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Study and Overview of Recipe Generators

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Abstract

This paper presents a literature survey focused on the development and effectiveness of recipe generators and nutrient tracking applications. The study explores the evolution of these tools, their underlying technologies, and their role in promoting healthier eating habits and personalized nutrition. Recipe generators leverage algorithms to recommend meals based on user preferences, dietary restrictions, and available ingredients, while nutrient apps provide detailed insights into food composition and help users monitor their dietary intake. The survey examines various case studies to highlight successful implementations, identifying key features such as ingredient substitution tools, meal planning functionalities, and real-time nutrient tracking. Additionally, the study investigates the challenges faced by these systems, including data accuracy, user engagement, and personalization limitations. The findings offer insights into how these digital solutions contribute to health management and propose future directions for improving their functionality through advancements in AI, user experience design, and interoperability with other wellness platforms.

1. Introduction

As technology continues to penetrate everyday life, the way individuals plan meals and manage nutrition has undergone a digital transformation. Recipe generators and nutrition apps have emerged as essential tools, facilitating personalized meal planning, ingredient tracking, and nutritional management. These systems aim to help users make informed dietary choices by leveraging technologies like artificial intelligence (AI), natural language processing (NLP), and data analytics. With the global increase in lifestyle-related diseases such as diabetes, heart disease, and obesity, there is growing emphasis on creating tailored meal plans that suit the user's specific health conditions, preferences, and restrictions. Recipe generators and nutrient tracking tools offer significant potential to enhance user's dietary habits, promoting healthier lifestyles by providing access to dynamic meal suggestions and diet-based recommendations. Automated recipe generation systems aim to simplify the decision-making process by curating dishes based on user input, available ingredients, and dietary preferences. Studies have explored the use of AI-based recommendation models to suggest recipes aligned with users' personal tastes and available pantry items. These systems are further enhanced by nutrient tracking apps, which offer users a platform to monitor calorie intake, macronutrients, and specific nutrients such as vitamins or minerals. Despite the promise of these tools, challenges remain. Developing effective ingredient substitution algorithms that provide suitable alternatives without compromising taste or nutrition is still an area of active research. Additionally, user engagement is critical for the success of these platforms, as users need to feel empowered by the recommendations to build long-term healthy habits. Another challenge lies in achieving interoperability across platforms, such as linking recipe apps with wearable fitness devices or health tracking systems. Furthermore, ensuring data privacy and security is paramount, especially as users share personal health information to generate customized meal recommendations. The objective of this literature survey is to provide an in-depth exploration of current advancements in AI-powered recipe generation and nutrition tracking applications. It seeks to identify key technologies, trends, and gaps within the field, highlighting both the opportunities and limitations of existing systems. By synthesizing research findings from various sources, this study aims to offer insights into how recipe recommendation systems and nutrition apps are evolving to meet the growing demand for personalized dietary tools.

2. Literature Survey

[1] Explores the evaluation of cooking recipes through parameters such as correctness and innovation, utilizing survey results to gauge understandability and willingness to cook. It introduces AutoChef, an evolutionary algorithm that generates valid and innovative recipes by leveraging existing culinary knowledge, employing techniques like natural language processing and genetic programming. Recipes are structured as trees, with nodes representing cooking actions and ingredients, enabling the evolution of recipes over generations. The system employs a fitness function to evaluate ingredient combinations, cooking methods, and instruction clarity, ensuring that only high-quality recipes are selected for further refinement. Knowledge is extracted from user-generated online recipes, providing a foundation for creating new, valid, and appealing dishes. AutoChef manages a population of recipes, pairing and evaluating old and new versions, with higher-scoring recipes selected for future iterations. Finally, the recipes are transformed into coherent text formats by traversing recipe trees and merging instructions. The findings reveal varying levels of recipe quality, with a focus on validity, edibility, and creativity, while also highlighting the potential for future enhancements in recipe generation through improved data on food combinations. This paper [2] also uses AutoChef, an autonomous recipe generator designed specifically for the Indian diaspora, filling a gap in recipe generation research. Using a genetic algorithm inspired by natural evolution, the system selects and refines the best recipes to create new, innovative culinary combinations. The methodology evaluates recipes based on tastiness, creativity, validity, and edibility. Results show that users rated the recipes highly for creativity, while validity and edibility received moderate scores, indicating that the generated recipes are generally understandable and acceptable. In addition to the genetic algorithm, the authors implemented several machine learning techniques, particularly in the realm of Natural Language Processing (NLP). They utilized neural network language models and N-gram models to analyze ingredient combinations and cooking instructions effectively. The study also incorporated an ensemble approach that combined classifiers such as Naive Bayes, Multinomial Logistic Regression, and Random Forest. This ensemble method achieved an impressive accuracy of 79% in predicting the cuisine based on ingredient sets, showcasing the effectiveness of the algorithms used. The paper highlights the importance of ingredient relationships and the mapping of these relationships to improve recipe generation. The paper [3] explores the classification of cuisines through structured recipes, emphasizing the significance of cooking processes and utensils alongside ingredients. The authors applied various classification techniques, including traditional machine learning models and advanced neural networks. The methodology of the study focused on classifying cuisines using the RecipeDB dataset, which comprises 118,071 recipes, 20,280 unique ingredients, 256 unique processes, and 69 unique utensils. Given the dataset's high sparsity ratio of 99.50%, effective preprocessing was crucial. The preprocessing steps involved tokenization, lemmatization, and the removal of digits and

symbols to minimize noise, resulting in a refined dataset containing 20,400 distinct entities. These entities were subsequently vectorized using TF-IDF and word embedding techniques to prepare them for analysis. The study employed a combination of statistical and sequential classification models. The statistical models included Logistic Regression, Naive Bayes, Support Vector Machines (SVM), and Random Forest, while the sequential models comprised Long Short-Term Memory (LSTM) networks and Transformers, specifically BERT and RoBERTa. The classification of cuisines through structured recipes emphasizes the importance of ingredients, cooking processes, and utensils in defining culinary identity. By treating recipes as sequentially structured data, the methodology enhances classification accuracy and provides deeper insights into the relationships among various culinary features. This comprehensive approach leads to more meaningful results in culinary research and applications. [4]The project investigates the application of natural language processing (NLP) techniques to assist in cooking by suggesting alternative ingredients and generating new recipes. The dataset was collected from Spoonacular, comprising 3,433 recipes across 15 cuisine styles, with an average of 229 recipes per cuisine. During data preprocessing, the original cooking instructions were preserved, and a new feature called "process" was created to pair cooking activities with ingredients, enhancing the understanding of ingredient usage in various contexts. The project employed the Skip-gram model to obtain word embeddings for ingredients, measuring similarity through cosine similarity of their embedding vectors. Two language models were developed: the traditional N-gram model, which often produces repetitive text, and the Long Short-Term Memory (LSTM) model, which generates more coherent recipes with recognizable steps and ingredients. The study found that recipes generated by the LSTM model included an average of seven recognizable cooking steps and eight ingredients, while those generated by the N-gram model included five cooking steps and three ingredients. Additionally, the project employs word embedding methods to suggest alternative ingredients based on similarity, emphasizing the need for further data collection and collaboration with culinary experts to enhance recipe generation and interpretation. These findings highlight the potential of NLP methods in recipe generation and the importance of context in ingredient substitution. [5]Presents a novel AI system designed to enhance personalized nutrition management, particularly for patients with chronic diseases. The primary objective of the project is to facilitate daily assessments of nutrient intake, enabling tailored dietary adjustments to meet individual nutritional needs. The methodology encompasses several key stages, starting with data collection, where patients are referred by healthcare professionals, and nutritionists compile essential information such as medical history and biological assessments. This data is crucial for determining dietary restrictions based on factors like height, weight, age, and physical activity. The system employs advanced image processing techniques, including classification, segmentation, and detection, to identify food items from images. The dataset used for training the system includes thousands of images of various food items, which are essential for accurate classification and nutrient estimation. Subsequently, machine learning algorithms are utilized to estimate the nutrient content of these identified food items, enhancing the accuracy of nutrient intake assessments. The system aims for an accuracy improvement of over 90% compared to traditional methods, which often yield biased results due to reliance on self-reported data. A significant focus of the project is on improving accuracy, as traditional dietary assessment methods often suffer from biases due to reliance on self-reported data, particularly among patients with cognitive impairments. The AI-based approach aims to mitigate these issues by reducing human error and providing real-time analysis of food images. Initial results suggest that the AI system has the potential to replace conventional food assessment methods, with ongoing efforts directed towards refining its accuracy and usability for better patient health outcomes. The paper [6] discusses the development of a system for Food Nutritional Detection, Visualization, and Recommendation aimed at health monitoring using image processing techniques. It addresses the challenges of maintaining a healthy lifestyle in a busy world by enabling users to identify food items through images, view their calorie content, and receive health recommendations. The system is structured into two main sections: an admin section for managing food data and a user-friendly Android application that allows users to upload food images. Key processes involved in the system include converting images to greyscale, segmentation, histogram calculation, feature extraction, and classification using algorithms such as Convolution Neural Networks (CNN). Additionally, the system incorporates a crowdsourcing approach to keep the food database updated, ensuring that users have access to the latest nutritional information. Overall, the project aims to assist users in managing their calorie intake and making healthier food choices. The paper also references various research studies and conference proceedings related to food recognition, calorie measurement, and nutrition monitoring using technology, particularly focusing on mobile devices and wearable systems. Key topics highlighted include artificial ripening detection, personalized healthcare recommendations, food recognition systems tailored for diabetic patients, and calorie management tools. The studies utilize advanced methods such as deep learning, image processing, and augmented reality to enhance dietary assessment and monitoring, further emphasizing the importance of technology in promoting healthier eating habits. [7-9]

2.1 Tables

Table 1 List of Recipes Combinations

Recipe ID	Continent	Cuisine	Recipe
2610	African	Middle Eastern	['water', 'red lentil', 'rom tomato', ,smooth', 'stir', 'heat']
3957	Asian	Southeast Asian	['olive oil', 'onion', 'garlic', 'ginger' 'stir', 'add', 'cook 'season', 'garnish', 'pot']
4153	Asian	Indian Subcontinent	['coconut milk', 'milk', 'white sugar', 'basmati rice' 'stir', 'cook', 'saucepan', 'bowl']
79897	Latin American	Mexican	['beef', 'chunky salsa', 'mushroom', 'garlic', 'heat', 'simmer', 'serve'. 'skillet']
138976	European	Deutschland	['oven buttermilk biscuit', 'onion', 'cream', ..., 'spread', 'sprinkle', 'bake', 'pan']
149191	North American	Canadian	['raisin', 'fig', 'water', 'date', 'butter' 'chill', 'cut', 'bowl', 'processor', 'pan']

Table 1 shows the recipe ID, continent, cuisine, and ingredients required for each recipe. The recipes are from African, Asian, Latin American, European, and North American cuisines. The ingredients required for each recipe are listed as a string of words, with each word representing a specific ingredient. For example, the recipe with ID 2610, from African cuisine, requires the ingredients water, red lentil, rom tomato, smooth, stir, and heat. Similarly, the recipe with ID 3957, from Southeast Asian cuisine, requires olive oil, onion, garlic, ginger, stir, add, cook, season, garnish, and pot. This table provides a concise overview of the different recipes and their corresponding ingredients.

Table 2 The Performance of the Models

Model	Accuracy (%)	Loss	Precision	Recall	F1 Score
Logistic Regression	57.70	1.51	0.56	0.57	0.56
Naïve Bayes	51.64	7.14	0.50	0.51	0.50
SVM (Linear)	56.60	2.97	0.54	0.56	0.54
Random Forest	50.37	2.32	0.48	0.50	0.49
LSTM	53.61	1.65	0.53	0.54	0.53
Transformers (BERT)	68.71	0.21	0.58	0.60	0.57
RoBERTa	73.30	0.10	0.67	0.71	0.69

Table 2 shows the accuracy, loss, precision, recall, and F1 score of different models used for information extraction from a recipe. The models include Logistic Regression, Naïve Bayes, SVM, Random Forest, LSTM, Transformers (BERT) and RoBERTa. The models were evaluated on a dataset of recipes and their performance is presented in the table. RoBERTa achieved the highest accuracy (73.30%) and F1 score (0.69), indicating it's the most effective model for this task.

2.2 Figures

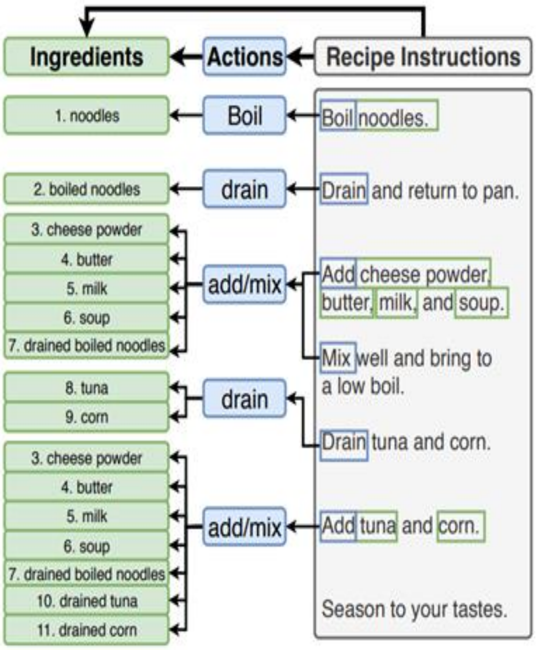

Figure 1 **Information Extraction from a Recipe**

Figure 1 shows Information extraction from a recipe [1] It illustrates the design flow for automatic digitization of a recipe, breaking down the recipe into three main components: Ingredients, Actions, and Recipe Instructions. The left column lists the ingredients, while the middle column specifies the actions applied to these ingredients. The right column combines the ingredients and actions into step-by-step instructions. This structured process enables the systematic extraction of recipe data, which can be used for digital applications such as automated cooking guidance or smart kitchen systems. Figure 2 represents the technique used by the authors and outlines the workflow of the AutoChef system, which automates the generation of new recipes through an evolutionary algorithm.

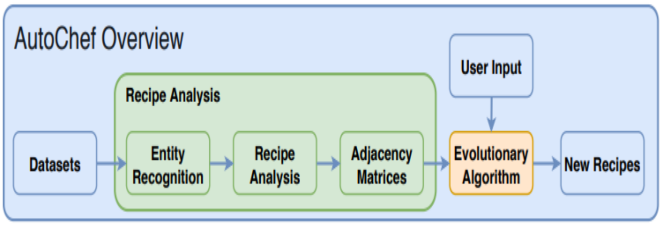

Figure 2 **Autochef System Overview**

In [1] , the process starts with Datasets, which are fed into the Recipe Analysis stage. This stage is composed of Entity Recognition, Recipe Analysis, and Adjacency Matrices, which work together to identify and map the relationships between ingredients and actions. The output of this analysis, combined with User Input, is passed to the Evolutionary Algorithm, which generates New Recipes based on both data-driven insights and user preferences. This architecture enables the automated creation of novel recipes, leveraging evolutionary algorithms to optimize combinations and outcomes.

3. Results and Discussion

3.1 Results

The studies under review have shown the usefulness of AI-based recipe generators, as well as nutrition apps, while they have also highlighted a few limitations. Particularly, numerous distinct methods, including evolutionary algorithms, genetic programming, and NLP models, were used to generate new and applicable recipes. Tasks in these studies indicate the need to manage multiple parameters on creativity, validity, edibility, and tastiness, implying that both data-driven and heuristic methods are essential to user satisfaction.

3.2 Discussions

The most widely used method in these studies seems to be the genetic algorithm, which evolves the recipes over many generations, concentrating on the improvement of ingredient combinations and the technology to prepare the dish. This is the case in AutoChef, which considers genes coded in trees to be recipes [1]. The fitness functions guarantee that the best recipes are only chosen for further refinement on the scales of flavor and ease of understanding of the recipe. Cuisine classification and ingredient prediction tasks are some of the tasks that had cross discipline algorithms such as Support vector machines (SVM), Naive bayes classifiers, Random forests, and neural networks (particularly, LSTMs and Transformers). A significant improvement in model performance is observed with Transformers which include BERT and RoBERTa as these performed better than other traditional classifiers with accuracy of over 73%. [3]Other ways in which the systems were improved include Natural Language Processing techniques such as Skip-gram, and N-gram models which were used to aid in generating more sensible ingredient substitutions and recipes that made more sense.[4]

Conclusion

AI-based recipe generators and nutrition systems are transforming culinary innovation and personalized health management through advanced techniques like evolutionary algorithms, genetic programming, NLP, and machine learning models. Platforms like AutoChef highlight the potential for creative recipe generation, though challenges remain in balancing creativity with practicality. Systems integrating nutritional tracking with real-time assessments offer promising solutions for healthcare applications. These AI-driven tools have the potential to revolutionize personalized cooking and nutrition, promoting healthier dietary choices and better user engagement. Continuous innovation will be key to addressing current limitations and unlocking their full potential.

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