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Personalized Recipe and Meal Planning System Using Cosine Similarity and KNN – Based Similarity Ranking

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Abstract
In the realm of personalized cooking experiences, improving the methods of finding and organizing recipes can enhance the cooking experience for a user. This research presents a Personalized Recipe Recommendation and Meal Planning System that supports recipe recommendations based on ingredients, cuisine, course, and dietary restrictions. Our system implements contemporary machine learning techniques, such as TF-IDF vectorization, cosine similarity, and KNN-based similarity ranking in order to develop intelligent matches from user input and ingredients while providing recommendations from a wide range of recipes. In addition to real-time personalized recommendations, we develop a meal planning module to help users more efficiently manage their weekly meals by providing a dynamically generated meal plan structure of their meals based on the user`s preferences. Our web-based interface is designed using Streamlit to provide a smooth and interactive user experience. Data normalization and feature encoding are used to ensure that similarity measurements are balanced and accurately represent user input and recipes across several types. Our experiments include results to showcase that our system was able to adapt to a user`s preferences, return highly relevant real-life recipe recommendations, while allowing users to better organize their weekly meals - in turn enhancing both the convenience and enjoyment of cooking at home.
Keywords: *Culinary Suggestions, User Preferences, Meal Planning, Machine Learning, Simplified Cooking.*

1. Introduction
The advent of digital platforms has changed how people find, plan, and prepare meals in the last few years. Among these innovations are recipe recommendation systems, which can provide users with a method for navigating the sheer abundance of recipes now found online. As more people focus on habits of healthy eating, personalized recommendations that correspond to an individual's dietary restrictions, specific cuisine styles, and available ingredients are becoming necessary. Modern hurdles like time constraints, specific diet plans (for health and personal reasons), and decision fatigue have all increased demand for intelligent systems that allow individuals to navigate meal planning more easily. Searching for a recipe that fits an individual's taste and health requirements innately is clumsy and inefficient. Personalized recipe recommendation systems provide users with recommended suggestions with ease based off user input that helps save time and mental energy and promotes enhanced meal choices based upon user input. Additionally, personalized recipe suggestion systems mitigate food waste, reduce unnecessary substitutions, and increase sustainable food preparation by taking into account available and also used ingredients. This project offers a personalized recipe and meal planning system that can respond to the user's preferences for cuisine, course, dietary restrictions or follow the user's available ingredients. In the project, machine learning techniques were used - specifically TF-IDF (Term Frequency-Inverse Document Frequency) was used for text vectorization and K nearest neighbor (KNN) was used for recommendation based on similarity. We use what is called cosine similarity - using cosine similarity functionality in Scikit-learn to determine how closely different recipes are related to user preferences. In addition to signing up for real-time recipe

suggestions, we implemented a dynamic meal planning component that creates structured meal plans based on user inputs (number of days, meals per day). The application is built in Streamlit and offers an easy-to-use platform for the user to input their preferences, and receive either personalized recipe suggestions, and organized meal plan schedules. By doing this we enable a personalized approach to cooking, while optimizing the efficiency of decision-making, health-considerations in eating, and reduction of household food waste.

2. Literature Review

Academicians are increasingly recognizing the role of AI in promoting healthy eating, As discussed by Namasivayam [5]. The need for nutritious meals is growing, especially for busy individuals, the elderly, and patients. Many rely on restaurants or domestic help, where nutritional quality can vary. Custom meal plans, though helpful, are often too expensive. The author proposes using AI to create affordable, nutritious meals for broader access to healthier options. AI and robotics now perform complex kitchen tasks, like chopping and cooking, ensuring consistency and safety. These systems save time, reduce costs, and minimize food waste while ensuring hygienic meal preparation. D'monte et al. explore the challenges of meal preparation, especially for those with limited cooking skills [4]. Many individuals, particularly in single- person households, struggle with managing ingredients, often resulting in food waste. The authors present Makeat, a beginner-friendly platform that provides personalized recipe recommendations based on real-time ingredient detection. The system uses a custom dataset of 1,296 images covering 39 categories of fruits and vegetables. It employs a YOLOv5-based ingredient detection model to identify ingredients via a mobile app. The identified ingredients are then used to recommend recipes through a hybrid system that combines content-based and collaborative filtering, with fuzzy string matching for recipe retrieval from a Firebase database. The app also supports multilingual instructions and voice commands using Natural Language Processing (NLP). The App achieved an 87% accuracy in ingredient detection, offering efficient recipe recommendations. Rodrigues et al. address the environmental, economic, and societal challenges posed by food waste [7]. They suggest leveraging technology, specifically machine learning and neural networks, to reduce food waste by recommending recipes based on available ingredients at home. The paper reviews various techniques employed in recipe recommendation systems and ingredient recognition. A key approach discussed is the use of Convolutional Neural Networks (CNNs) to recognize and categorize food items from images. These models require large, labelled datasets of culinary items for accurate ingredient recognition. Some systems also utilize external databases, such as the Edamam API, to offer extensive recipe recommendations based on detected ingredients. The studies reviewed have systematic approaches, such as the PRISMA framework, which shape the ways of ensuring reliability by forming research questions, defining inclusion criteria, and carrying out systematic searches in databases such as IEEE Xplore and ACM Digital Library. Patil and Potdar explore a schedule of the trail of recipe recommendation systems with a focus on methods and datasets that constitute the basis for their effective usefulness [10]. This paper also speaks of various techniques used to customize recipe suggestions based on users' preferences and health conditions. Key methodologies discussed include the 2 factors. First the Automatic Generation of Recipe Recommendations Based on Outlier Analysis: This method employs machine learning to personalize dish suggestions by analyzing users' health conditions and preferences. It uses an Outlier Detection Model (ODM) and a Recipe Generation Model (RGM) for tailored recommendations. Second, the Automatic Recipe Metadata Generation Based on Users' Moods: This technique sorts recipes according to moods using comparative feature vector extraction. Desai et al. presented a system that recommends recipes using a combination of content-based and collaborative filtering methods [3]. The dataset comprises recipes, ingredients, and nutritional content drawn from various online applications. The methodology followed is a hybrid one, Content-based filtering-that

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looks at ingredients and nutritional values to match recipes with the requirements of the users; Collaborative filtering-that predicts for new recipes by looking up user preferences and past behavior. Also included in the system is the installation of an image processing module that allows users to upload images of ingredients-on which ingredient identification will be performed and recipes will be suggested. The Java-MySQL based system is implemented in a web application and on an Android app. It was found to provide great improvements in terms of accuracy and personalization of recipe suggestions, compared with existing systems. Pooja et al. designed a system which help users easily select recipes based on some ingredients they have [9]. It adopts machine learning approach and suggests only personalized recipes where some ingredients are missing. The dataset includes recipes, ingredients, and their nutritional values compiled from multiple websites, and after a thorough pre-processing step, the user input ingredients are aligned with relevant recipes for effective recommendations. Combining content-based filtering and machine learning, OpenCV is utilized to detect and extract features from ingredient images. Ingredients are determined using processing techniques like gray scaling and histogram analysis, while recipes are provided on the basis of the frequency of co-occurrence of certain ingredients in the dataset. Results have been encouraging; in that they showcase a system that achieves recipe recommendation based on ingredient images. The system is user-friendly, enabling recipe searching, feedback, and other activities like user registration and login. Bharam et al. specialized a recipe recommendation system for Indian cuisine [11]. This system proposes personalized recipe suggestions based on the ingredients that a user has on hand and also addresses the difficulty in cooking with few ingredients while respecting customary Indian cooking methods. This system compiled the dataset from web scraping, extracting the recipes data from various Indian cuisine websites, along with details of the ingredients, methods of preparation, and nutritional details. The data sets were pre-processed to prompt an efficient recommendation. The approach uses content-based filtering, Cosine similarity measures were used to line the user-inputted ingredients with recipes in the user database. The system provides a web- application based interface where the users are allowed to provide ingredients and then recommend personalized recipes. Results show that the content-based filtering algorithm generates recipe recommendations based on available ingredients rather effectively. The system has user registration, recipe search, and admin management functionalities. D'souza et al. presented a deep learning-based system for food image classification and recipe recommendations [2]. This system enables users to identify food items from images and obtain corresponding recipes, including ingredients, preparation steps, and cooking times. The dataset used; Indian Food Images (Top 20) consists of 5,828 images of 20 popular Indian dishes. The images are split into training and validation sets to train the models effectively. The methodology incorporates, Convolutional Neural Network (CNN): InceptionV3 was enhanced with additional dense layers, dropout, batch normalization, and a softmax function for classification. The CNN architecture included multiple pooling and convolutional layers for robust feature extraction. Image Preprocessing and Data Augmentation: Techniques such as image resizing, Sobel filtering, brightness normalization, and data augmentation (rotation and flipping) were applied to improve model accuracy. The system achieved a training accuracy of 99.58% and a testing accuracy of 88.9%. InceptionV3 outperformed other models, and heatmaps highlighted the significant areas of food images affecting classification. Rane et al. focuses on evaluating various machine learning models for recipe recommendation and investigating a transformer-based approach for recipe generation [8]. Their aim is to improve both the efficiency and user experience in meal planning. The study utilized a dataset gathered from popular cooking websites, containing detailed information on recipe names, ingredients, cooking times, and instructions. This dataset was increased with translations of regional recipes to serve as an enhanced training set for the

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models. The authors performed a comparative evaluation of four machine learning models: Decision Trees, Random Forest, Support Vector Machine (SVM), and K-Nearest Neighbors (KNN). Although the Random Forest performed best among them with the highest accuracy in recommending recipes due to its ability to deal with complex datasets and missing values, it was always coupled with GPT-2 model for recipe generation used to fine-tune Indian recipes to some extent for more diversity and coherent recipe suggestions. The findings emphasize that Random Forest did well in recipe recommendations, while GPT-2 showed potential in providing creative and diverse recipes. The paper proposes future research relating to the integration of multimodal data that is made up of images and user preferences to enhance the intelligent recipe recommendation system and food system sustainability. Chhipa et al. developed a mobile application aimed at helping users find recipes based on the ingredients they have available [12]. This system employs Term Frequency-Inverse Document Frequency (TF-IDF) and Cosine Similarity to enhance recipe searches, particularly beneficial for users with limited ingredients. It simplifies meal planning by incorporating various filters such as type of course, dietary restrictions, and budget considerations. The foundation of this project is the 6000+ Indian Food Recipes Dataset, which contains a wide range of recipes sourced from ArhanasKitchen. To improve this dataset further, the authors created a script that scrapes additional recipe images and integrates them with essential information like ingredient lists, serving sizes, and preparation times. Their method utilizes Natural Language Processing (NLP) techniques to encode these ingredients using TF-IDF, enabling an analysis of how relevant different recipes are according to what users' input. Additionally, Cosine Similarity measures how closely users' ingredients correlate with those found in the dataset. Constructed on the Flask framework and employing the pickle library for model preservation, this system ranks recipes according to their relevance effectively. Results indicated that it successfully offered relevant recipe suggestions while allowing users to apply filters based on course type, diet preferences, and financial constraints. Potdar and Patil developed a system that suggested recipes according to a user's Body Mass Index (BMI) and other dietary preferences [1]. It categorizes recipes into breakfast, lunch, and dinner, and provides both vegetarian and non-vegetarian options. This system makes use of the K-Nearest Neighbour (KNN)-based recommender algorithm to selectively suggest recipes that are healthy and most fitting for the user's health profile. The KNN algorithm uses Euclidean distance for similarity metric and classifies recipes with respect to how well they fit the user profile. The recommendations are further adjusted for time of day by using various probability thresholds: breakfast=0.4, lunch=0.6, and dinner=0.8. The K-nearest neighbor algorithm thus obtains an accuracy rate of 85.74% on recommendation, which stands out effectively than Decision Tree (78.86%) or Naive Bayes (79.56%). Vivek et al. introduced a system that integrates machine learning with an emphasis on collaborative filtering to improve recipe recommendations [13]. The dataset used in their research includes an extensive compilation gathered from the Allrecipes website, featuring 46,336 recipes along with 1,966,920 user reviews and contributions from 530,609 users. In addition to this substantial dataset, they also developed a smaller simulated set consisting of 24 users, 124 recipes, and 323 user preferences for more detailed analysis. The system employs two primary collaborative filtering methods: item-based collaborative filtering and user-based collaborative filtering. Item-based collaborative filtering evaluates the similarities between recipes utilizing metrics like the Tanimoto Coefficient and Log-Likelihood Similarity. Conversely, user-based collaborative filtering analyzes similarity among users' preferences through techniques such as Euclidean Distance and Pearson Correlation. To enhance the recommendation process further, strategies involving fixed size neighborhoods as well as threshold-based neighborhoods were implemented. Results reveal that user-based filtering, particularly using Euclidean Distance within a neighborhood of approximately 100 to 500 users

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outperformed the item-based method in terms of accuracy on this dataset. Ueda and Nakajima developed a method that enhances the process of recommending recipes by incorporating user preferences alongside the quantities of ingredients used [15]. Their research utilized a dataset comprising 8,050 recipes sourced from the Japanese culinary platform Ajinomoto Park. This was complemented by data on user interactions, enabling a nuanced understanding of individual preferences and improving recommendation accuracy. The proposed methodology features two primary components. First, user preferences are identified through an analysis of how frequently certain ingredients are used in recipes as well as which ingredients users tend to avoid based on their browsing history. Second, they introduced an innovative scoring system designed to assess recipes not merely based on whether preferred ingredients are included but also considering their respective quantities. Recipes receive higher rankings when they have larger amounts of favored ingredients. According to the Normalized Discounted Cumulative Gain (NDCG) metric, the proposed method achieved an NDCG score of 0.9381, compared to scores of 0.8996 for popular website recommendations and 0.9072 for those influenced solely by browsing histories, reflecting its superior alignment with user preferences. Ueda et al. designed a conceptual recipe-recommendation system that recommends dishes based on the mood of users, as opposed to merely ingredient-based means [16]. The system employs a dataset of 480 popular homemade recipes and 1,758 words that are mood-related and categorized into six areas: body, mental, taste, time, price, and modification. This research explored how various moods influence food choices, associating hearty moods with ingredients such as meat and bread and healthy eating with mushrooms and seaweed. The prototype system has a functionality that permits users to input their mood using slider bars for the six respective aspects, after which the system suggests customized recipes suited to the inputs. According to the opinion survey of 43 cooking school students, over 80% thought that the system was helpful, and it is noted that time and taste were guiding factors. The research marks the introduction of an innovative personalized meal planning system that is able to align recipes to the mood of users with the goal to make cooking more instinctive and fun. Maheshwari and Chourey developed a recipe recommendation system specifically for Indian cuisine, employing machine learning techniques to facilitate ingredient pairing and propose alternatives. This innovative approach aims to foster culinary creativity while also addressing dietary restrictions or instances when certain ingredients are unavailable. The dataset utilized in their study was sourced from Yummly.com, which included a diverse array of recipes, ingredients, and flavor components [14]. This data underwent thorough cleaning and pre-processing prior to analysis. The system is grounded in a Vector Space Model that incorporates Term Frequency-Inverse Document Frequency (TF-IDF) along with Cosine Similarity to match ingredients based on their flavor profiles. In this model, each ingredient is regarded as a document, with the flavor components serving as terms; TF-IDF scores coupled with cosine similarity determine pairs that exhibit similar flavors. Furthermore, the researchers employed the Word2Vec model to represent ingredients as vectors, thereby enabling the identification of substitutes through semantic analysis. The findings indicated that vegetables, fruits, cereals, and pulses typically align with established hypotheses regarding ingredient interactions; however, this alignment does not hold true for spices and dairy products. Overall, the system demonstrates its effectiveness in both ingredient pairing and substitution processes, ultimately supporting culinary innovation while accommodating various dietary preferences. Yanai et al. introduced a smartphone-based cooking recipe recommendation system that leverages real-time visual recognition to identify food ingredients and suggest related recipes [13]. This user-friendly application aims to assist users in meal planning, whether they are shopping or cooking at home. The dataset comprises 30 types of food ingredients, including fish, meats, vegetables, and fruits, with 10

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short videos per category collected from grocery stores in Tokyo. The system utilizes the smartphone's camera for ingredient recognition through visual object recognition. It extracts image features using Speeded Up Robust Features (SURF) and grid-based colour histograms. The algorithm is chosen for its resilience to scale, rotation, and lighting variations, while colour histograms capture the visual importance of colour. These features are transformed into a Bag-of-Features (BoF) vector using a 1000-dimensional codebook. For classification, a linear Support Vector Machine (SVM) with a one-vs-rest strategy is employed, balancing accuracy and computational efficiency for real-time recognition on mobile devices. The system connects to commercial recipe sites like CookPad and PunchFork via Web APIs to recommend recipes based on recognized ingredients. Users point their smartphone camera at an ingredient, and the system presents the top six recipe options. If the top suggestion is incorrect, users can manually choose from the six candidates. Testing results showed a classification accuracy of 44.92% with combined RGB colour and SURF features, and 83.93% accuracy within the top six candidates. User feedback indicated that while manual selection could be quicker, the system's efficiency and ease of use were appreciated when ingredient recognition was accuracy.3.

3. Problem Statement

With growing access to online platforms, people have a variety of online recipes to choose from. Despite the wide range of options available in the market, consumers still find it hard to discover suitable recipes specific to their dietary requirements, preferences, and health-conscious aims. This problem is worsened by time drains due to searching through huge recipe databases, leading to poor meal choices, less motivation to prepare meals, or inordinate amounts of food waste. Additionally, current recipe systems do not satisfy the pressing need for personalized, customer-friendly recommendations considering the dietary restrictions, available ingredients, and cuisine preferences. A significant drawback that the customers are therefore facing is the unavailability of a personalized recipe recommendation system that helps in motivating better eating while automating meal-planning activity. Hence, an intelligent configurable system that utilizes machine learning algorithms to generate personalized recipe recommendations based on the user's spec needs and preferences is thus required to aid meal planning that ought to be quick, in-line with health-conscious eating.

4. Objectives

The identified gap after reviewing similar studies in Recipe Recommendation is discussed below:

Existing systems like those of Desai et al. (2017), and Pooja et al. (2017) offer customizability with content-based filtering or ingredient analysis. This one aims to go beyond this by incorporating a broader spectrum of user preferences such as course, cuisine, ingredients, dietary needs and possibly even Meal planning feature that provides user's a structured meal plan all in a single view to decrease user effort. **Compared to Patil and Potdar (2016)**, who elaborated on mood-recommendations, and Ueda and Nakajima (2017), who justified ingredient quantities, this system leverages a user-centric interface, developed using Streamlit, for simple input which led to quicker recipe suggestions. This system merges content-based filtering with the KNN machine-learning model, thus presenting more extensive personalized recommendations than singular-method approaches.

The Objectives are as follows:

- To create a comprehensive recipe recommendation system that incorporates several user inputs—course, cuisine, ingredients, dietary needs, and a structured meal planning interface—into one easily navigable experience.
- To create a simple, user-friendly interface using Streamlit, that is designed for the user to minimize input and maximize the speed at which we can suggest recipes.
- To use a hybrid recommendation approach that fuses content-based filtering and the K-Nearest Neighbors algorithm for better recommendations than single-method

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approaches.

- To leverage a meal planner that creates multi-day, multi-meal plans from the top recommendations that adds usability and forces less decision-making for the users.

5. Methodology

5.1 Dataset

The dataset used Food_recipes.csv from Kaggle, curated from Archana's kitchen consists a total of 7,540 rows and 11 columns.

- **Name:** The name of the recipe.
- **Description:** A brief description of the dish.
- **Cuisine:** The type of cuisine the recipe belongs to (e.g., South Indian, Continental).
- **Course:** The meal type, such as lunch, dinner, or breakfast
- **Diet:** Indicates whether the recipe is vegetarian or non-vegetarian.
- **Ingredients_name:** A list of the ingredients required for the recipe.
- **Ingredients_quantity:** The corresponding quantities for each ingredient.
- **Prep_time (in mins):** The time required to prepare the dish.
- **Cook_time (in mins):** The time required to cook the dish.
- **Instructions:** Step-by- step instructions for preparing the recipe
- **Image_url:** A link to an image of the prepared dish.

5.2 Detailed Methodology

The machine learning model used in this project is K-Nearest Neighbour (KNN) along with Content-Based Filtering with TF- IDF and Cosine Similarity. Mainly used to focus on the attributes of the recipes (ingredients, cuisine type, etc.) and match them with user preferences. The K-Nearest Neighbors (KNN) algorithm is selected due to its ease of use and efficiency in offering customized recipe suggestions. By calculating the distances between feature vectors, including cuisine type, dietary preferences, cooking time, and course, KNN finds recipes that are most comparable to user preferences. Real-time and dynamic suggestions are made possible by its smooth web interface interaction. Its interpretability makes it simple to comprehend and explain, and its flexibility guarantees that user inputs are handled instantly without the need for retraining. Because of these features, KNN is the best option for providing effective and user- focused recipe recommendations in this study. This Project focuses on recommending recipes based on user-specified criteria like Ingredients, cuisine, course, and dietary requirements. This is more convenient with a content-based filtering method, as shown in Figure 1 which recommends items that a user has already expressed interest in. Unlike collaborative filtering, which focuses on user-to-user interactions, content- based filtering uses item attributes to produce individualized recommendations.

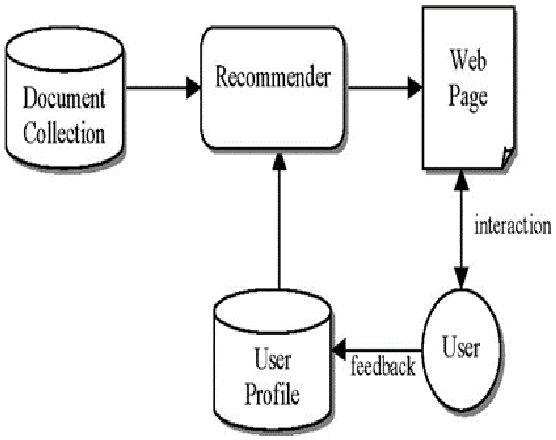

Figure 1 Content Based Filtering

TF-IDF (Term Frequency-Inverse Document Frequency) is a numerical technique for representing textual data (recipe names, cuisines, and dietary restrictions). It incorporates the word frequency in a recipe (term frequency) part, with how common it is across the dataset (inverse document frequency). This guarantees that vital key terms would be weighted more, hence increasing the level of accuracy in which recipe content is presented.

Term Frequency

TF refers to the frequency of a word in a document

It is calculated as follows:

TF = (Number of times a word "X" appears in a Document)/ (Number of words present in a Document)

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Inverse Document Frequency

IDF is a statistic that reflects how rare a word is across a corpus (a collection of documents)

It's calculated as:

IDF = log ((Number of Documents present in a Corpus)/ (Number of Documents where word "X" has appeared)) Cosine similarity is a mathematical function that examines how similar two vectors (user input and recipe representation) are. The cosine similarity calculated between the user's preferences and recipe vectors enables recipes to be discovered that closely match the user's requirements. In this research Sklearn's cosine similarity () function is used to calculate the cosine similarity between the user's input and the recipes present in the dataset.

$$\textbf{Cosine Similarity} = \cos(\theta) = \frac{(A \cdot B)}{|A| \; X \; |B|}$$

The dot product (A · B) is calculated as:

$$\mathbf{A.\ B = \sum i = ln\ (Ai\ x\ Bi)}$$

The magnitudes (|A| and |B| are calculated as:

$$|\mathbf{A}| = \sqrt{\ } (\textstyle\sum i = ln\ Ai^2)$$

$$|\mathbf{B}| = \sqrt{\ } (\textstyle\sum i = ln\ Bi^2)$$

The methodology of this project follows a structured workflow demonstrated in figure 2, comprising of data preprocessing, feature extraction and model implementation discussed below:

- **Load the dataset:** Fill missing values with empty strings or default values. Convert prep_time and cook_time to numeric format, replacing invalid entries with 0. Preserve original time values for later use in meal planning.
- **Feature Engineering:** Tokenize and vectorize ingredient lists using TF-IDF with stop-word removal and a limited vocabulary size. Encode cuisine, course and diet using Label Encoding, replacing missing values with unknown. Normalize prep_time and cook_time using MinMaxScaler to scale values between 0 and 1.
- **Feature Matrix Construction:** Combine the TF-IDF ingredient vectors, encoded categorical features, and scaled numerical features into a unified recipe feature matrix for similarity comparison.
- **User Preference Vector Generation:** transform user input (ingredients, cuisine, course, diet) into a user vector using the same preprocessing steps (TF-IDF, label encoding, scaling) to ensure compatibility with the recipe feature matrix.
- **Recommendation Logic:** Compute cosine similarity between the user vector and all recipe vectors. Rank recipes by descending similarity scores. Filter results based on ingredient match ratio (e.g., ≥ 50% overlap). If no suitable matches are found, apply K-Nearest Neighbors (KNN) using cosine distance as a fallback to retrieve similar recipes.
- **Ingredient Match Messaging:** For each recommended recipe, compare its ingredients with the user's input. Display matched and missing ingredients to guide user decisions.
- **Personalized Meal Plan Generation:** Use the top-ranked recipes to create a custom meal plan based on user-defined parameters (e.g., number of days, meals per day).

The system uses a hybrid recommendation approach that mixes TF-IDF based content filtering with KNN ranking. Recipe data preprocessing included dealing with missing values, vectorizing ingredient lists, encoding categorical features and normalizing numerical features. A single feature matrix is built, a user vector is generated based on input preferences, and then recipes are ranked based on cosine similarity as filtered by ingredient match ratio, and then KNN if needed. The top ranked recipes will then be used to create meal plans personalised for the user. The workflow is described below in figure 2.

6. Results and Discussion

6.1 Results

In order to evaluate the effectiveness of the proposed hybrid recommendation system, its performance was compared the against baseline approaches. The evaluation metrics chosen include precision, recall and F1-Score, as well as average cosine similarity for internal validation. The results of the proposed system are shown in Table 1 along with the results from both baseline approaches. The hybrid model (TF-IDF + KNN) produced a Precision of 0.81, a Recall of 0.76, and an F1-Score of 0.78 overall, which surpassed both TF-IDF only (0.70 F1-Score) and KNN only (0.72 F1-Score). The average cosine similarity was also highest for the hybrid model (0.72) indicating a stronger connection between user inputs and recommended recipes.

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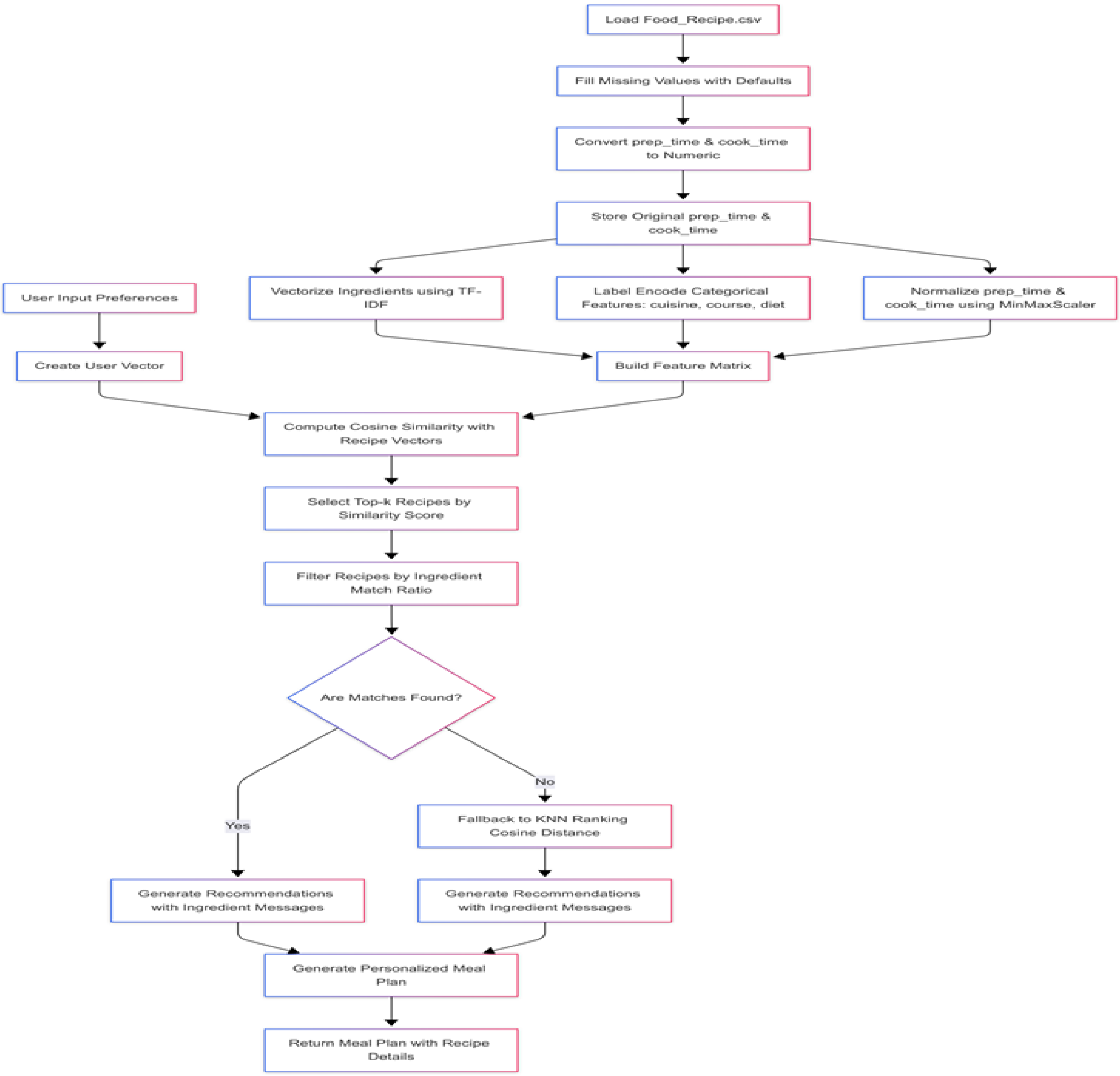

Figure 2 **Model Workflow**

Table 1 **Performance of Baseline and Proposed Hybrid Model**

Model Variant	Precision	Recall	F1 - Score	Avg. Cosine Similarity
TF-IDF only	0.72	0.68	0.70	0.65
KNN only	0.75	0.70	0.72	0.67
Hybrid	0.81	0.76	0.78	0.72

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In order to quantify the relative strength of this method, Performance was assessed of the proposed system against prior reported studies on recipe recommendation (Table 2).

Table 2 Performance Comparison with Existing Models

	Model	Precision	Recall	F1 - Score
Yanai et al.	SURF	0.45	0.44	0.44
D'monte et al.	YOLOv5	0.70	0.72	0.71
Potdar and Patil	BMI-Based KNN	0.74	0.76	0.75
	Proposed Hybrid	0.81	0.76	0.78

The bar chart in Figure 3 further illustrates the improvements, as shown here the hybrid model continues to exceed the performance of both baselines on all evaluation metrics.

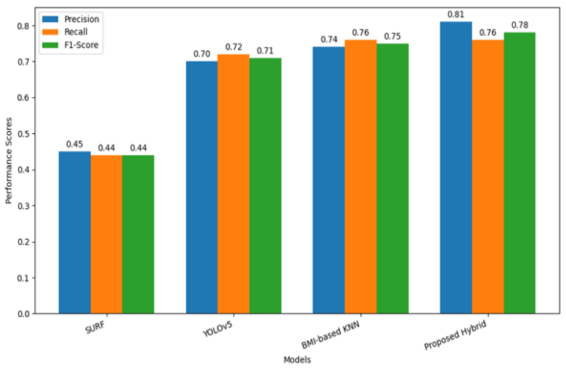

Figure 3 Comparison of Other Models

6.2 Discussion

The findings confirm the validity of a hybrid recommendation approach in the combination of TF-IDF content-based filtering and KNN ranking. This system joins together ingredient level textual similarities with feature-based neighbors to produce stronger recommendations. Moreover, the system also incorporates a meal planning module utilizing the top ranked recipes, which gives the structure a practical usage to the end-user. This system has many vital features used to study a comprehensive performance evaluation. The prescriptive potential analyzes the relevance of finalized suggestions, reiterating the importance of suggestions that are closely aligned with user preferences. Recall measures the effort that a system might make to retrieve relevant recipes, in addition to expressing its efficiency. System Speed seeks how fast and efficient a recipe is completed within a system, constituting a friendly user interface for users. The focus was to deliver suggestions that introduce the user to novel and unknown dishes, promoting culinary discovery. System responsiveness assesses the speed and efficiency of suggestion creation, resulting in a smooth user experience. As shown in Figure 4, the recommendations prioritize introducing users to novel and unknown dishes, promoting culinary discovery.

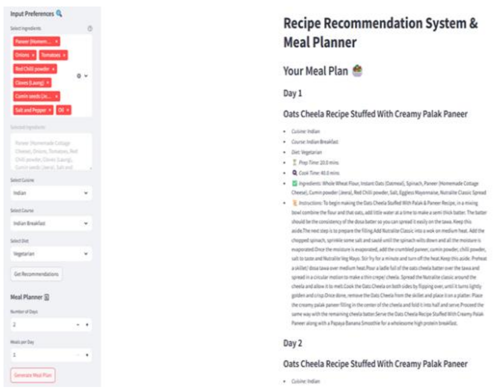

Figure 4 Meal Plan Generation

Conclusion

The proposed Personalized Recipe Recommendation and Meal Planning system combines content-based filtering, TF-IDF vectorization, feature encoding, and cosine similarity calculations to provide highly relevant recipe suggestions based on user preference. The use of the K-Nearest Neighbors (KNN) algorithm assures that the recipes suggested and ranked are the most appropriate based on overall similarity scores. The combination of ingredient level matching, alongside encoded categorical preferences (cuisine, course, and dietary) and normalized

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numerical features (prep and cook time), improves recommendation quality and practicality. The implementation of a meal planning feature allows users to generate a structured, multi-day meal plan based on top recommended recipes providing a more managing approach to meal planning and lessening the decision fatigue associated with keeping track of meals on a weekly basis. The system is implemented via an easy-to-use Streamlit-based web interface that hones in on interaction with the system in real time to facilitate recipe suggestions and meal plans. Overall, the solution is meant to connect user needs and intelligent recipe discovery while simultaneously providing a more efficient, personalized, and sustainable way of preparing meals. Future work may include strategies such as collaborative filtering, image-based food recognition, and built-in adaptive learning of real-time user activity to further enhance personalization and engagement.

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