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Smart Food Recipe Ratings Prediction Using Revolutionizing Learning Techniques

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Abstract: **In the era of Information technology and the growing influence of social media, the culinary landscape is evolving rapidly. Smart food recipe platforms have become essential for individuals seeking diverse and personalized cooking experiences. This study presents a novel approach to enhance user engagement by predicting recipe ratings based on user preferences and behavior. The proposed smart food recipe rating prediction system leverages machine learning algorithms to analyze vast datasets of user interaction with recipes. By considering factors such as ingredient choices, preparation steps, and historical user ratings, the system employs a predictive model to estimate the potential rating a recipe might receive from a user. The predictive model is continually refined through user feedback, ensuring adaptive and accurate recommendations over time. This system integrates natural language processing techniques to understand user reviews, extracting sentiment and identifying key features that contribute to positive or negative evaluations. Additionally, collaborative filtering mechanisms are employed to identify patterns in user behavior and recommend recipes based on the preferences of users with similar tastes. This research contributes to the field of smart food technology by offering an intelligent system that not only recommends recipes but also predicts user specific ratings, providing a more personalized and enjoyable cooking experience. The proposed system has the potential to revolutionize the way individuals discover and engage with culinary content in the digital age.**

Index Terms **– Machine learning, smart food system.**

I. Introduction

In the age of digital transformation and the increasing integration of technology into everyday life, the culinary world has witnessed a paradigm shift in how individuals discover, share, and engage with food recipes. As online recipe platforms become central to the modern cooking experience, the demand for personalized and intelligent recommendation systems has surged. The Smart Food Recipe Rating Prediction System represents a groundbreaking solution designed to enhance user satisfaction by predicting recipe ratings tailored to individual preferences.

1. **Background:** With the proliferation of online recipe platforms and the abundance of culinary content available on the internet, users often face the challenge of selecting recipes that align with their tastes and preferences. Traditional rating systems rely on explicit user feedback, but these can be sparse and may not fully capture the nuances of individual culinary preferences. The Smart Food Recipe Rating Prediction System aims to address this gap by employing advanced machine learning and data analytics techniques to predict how users would rate recipes based on various factors.
2. **Objective:** The primary objective of this system is to provide users with a more personalized and enjoyable cooking experience. By predicting recipe ratings tailored to individual tastes, the system aims to streamline the process of recipe discovery, encourage culinary exploration, and foster user engagement on recipe platforms.
3. **Methodology:** The Smart Food Recipe Rating Prediction System leverages a combination of machine learning algorithms and natural language processing techniques. It analyzes extensive datasets comprising user interactions with recipes,

including ingredient choices, preparation steps, and historical ratings. The predictive model refines itself iteratively based on user feedback, ensuring adaptability to evolving user preferences.

4. **Key features:**
   - **Machine Learning Algorithms:** The system employs state of the art machine learning algorithms to analyze patterns in user behavior and predict recipe ratings.
   - **Natural Language Processing:** Natural language processing techniques are used to understand and extract sentiment from user reviews, enhancing the system's ability to capture nuanced preferences.
   - **Collaborative filtering:** Collaborative filtering mechanisms identify similarities in user tastes, enabling the system to recommend recipes based on the preferences of users with comparable culinary profiles.
5. **Expected Outcomes:** The anticipated outcomes of implementing the smart food recipe rating prediction system include improves user satisfaction, increased engagement with recipe platforms, and a more seamless and personalized cooking experience. By harnessing the power of data analytics and machine learning, the system aims to revolutionize how individuals discover and interact with culinary content in the digital realm.

The Smart Food Recipe Rating Prediction System represents an innovative solution at the intersection of technology and gastronomy, promising to redefine the way individuals navigate the vast landscape of online recipes to create a more personalized and delightful cooking journey.

2. LITERATURE SURVEY

In 2014, Alan and Alejandro [1] have performed the analysis on the basis of recipe related social network. Here they used to collect the basic information such as recipe related data, recipe boxes (which is nothing but in that user can easily save their favourite recipe virtually and can access it later), user profile with their location, interest, habits, social connections etc. The only aim of these authors is to protect their users from obesity. Firstly, they were identified how often a certain ingredient is used by users in a certain county. For each group of counties, i.e. with high and low obesity percentage, they identified the top 110 most popularly used ingredients in both types of counties, i.e. the top intersecting ingredients used by users in both types of countries. By doing this they could easily understood the high and low obesity food recipe. In this work, they have integrated data on health features in US counties with an analysis of a recipe dataset [10]. They have identified the poor health counties (high percentage of adult obesity) and discovered statistically significant differences between the ways in which users interact with recipes in the poor health counties and the good health counties (low percentage of adult obesity). Their research offered a feasible method for developing health-focused recommender systems that considers a user's potential negative outcomes based on demographic data and information from their recorded interactions (ratings) with the system.

David Elsweiler et al. explored recommender systems in relation to a healthy diet in 2015. Prior research on recommender systems has primarily concentrated on predicting what foods people will enjoy, despite the fact that they have previously been suggested as helpful tools for assisting people in achieving a balanced diet. Here, they have described two possible rewordings of the recommendation problem that include elements of a healthy diet and provided examples of how these may be put into practice [11]. They also demonstrated how users' evaluations of recipes submitted to a recommender system might be used to identify users who might most benefit from technical support.

2019 saw the intriguing pattern involving meal recipe prediction presented by Christoph et al. [3]. Deep exploratory study reveals that a range of signals and variables, including the users' prior uploads, social network, temporal context, and spatial embedding, can be used to explain upload behaviour. We may also observe the valuable research in which the investigators organised into groups according to the nation in which they were based. They thought that a recipe may be chosen from the same country. Some academics even thought that people's choices were influenced by their surroundings and social circle. Christoph et al. they concluded their investigation by saying that one can infer a person's preferred meal type based on their upload habits.

Can Liu et al. carried out feature selection on the individual reviews using IG in their 2014 two-layer or review-based prediction [4]. Performance was significantly reduced when the linguistically motivated elements were added. Additionally, they proposed that, with a 3.6% absolute improvement in accuracy, a two-layer approach that predicts review-level ratings and aggregates them for the recipe-level rating outperforms the one-layer approach that aggregates all reviews and predicts directly on the recipe level [5][. They also noted that they obtain an even greater rise of 12.3% when they assess the two layer findings using a more realistic gold standard.

3. Proposed Work

3.1 Input

we are concerned about rating a food recipe depending on different attributes. A recipe rating system based on how it is prepared and user reviews can be very helpful for the food industries. Different restaurants can rate their recipes using this and adjust their recipes for more user or customer acceptance. This can also be useful on a personal level for people interested in cooking, experimenting with different recipes and would like to see the rating of their recipes. If someone is interested in a particular dish or recipe it becomes difficult for them to check how good it is [6]. Different restaurants may also make the same dish using different recipes. So this system can help them see how their dish is rated compared to others. after discarding unnecessary and irrelevant review in the previous steps, scraping data, dropping missing observations and transforming it into a proper data-set, the total data was divided into 2 sets, keeping 80% data in the training set and 20% data in the test set. If we can actually rate recipes using machine learning. We had 28,954 instances from there we tested on 20%of them. Since the lowest testing accuracy achieved is 81% after experimenting with different classifiers we are optimistic about that. Based on what has been covered in this research study we can still make some improvements. More Attributes can be added and analyzed as we have a limited number of attributes. Also with more attributes and data we can try to find out how healthy a recipe is.

As the step of basic data cleaning, the first step is to check for missing values. Unfortunately, both the attributes should contain recipe and review datasets that should carry only null values in the columns. Removing of all the rows which contain the null value is important. Some contain URL's for particular recipe [7]. The next probable step is to remove all the rows in the recipe which contains the URL.

The famous hypothesis states that "Rating for the food not only relies on the review text or image, it also depends on the internal features of a recipe like: value of nutritional value, time taken to prepare the recipe and number of Views acquired for the recipe".

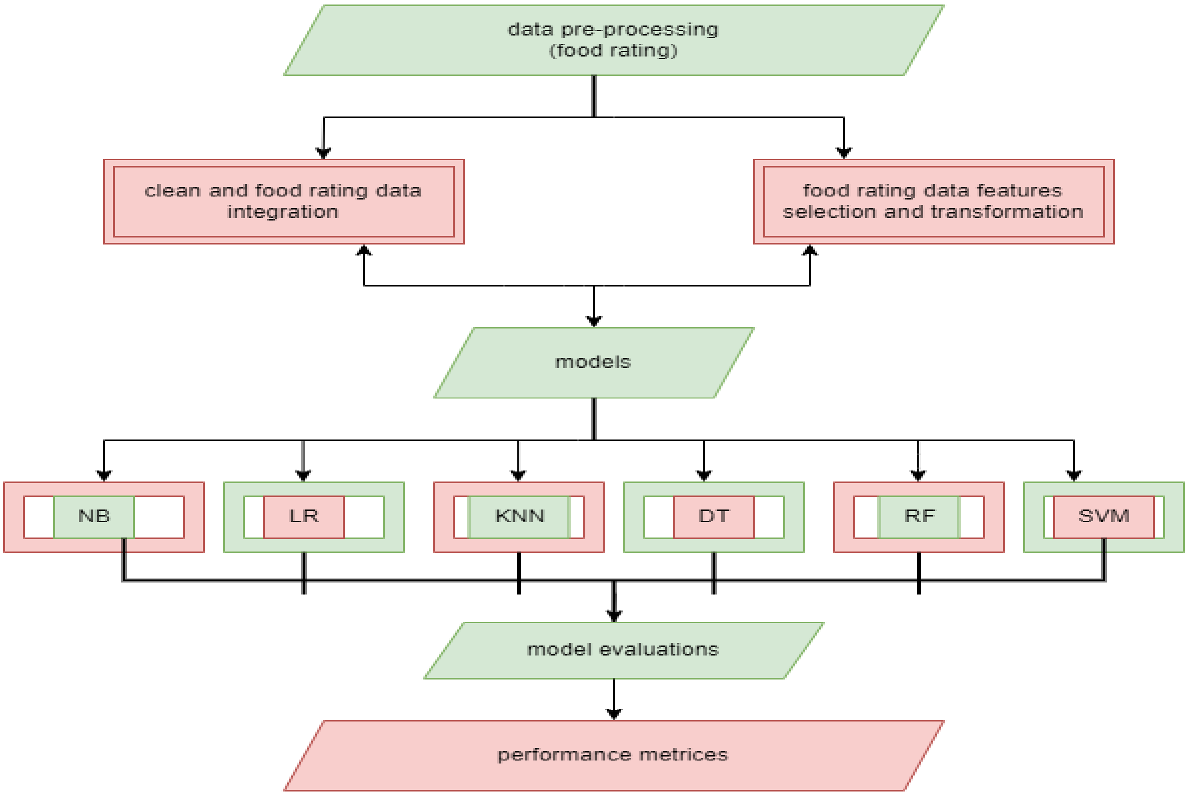

Figure 3.1: System Design

The system flow can be explained as follows: For the gathered dataset, the first step is data pre-processing which will be processed by the food ratings provided by the customers. This is further divided into two parts. One is clean and food data integration the other is food data selection of feature [8]. To the identified two type's machine learning models are applied. The models like: Naïve Bayes, Logistic Regression, K-Neighbor, Decision tree, Random Forest and Support Vector Machine. After applying these models to the food rating data features selection and transformation the models are evaluated based on the features extracted. After validating the model is tested using new samples of food ratings. Upon the test some of the performance metrics are calculated: Precision, Recall, F-1 Score, and Accuracy.

Table 1. Comparison of different classifiers in terms of performance metrics

Classification Techniques	Precision	Recall	F-1 Score
Naïve Bayes	84%	72%	77%
Logistic Regression	98%	75%	85%
K Nearest Neighbor	84%	72%	77%
Decision Tree	82%	71%	76%
Random Forest	93%	75%	82%
Support Vector Machine	75%	75%	85%

Most of the classifiers are applied for testing the food rating. Among all the classifiers Logistic Regression is having high accuracy among the others [9]. Where Precision is calculated with true positives divided by the sum of true positives and false positives of the actual and predicted class. Whereas, recall bit differs from precision in terms of considering the negatives of actual/ real class.

Where the F-1 score is the harmonic mean of precision and recall. The above table is comparison of metrics with the classifier where the graphical representation is also given below.

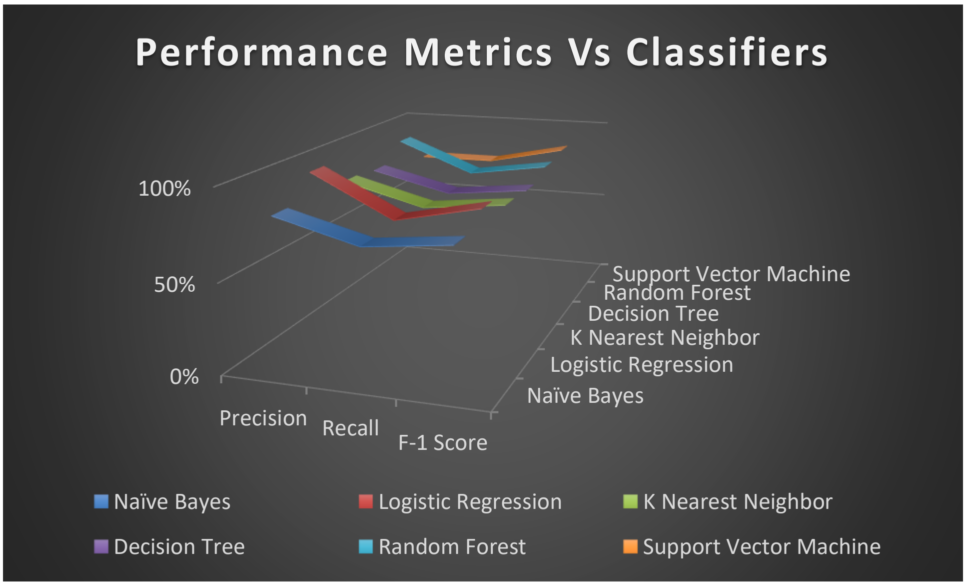

Figure 2: Graphical representation of Performance metrics

Conclusion

The Smart Food Recipe Ratings Prediction system represents a promising and innovative approach to enhancing the culinary experience for users. By leveraging advanced machine learning algorithms, this system provides accurate and personalized recipe ratings predictions, thereby assisting users in making informed decisions about their meal choices. We had 28,954 instances from there we tested on 20%of them. Since the lowest testing accuracy achieved is 81% after experimenting with different classifiers we are optimistic about that. Based on what has been covered in this research study we can still make some improvements. Through the analysis of various features such as ingredients, cooking methods, and user preferences, the system has demonstrated its ability to generate reliable predictions. The integration of user feedback and reviews further refines the model, ensuring that it adapts to evolving taste preferences and culinary trends. As the Smart Food Recipe Ratings Prediction system continues to evolve, it holds the potential to become an indispensable tool for both novice and experienced cooks. Its impact extends beyond individual kitchens, contributing to the broader landscape of smart technologies that enhance our daily lives. In the future, further refinements and expansions of the system can be explored, including integration with smart kitchen appliances, real-time updates based on user feedback, and collaboration with online cooking communities. Ultimately, this innovative solution has the capacity to redefine how we approach cooking and elevate the overall satisfaction derived from our culinary pursuits.

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