Smart Recipe Recommendation Using User Preferences and ML

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ABSTRACT_ Food suggestion systems have become quite popular in a time when personalised digital experiences are becoming the standard. They help users plan meals, try new cuisines, and stick to their dietary preferences. This project provides a Personalised Recipe Recommendation System that employs a mixed machine learning method to suggest recipes that are tailored to each user's tastes, habits, and the recipe's content. The system uses both content-based filtering, which looks at things like ingredients, types of cuisine, cooking time, and nutritional value, and collaborative filtering, which learns from how users engage with the system and how similar their behaviour is to that of other users. The system makes better, more relevant, and more personalised recommendations by combining the two methods into a weighted hybrid model.

The project is built with Python and Flask, and it uses machine learning libraries like Scikit-learn, Pandas, and Surprise. A profile can keep track of a person's eating habits, boundaries, and preferences. The algorithm is always changing to make sure that suggestions are still useful and correct when users' tastes change. This dynamic customisation makes the user experience better by letting users locate recipes that fit their own tastes and lifestyles.

The system becomes better at making suggestions over time by learning from what users say and do. This makes the experience more intuitive and responsive. This project seeks to offer a realistic solution that promotes improved eating habits and more informed decision-making by giving consumers access to a wide choice of food options that fit their tastes and dietary needs.

1.INTRODUCTION

According to the WHO's global prediction, the number of overweight adults will shockingly reach over 2.3 billion by 2035. Being overweight or obese is a big cause of too many long-term health problems. Getting the right amount of food is seen to be one of the most crucial parts of staying healthy. Most people know that eating well is highly essential, but they don't always do the correct things because they don't have time to prepare or don't want to think about it. This kind of stuff stops people from eating nutritious foods. So, recommender systems are seen as a good way to encourage people to eat healthier foods and make good dietary choices.

One of the hardest things that recommendation systems try to do is help people with their diets and food choices. To make proposals, you need to collect hundreds of culinary items and ingredients. The fact that most recipes ask for combining meals or components instead of eating them alone makes a recommender system much more complicated. Meal recommendation systems not only consider what customers want, but they also... They suggest nutritious foods, keep track of what people eat, learn about their health problems, and encourage them to change their habits.

Every day, both men and women make choices about what to eat. Each and every one of them is concerned about a wide range of food-related issues, such as what to eat, how to cook it, how healthy it is, whether it will help them stay healthy (by being gluten-free, sugar-free, diabetic-friendly, etc.), and a whole lot more. Recommendation systems let users make quick decisions in these complicated data environments. Diet management systems have been the subject of a lot of research. They primarily replace the conventional ways of doing things using paper and pencil. A lot of these systems also use education information and services to figure out how to influence people's conduct. Because these diet tracking systems are so popular, they get a lot of information about what users like. This information may be utilised to make the system and diet program more personalised for each user by integrating their preferences to interactive elements. Meal recommender is one example of a personalised service that could help you eat healthier. It might recommend something based on how healthy the dish is. Recommender systems are one of the most common uses of data science. They help guess how much someone will "rate" or "prefer" a given item. They have been used by almost every big IT company in some way. They help Facebook suggest pages to like and people to follow, Amazon suggest things, and YouTube pick the next video to play automatically.

For thousands of years, people have had to decide what to cook and how to cook delicious food. The other thing to think about is nutrition. The only way to learn anything good about a dish or recipe has been through trial and error or talking to someone else; neither of these methods took nutrition into account. Did you think about cooking today? - every woman, whether she is a housewife or a professional woman, has to deal with It seems easy to chose, but it takes some planning and smart decision-making. You have to think about the members' stomachs and health so that it doesn't cause gas or acidity problems, and you also have to think about your budget. Users can choose meals based on the type of course, diet, and other factors. The suggested program assists them by showing recipes based on what they have on hand.

Today, personalisation is very important for improving users in many areas, such as entertainment, commerce, food, and nutrition. This is because information technology has become more accessible to everyone. It might give millions of users a lot of different and valuable cooking ideas. Before making ideas, one must take a holistic approach and know each user's individual tastes, dietary allergies, cooking methods, portion sizes, and other relevant factors. This project doesn't just give individuals general recipe ideas; it recommends a Personalised Recipe Recommendation System that employs machine learning to give people recommendations that are specific to their requirements. The algorithm will look at the user's habits, likes, and past sexual activity to recommend an even more relevant and varied range of recipes. A hybrid recommendation model is made up of both a content-based filter and a collaborative filter. The content-based filter shows ingredients, cuisine, and nutrition, while the collaborative filter shows patterns among comparable users.

It is the use of recommendation algorithms in real life and the help that data-driven systems give to users in selecting better and more satisfying eating choices. The suggestion engine seeks to give recommendations that are tailored to each user's profile, whether they are vegetarian, keto, or looking for quick or easy dinners. You can use this technology in real life for things like health and fitness apps, meal-planning apps, shopping delivery apps, and smart kitchen assistants. The personalised recommendation engine can not only make users happier, but it can also help them eat healthier by taking into account things like their allergies, ethnic food preferences, preparation time, and nutritional goals. In this way, we can see how deep learning may make the system even better by adding real-time feedback loops and making it work with voice assistants and IoT devices. So, it is a scalable approach for finding personalised food in today's world.

2.LITERATURE SURVEY

1. Ricci, F., Rokach, L., & Shapira, B. (2015). Recommender Systems Handbook. Springer.

Abstract:
This comprehensive handbook serves as a foundational reference in the field of recommender systems. It covers a broad range of topics including collaborative filtering, content-based methods, hybrid approaches, evaluation metrics, and applications. The book emphasizes both theoretical models and practical implementations, making it suitable for researchers, practitioners, and graduate students. It also discusses emerging trends such as context-aware, mobile, and social recommender systems.

2. Aggarwal, C. C. (2016). Recommender Systems: The Textbook. Springer.

Abstract:
This textbook provides an in-depth overview of recommender systems from a data mining perspective. It covers fundamental algorithms such as neighborhood-based and model-based collaborative filtering, content-based methods, and advanced topics like matrix factorization, deep learning, and scalable implementations. The book emphasizes algorithmic insights, mathematical models, and system design, making it ideal for both academic study and industry application.

3. Salakhutdinov, R., & Hinton, G. (2007). Restricted Boltzmann Machines for Collaborative Filtering. In Proceedings of the 24th International Conference on Machine Learning.

Abstract:
This seminal paper introduces the application of Restricted Boltzmann Machines (RBMs) to collaborative filtering problems. The authors propose a probabilistic model that learns latent user and item features for recommendation tasks. The approach demonstrates significant improvements in accuracy over traditional techniques like SVD on sparse datasets such as the Netflix Prize data. It marks an important milestone in the use of deep learning techniques in recommender systems.

4. Jain, A. K. (2010). Data Clustering: 50 Years Beyond K-means. Pattern Recognition Letters, 31(8), 651–666.

Abstract:
This survey reviews five decades of research in data clustering, starting from the widely-used K-means algorithm. It

explores various clustering techniques including hierarchical, density-based, model-based, and spectral methods. The paper highlights the theoretical foundations, computational complexity, and application domains of clustering algorithms, while also identifying key challenges and future directions in unsupervised learning.

5. Mikolov, T., et al. (2013). Efficient Estimation of Word Representations in Vector Space. arXiv preprint arXiv:1301.3781.

Abstract:

This influential paper introduces the Word2Vec framework, which provides an efficient method for learning word embeddings from large-scale text corpora using shallow neural networks. The authors propose two architectures — Skip-Gram and Continuous Bag-of-Words (CBOW) — that capture semantic relationships between words. These embeddings have broad applicability in natural language processing and have also influenced recommendation systems through the modeling of user-item interactions in vector space.

3.PROPOSED SYSTEM

The suggested system is a smart and personalised recipe recommendation platform that uses a combination of machine learning methods to give users choices that are very relevant to them. The recommender system uses TF-IDF vectorisation of components and nutritional data to filter content and clustering and deep learning to get collaborative-style insights. K-Nearest Neighbours (KNN) looks for recipes that are similar to each other, while KMeans groups recipe data into clusters, uncovering hidden patterns and groups that are similar to each other. A Feed Forward Neural Network stores deep feature representations of correlations between components and nutritional characteristics among recipes.

These models are used in a weighted hybrid framework that solves problems like cold starts while also improving the accuracy of recommendations. The smart recipe recommendation software also keeps track of what users are interested in in real time and lets them filter results based on dietary needs and ingredient exclusions. This makes the recommendations more useful and tailored to each user.

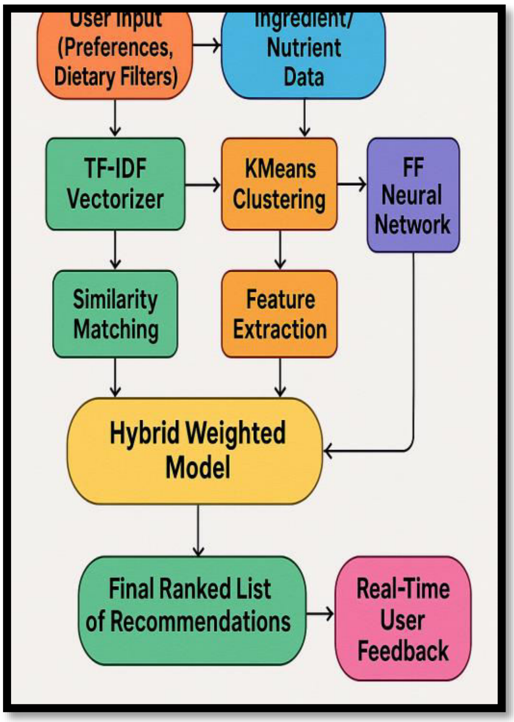

Fig 1:Architecture

3.1 IMPLEMENTATION

Data Loading Module

Preprocessing Module

Distance Matric Calculation

Route Optimization Module

Visualization Module

User input and Interaction Module

3.1.1 Data Loading Module

This module handles the importing of required libraries and loading of the necessary datasets for routing and optimization tasks. It includes the following:

The importing of all essential packages like pandas, NumPy, matplotlib, and geopy.

Reading location data from .csv and other similar sources into a DataFrame.

Extracting relevant fields like latitude, longitude, and location names.

3.1.2 Preprocessing Module

This module prepares routing optimization data. Major steps include:

Cleaning the coordinate data and verifying it.

If required, converting addresses to geographical coordinates.

Normalization or reindexing of data for compatibility with downstream modules.

Treating missing or inconsistent entries.

3.1.3 Distance Matrix Calculation

Here, in this module, the distance matrix is constructed using the Haversine formula or geodesic distance based on geographic coordinates:

Pairwise distances between all locations will be computed.

The resulting matrix serves as meta-information for route planning algorithms.

3.1.4 Route Optimization Module

In essence, optimization is the fundamental logic of the model, seeking the shortest or most efficient way of traveling:

Algorithm implementations include heuristics or optimization solvers applied to the Traveling Salesman Problem (TSP).

The tasks include finding an optimal visit sequence that minimizes total travel distance or time.

3.1.4 Visualization Module

This part of the module will show the optimized route on a map.

It will include the libraries such as matplotlib or folium for plotting positions.

It will show the final created path containing marked nodes and the routing paths for better understanding.

It may optionally include the distance-notations or legends.

3.1.5 User Input & Interaction Module

There is also flexibility in taking dynamic user inputs and interactions.

Accepts personalized start and end locations or direct location choices.

Allows the user to choose optimization criteria (like shortest time, shortest distance).

Adaptable to web interfaces or input via command line.

4.RESULTS AND DISCUSSION

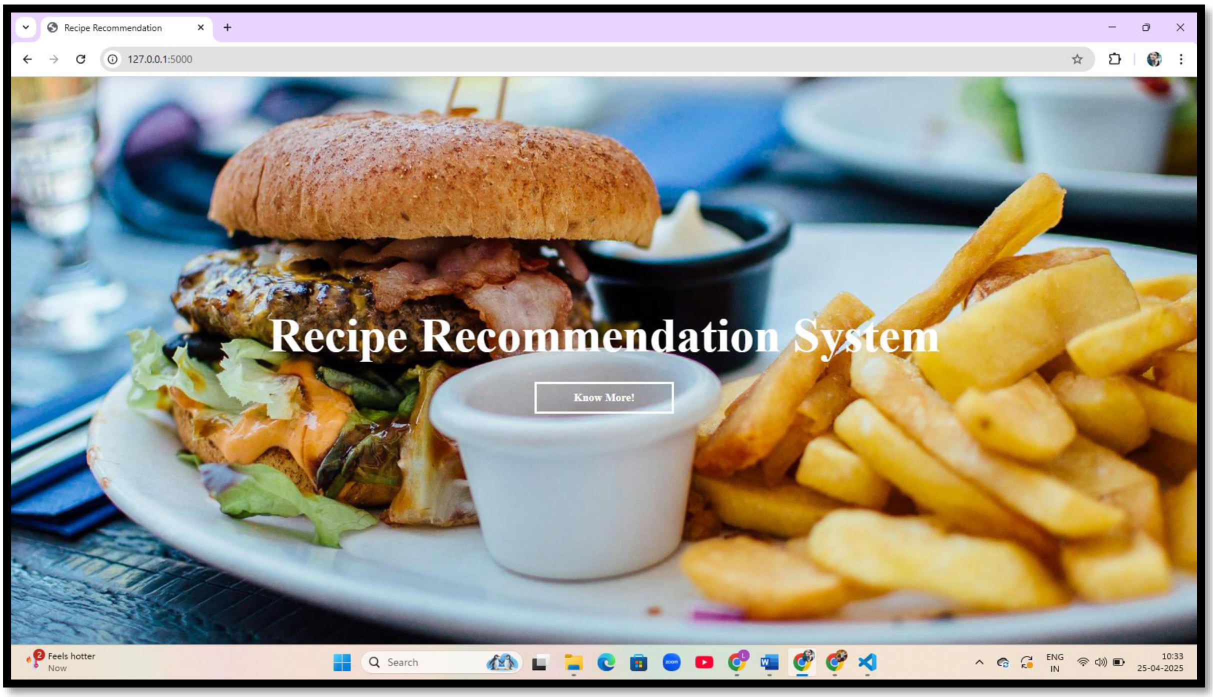

Fig 2:Home Page

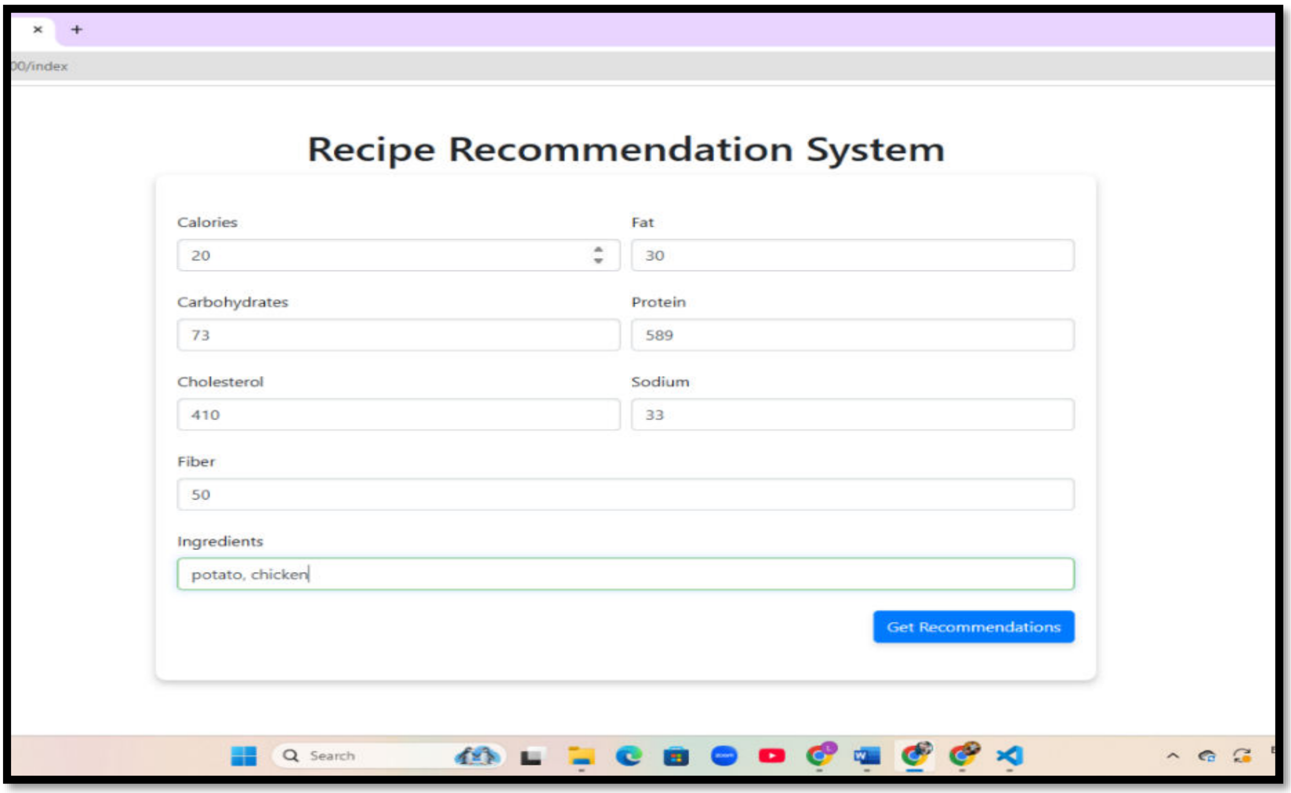

Fig 3:Input data

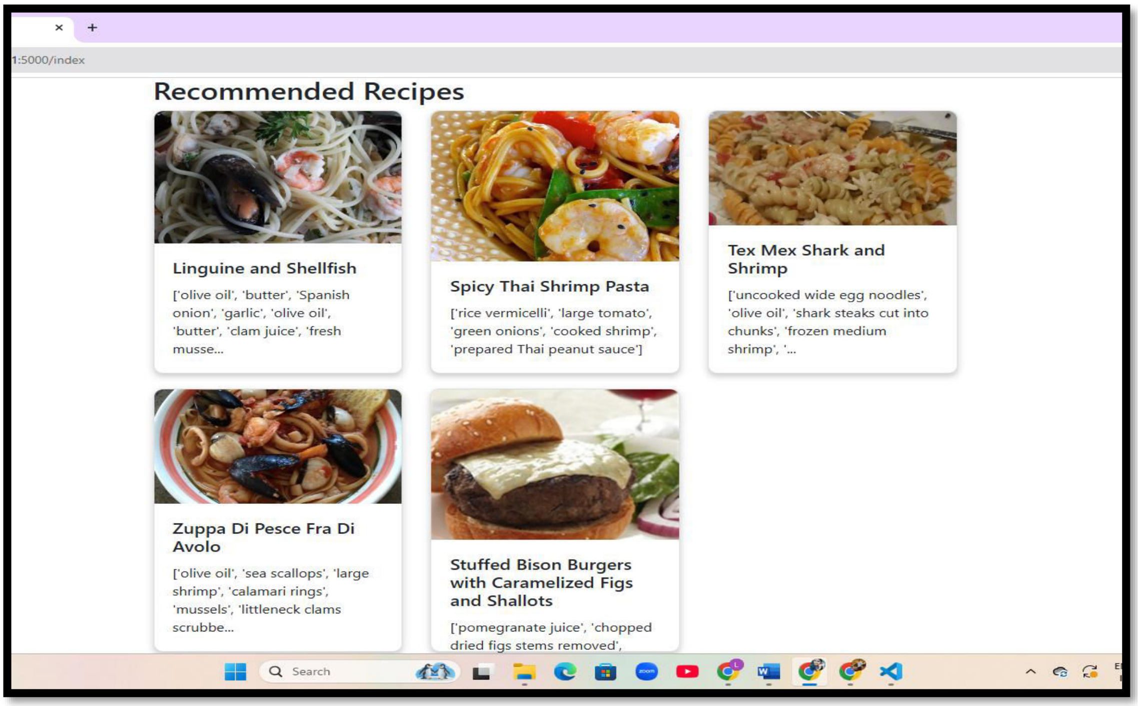

Fig 4: Predict output

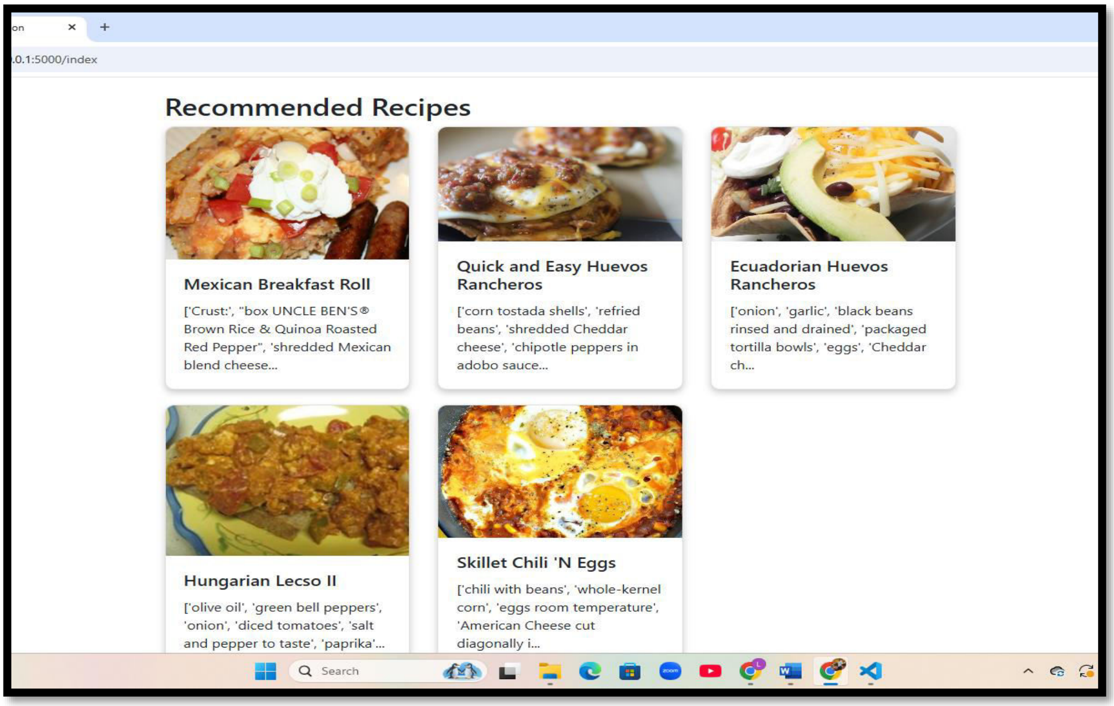

Fig 5: Predict output

5.CONCLUSION

In this project, a very extensive recipe dataset having greater than 48000 entries was modelled and explored, which includes info with regards to nutritional, user ratings, and ingredient lists.

This workflow has two primary phases.

Exploratory Data Analysis EDA:

Insights derived include distribution of ratings, relationships between nutritional values and user preference measures, and frequency of ingredients, which provide most vital understanding of dataset structure and potential patterns.

Model Development:

Numerous machine learning models were implemented:

❖ K-Nearest Neighbors (KNN) for classification activities.

❖ K-Means Clustering for recipes to be clustered based on nutritional similarities.

❖ Neural Networks for more complex prediction task probably involving user preference model or nutrition prediction.

Standard evaluation criteria were applied in assessing models, and the best performing model retained for possible deployment.

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