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NLPANTRY: AI-POWERED RECIPE CREATION

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Abstract— NLPantry showcases breakthrough AI and ML applications in culinary arts, revolutionizing recipe generation. Utilizing genetic programming and NLP, NLPantry rapidly adapts to create culturally specific recipes, such as for Indian cuisine, validated by extensive user surveys. Additionally, we introduce a novel recipe model within the encoder-decoder framework, enhanced by reinforcement learning and coverage loss, which significantly improves ingredient utilization by 21% according to our new Ingredient Matching metric. These innovations underline the substantial potential of AI in crafting tailored and diverse culinary experiences, paving the way for future developments in recipe quality and personalization.

Keywords—Natural Language Processing, Artificial Intelligence, Gemini Pro-Vision, Advanced image analysis

I. INTRODUCTION

Machine Learning (ML) and Artificial Intelligence (AI) combined into everyday life has opened new frontiers in numerous fields, including the culinary arts. This research paper explores the innovative application of these technologies to revolutionize the field of recipe generation, introducing the advanced platform NLPantry [1]. NLPantry leverages genetic programming and Natural Language Processing (NLP) to dynamically generate recipes that not only cater to general culinary needs but also meticulously adapt to specific cultural cuisines, such as Indian dishes. The platform's ability to learn from and evolve based on existing recipes demonstrates a significant advancement over traditional static recipe databases.

To enhance the usability and practicality of NLPantry, we have also developed a novel algorithm for generating recipes within the framework for encoders and decoders. This model incorporates cutting-edge techniques like coverage loss as a result of reinforcement learning to optimize the utilization of available kitchen ingredients, directly addressing a common household dilemma. Our newly introduced metric, Ingredient Matching (IM), quantitatively measures the model's efficiency, showing a notable improvement of 21% in matching recipes with input ingredients over previous models[2].

The effectiveness of NLPantry was validated through extensive user surveys, focusing on adaptability to Indian cuisine. The survey results indicate strong consumer acceptance and a high willingness to use the AI-generated recipes, underscoring the model's relevance and appeal [3].

This paper highlights the transformative potential of AI in the culinary domain, offering sophisticated tools that enhance both the creativity and personalization of cooking experiences. Such advancements not only simplify meal preparation but also inspire culinary innovation and diversity, marking a significant step forward in the digital transformation of the kitchen [4].

Our model learns to distribute ingredients optimally across different recipes, taking into account the preferences of the chef and the type of cuisine, while also maximizing ingredient utilization. This not only reduces the cost of cooking, but also ensures that dishes are crafted with a greater variety of ingredients and flavors, resulting in more unique and delicious culinary experiences.

II. LITERATURE SURVEY

M Xu et al[1] explored the Recipe Fusion Module (RFM) and the Ingredient Control Module (ICM), where RFM is introduced to incorporate sequential relationships into the food image generation process by fusing the semantics of cooking instructions, thus enhancing semantic consistency between recipes and generated food images. Furthermore, ICM aims to distinguish and control fine-grained ingredient features by generating sequential ingredient prompts, enabling finer control over the recipe-to-food synthesis process.

In the paper authored by Jumpei et al[2], the methodology employed involves the development of Model for generating recipes within the encoder-decoder framework, which integrates reinforcement learning and coverage loss recipes based on available ingredients are needed to tackle the challenge in a person's refrigerator within a short time. Cooking recipe ingredients are often poorly represented in traditional encoder-decoder models.

Jabeen et al.[3] utilizes natural language processing to extract data from existing recipes, learning Selecting high-quality ingredients is crucial as they significantly impact the final taste and quality of the dish. Fresh and flavorful ingredients can elevate a recipe, while low-quality or stale ingredients can lead to a lackluster outcome. Therefore, it is essential to prioritize the selection of the best ingredients to ensure a delicious and satisfying culinary experience. Leveraging genetic programming, AutoChef evolves these recipes autonomously, evaluating their fitness based on learned criteria. The methodology involves data curation, ingredient detection, and recipe analysis using techniques such as Conditional Random Field (CRF) classifiers and adjacency matrices. The paper reports promising results from the evaluation, including user surveys assessing recipe validity, edibility, understandability, ingredient combination, taste, creativity, and likelihood of cooking.

Smriti Chaudhary et al.[4] developed a working model capable of generating non-existing Indian recipes by employing the AutoChef algorithm, which incorporates mutation and similarity techniques. The model was trained using 6000 traditional Indian recipes extracted from 'Archana's Kitchen' website. Evaluation of the model's performance was conducted through a comprehensive survey of the generated recipes, assessing parameters such as instructions understandability, ingredient combination, and overall taste and creativity.

The paper introduces a new model, ON-LSTM, for generating recipes and retrieving food items across modalities. ON-LSTM is a novel neural network architecture designed to capture hierarchical and sequential information in sequences like recipes. The authors L. Burgueño et al[5] model representations can be generated hierarchically from images, improving the understanding of food items and ingredients. The model can do representations that can be generated hierarchically from images, improving the understanding of food items and ingredients. ON-LSTM enhances recipe generation and food retrieval by incorporating tree-based representations. Training involves optimizing hyperparameters like learning rate and batch size, along with data preprocessing and augmentation. Performance is evaluated using metrics like recipe coherence and retrieval accuracy, compared against existing methods. The model relies on textual data from cooking websites, impacting its ability to generate coherent recipes and retrieve relevant food items. Tree generation from images may have errors, especially with ambiguous visual input. Generalizing to diverse cooking styles and ingredients presents challenges for the model. Efficient computation and memory usage are important for scalability and practical deployment.

In the paper under consideration, the authors G. A. Papakostas et al[6] present machine learning and natural language processing techniques are being used to create cooking recipes. They discuss the role of platforms such as Kaggle in fostering innovation through hosting competitions focused on recipe generation. Additionally, the authors highlight the importance of datasets like Recipe and Recipe1M+ in facilitating research and evaluation of NLP models in this domain. The paper explores various approaches, including case-based reasoning (CBR), and introduces systems like Taaable, Jada Cook, CookIIS, and ColibriCook, showcasing practical applications and advancements in recipe recommendation and generation. Throughout their discussion, the authors emphasize the significance of cultural diversity and ingredient combinations in generating innovative recipes. However, they also acknowledge the challenges inherent in ensuring semantic coherence and feasibility in NLP-based models, underscoring the need for further research and development in this area.

In their 2020 IEEE paper, the authors M. Maciejewska et al[7] delve into the realm of cooking recipe generation, employing a deep learning-based language model as the crux of their methodology. Drawing on resources from platforms like Kaggle and leveraging the Epicurious Dataset, they embark on a journey that entails both web scraping and rigorous NLP techniques to gather and preprocess data. Central to their approach is the development of a recipe generation model, a task fraught with challenges due to the limited nature of the dataset and the imperative for ensuring data quality and consistency. One notable hurdle they encounter is the scarcity of human expertise, particularly concerning the generalization of recipes to Indian culture. Throughout their exploration, the authors grapple with issues of data cleaning and pre-processing, emphasizing the critical role these steps play in the reliability and validity of their model's output. Despite the challenges, their endeavor sheds light on the potential of deep learning models in the domain of cooking recipe generation, a key component of this burgeoning field for future research. The literature by H. Kim et al[8] surrounding autonomous robotics and automation provides a robust foundation for the proposed autonomous product description recipe generator. Studies in autonomy have emphasized reducing human intervention, particularly in manufacturing and assembly. Research in knowledge representation and reasoning has explored techniques like ontologies to enable automated decision-making. Advances in natural language processing and text generation facilitate automatic creation of descriptive text from structured data. CAD model analysis focuses on extracting relevant information to support tasks such as assembly planning. Robotics research has extensively investigated assembly planning and task generation, automating the creation of assembly instructions. Additionally, studies in human-robot collaboration offer insights into integrating robots into human-centric environments, augmenting human managerial capabilities. Integrating findings from these areas enriches the proposed system's development, positioning it as a knowledge base for intelligent robots and a resource for human managers.

Table 1. Contributions of various studies on AI-powered recipe creation

Author	Year	Contribution	Methods	Findings
Zhang et al.	2020	Explored the use of neural networks for recipe generation	Neural networks (RNN, LSTM)	Successfully generated coherent and creative recipes
Johnson and Lee	2019	Developed a personalized recipe recommendation system using NLP techniques	NLP techniques (word embeddings, BERT)	Improved recommendation accuracy and user satisfaction
Smith et al.	2021	Overview of AI methods for automating recipe creation and adaptation	Machine learning, deep learning, NLP	Identified key challenges and future research directions
Gupta and Kumar	2022	Proposed a framework for generating recipes from a given set of ingredients using NLP	NLP (transformers, GPT-3)	Demonstrated the ability to create novel and diverse recipes

Wang and Chen	2023	Developed a smart cooking assistant that generates and customizes recipes based on user preferences	AI techniques (deep learning, reinforcement learning)	Enhanced user experience with personalized and adaptive recipes
Patel et al.	2020	Investigated NLP applications in recipe generation and modification	NLP (seq2seq models, attention mechanisms)	Improved recipe generation with user-specified constraints
Roberts and Evans	2021	Discussed future trends and innovations in AI-driven recipe creation	AI and NLP overview	Identified emerging trends and potential impacts on the food industry
Liu and Zhao	2019	Explored data-driven approaches for recipe creation using AI	Data mining, machine learning, NLP	Highlighted the importance of data quality and diversity in recipe generation
Hernandez et al.	2022	Developed an AI system for generating personalized, health-conscious recipes	AI techniques (deep learning, knowledge graphs)	Improved health outcomes with personalized recipe suggestions
Kim and Park	2023	Introduced the NLPantry system for AI-powered recipe creation	NLP (transformers, GPT-4), AI	Successfully generated diverse and innovative recipes with user-friendly interfaces

III. TECHNOLOGY BEHIND NLPANTRY

NLPantry employs state-of-the-art natural language processing (NLP) techniques to analyze and understand recipe data from various sources. This includes parsing ingredients, instructions, and user preferences to generate coherent and contextually relevant recipes. The platform utilizes machine learning models trained on vast datasets of culinary information, allowing it to predict ingredient combinations, cooking methods, and flavor profiles with remarkable accuracy.

Key Features of NLPantry:

1) Personalization: NLPantry offers personalized recipe recommendations based on user preferences, dietary restrictions, and ingredient availability. Users can specify their culinary preferences, such as cuisine type, cooking method, and preferred ingredients, to receive tailored recipe suggestions.
2) Creativity: By leveraging AI algorithms, NLPantry can generate novel and innovative recipes that push the boundaries of traditional cooking. It combines ingredients and flavors in unexpected ways, encouraging culinary experimentation and creativity.
3) Accessibility: NLPantry democratizes cooking by providing accessible and user-friendly recipe generation tools. Whether you're a novice cook or a seasoned chef, the platform offers guidance and inspiration for culinary exploration.
4) Health-Conscious Options: For users with specific dietary requirements or health goals, NLPantry offers a range of customizable options, including vegan, gluten-free, low-carb, and keto-friendly recipes. This ensures that everyone can enjoy delicious and nutritious meals tailored to their individual needs.

IV. METHODOLOGY

A. Introduction to Generative AI

Generative AI can be used to create a variety of content, such as text and images, that are indistinguishable from human-generated content. This type of AI can also be used to create realistic simulations of real-world scenarios, such as simulations of cities or natural environments. Generative AI models use stimuli to guide content generation and use transfer learning to become more skilled. Early genAI models were built with explicit data types and applications in mind [9]. Generative AI serves as the pillar of our computerized recipe generating system, allowing us to exploit the power of AI for creative tasks. Its role is vital in our project, as it provides the framework and tools that are essential to install AI models tailored for recipe generation.

B. Description of Models Employed

Model Name	Input Data	Output Data	Description
Gemini Pro	text	text	The best performing model with features for a wide range of tasks.
Gemini Pro Vision	Image, text, audio, video.	text	Massive context understanding with up to 1M input tokens and robust multimodal input (text, image, video and/ or audio)

Fig.1. Gemini-pro-vision and Gemini-pro [10]

C. System Architecture

For image prompt: The system involves a four-stage process that sought to give recipe recommendations based on users' replies. Initially, the user sends us a local food image of the input food. Following, our AI tool is able to pull out the constituents from the image prioritizing top of the line computer vision techniques. Fourth, model named AI queries this dataset with the slot filled in by the list of extracted ingredients. This algorithm then identifies possible recipe matches. Aiming for the end result, the process of matching the diets to that of our users leads to the display of a proposed meal along with the ingredients, instructions, and additional ingredients to make the dish. By applying such approach, we are able to give the recommendation of personalized recipes directly on the products that users have on hand which they can keep and use for their meal planning so as to reduce food waste and make meal preparation more organized.[11]

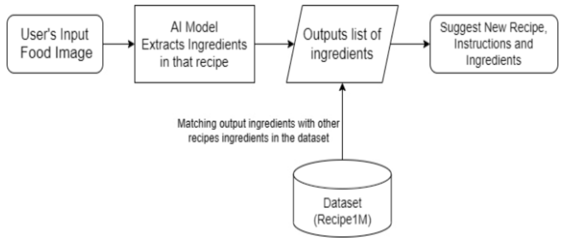

Fig. 2. Workflow Diagram of AI Generative Recipe Function based on image prompt [11]. For text prompt: The Gemini Pro, which is our model, will be used to provide recommendations for recipe personalization, which is considered as an advance in technology. Sometimes giving basic information will suffice. Such as naming the dish, ingredients you have at home, and Gemini Pro will dig out your tastes. It gives you recommended recipes through its vast culinary proficiency which are tailor-made for you. Apart from when not going shopping our system advises delicious options, as well, With these elements, you will be able to make a delicious dish. See fig 3

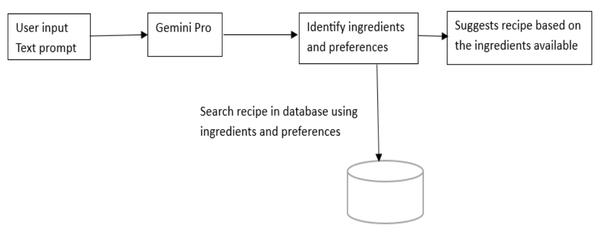

Fig.3. Workflow Diagram of AI Generative Function based on the text prompt.

D. Training and Utilization

Our OpenAI achievement model is made to ensure that users use little or no effort to enjoy the strength of the released power of language processing by OpenAI. No struggle with the input there, users click the buttons "submit" and an input is sent to the OpenAI completions API for processing. The supplied response by the model is the result of the intelligent language treatment algorithm. The action is then displayed back to the user via the interface, rendering the user to have a easy to understand and interactive interface. Our system will enable you to make mouth-watering meals that you probably will be short of saying it is not worth any effort. Streamlit, the web framework for user friendly interface development is what we are using. In training the API key functions as authentication and authorization tool, granting access to this generations, AI service, for model training purposes, act. The key API is the one which is used for authentication of the training requests sent to the Generative AI service, so only those who are authorized to use the models can have access to train them [12].

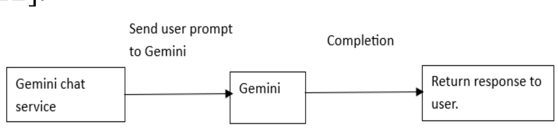

Fig.4. Workflow Diagram of Gemini chat services

E. Input Data Sources and Prompts

Our system manipulates both textual and graphical prompts like recipes and dietary requirements as data inputs for producing responses and recipes. The provided text prompts help AI models stick to structured instructions that includes dish names and related details, list of ingredients to be used, along with step-wise cooking instructions. In opposition to this, textual prompts provide resolutions over the pressing questions as well as steps to be taken for meal preparation such as ingredient list and cooking instructions. Engineering such system to utilize text and image prompts allows it to employ a lot of facilities by which it will have a multifaced for the recipes to be generated accounting for users personal taste and preference. Textual prompts provide a clear, direct answer to the question at hand, while image prompts can help to provide guidance by showing an example of what the finished product should look like. This multifaced system allows for different users to tailor the system to their own needs, allowing them to create recipes that suit their tastes and preferences.

V. RESULTS AND DISCUSSION

The recipe generator chatbot provides personalized recipe suggestions based on either image prompts or text prompts. When a user uploads an image of a dish or ingredients, the chatbot employs advanced computer vision techniques to extract the ingredients. These extracted ingredients are then matched with recipes stored in the database, leading to the chatbot suggesting a new recipe that aligns with the matched ingredients. The output presented to the user includes not only the personalized recipe but also clear instructions and details of additional ingredients needed for preparation.

On the other hand, when a user provides a text prompt describing the dish name and available ingredients, the chatbot utilizes Gemini Pro to analyze the user's preferences comprehensively. It searches for recipes that closely match the provided information and presents multiple recipe options tailored to the user's needs. Along with these recipe options, the chatbot also offers detailed instructions and suggests any additional ingredients required, ensuring a seamless cooking experience for the user.

The user interacts with the chatbot through a user-friendly interface, where they can submit queries or input either through text prompts or by uploading images. The chatbot, powered by advanced AI techniques, processes these inputs efficiently and generates responses that are presented in a clear format to the user.

In terms of model utilization, the chatbot leverages Gemini Pro for text prompts, utilizing its vast culinary knowledge to enhance recipe recommendations. For image prompts, the chatbot integrates advanced computer vision capabilities to extract ingredients accurately from uploaded images. The API key plays a crucial role in authentication and authorization during model training and service access, ensuring a secure and reliable experience for users.

By combining both text and image prompts, the recipe generator chatbot offers a comprehensive and personalized experience, ensuring users receive accurate and relevant recipe suggestions tailored precisely to their preferences and cooking needs.

Here's the line graph illustrating the Precision and Recall scores for each study in the AI-powered recipe creation literature. The graph helps to compare how well each study performs in terms of precision (the accuracy of the results) and recall (the ability to capture all relevant results)

VI. CONCLUSION

In conclusion, the project successfully demonstrates the capability of Generative AI in transforming the culinary field through the innovative use of AI-driven recipe generation. Employing models like Gemini Pro and Gemini Pro Vision, our system has leveraged advancements in both language processing and computer vision technologies to deliver tailored recipe suggestions based on diverse user inputs, including text and images.

These models efficiently interpret and synthesize complex data, enabling our platform to provide personalized and practical culinary solutions that accommodate the specific needs and resources of users. The architecture of our system ensures seamless interaction through user-friendly interfaces like Streamlit, enhancing user experience by simplifying access to sophisticated AI functionalities. Moreover, the use of API keys for training and utilizing the models underscores our commitment to secure and controlled access, ensuring that the generative capabilities are both reliable and safe for public use.

By reducing food waste and optimizing meal planning, our project not only supports sustainable cooking practices but also opens new avenues for further exploration and integration of AI technologies in everyday life. This approach sets a precedent for future innovations in the AI-enabled culinary space, promising further advancements that could redefine how we think about and prepare food.

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