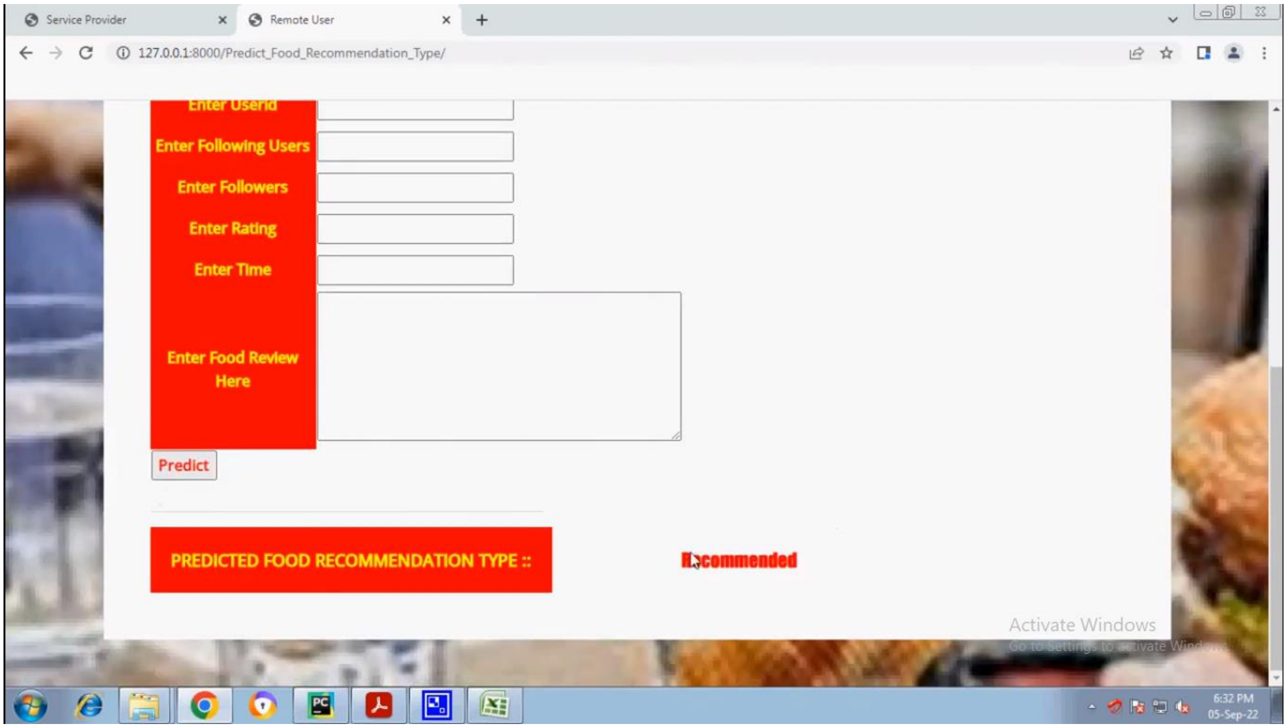

Fig 12. Result screenshot 12

Furthermore, the holistic-like approach employed in the system to account for time and user-community related issues played a crucial role in enhancing the quality of recommendations. By considering temporal factors such as seasonal variations in food preferences and time-of-day eating patterns, the system ensured that recommendations remained relevant and timely, aligning with users' current dietary preferences and lifestyle choices. Moreover, by incorporating user-community related aspects such as social influence and community preferences, the system provided more personalized and context-aware recommendations, thereby enhancing user satisfaction and promoting healthier eating habits. Overall, the results of the study underscored the effectiveness of the developed food recommender-system in addressing the limitations of previous systems and providing users with accurate, timely, and personalized recommendations tailored to their individual preferences and dietary habits.

CONCLUSION

With the development and increasing popularity of the Internet and the growing number of web users, recommender systems that select items that are reasonably appropriate to the needs of users are gradually becoming more widespread. A variety of lifestyle applications rely on food recommender systems, which are integral parts of many lifestyle services. A novel hybrid food recommender-system is developed in this paper to overcome the shortcomings of previous food recommender-systems, such as ignoring food ingredients, time stamp, cold start users and cold start foods and user community. Using user-based and content-based models as well as using time information, trust network, and user communities, the proposed method addresses all four issues simultaneously and aims to improve the final accuracy of the recommender-system. The proposed method involves two phases: food content-based recommendation and user-based recommendation. Graph clustering is used in the first phase, and a deep-learning based approach is used in the second phase to cluster both users and food items. The model has been compared to the newest proposed food recommender-system including LDA, HAFR and FGCN methods with respect to five different

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metrics: Precision, Recall, F1,AUCand NDCG.The experimental results indicated that the developed food recommender-system achieved the best performance and outperforms the state-of-the-art food recommender-systems by a noticeable margin. We aim to incorporate the side information of users (e.g., gender, age, weight, height, location, and culture) into the food recommendation framework in the future works to further improve the final performance of the food recommendation. In addition, a proper eating habit can lessen the severity of symptoms associated with non-infectious diseases. In future works, we aim to use nutritional characteristics of each food as additional information and recommend foods according to each person's health status and diseases.

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