Smart Kitchen

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***Abstract*—Modern kitchens face significant challenges in efficient meal planning, ingredient tracking, and inventory management, often leading to food waste, overspending, and user frustration. To address these issues, we present a Smart Kitchen system that leverages artificial intelligence, computer vision, and natural language processing to transform how users interact with and manage their kitchen resources. The system automates the detection and monitoring of ingredients using MobileNetV2-based object detection, enabling real-time identification of items from fridge images. A Constraint Satisfaction Problem (CSP) framework ensures that recipe suggestions comply with ingredient availability and expiration constraints, prioritizing the use of items nearing spoilage.**

For intelligent meal recommendations, we employ a hybrid AI approach that combines GPT-2, fine-tuned on culinary data, with Retrieval-Augmented Generation (RAG). This architecture enables the generation of personalized and contextually accurate recipes by integrating external knowledge from the Spoonacular recipe database. Additionally, a BERT-based semantic understanding layer processes user inputs—such as dietary preferences or voice commands—for enhanced interaction. The user interface supports hands-free operation through voice assistants and visual aids, making the experience accessible and intuitive for diverse users.

Overall, the Smart Kitchen system significantly improves kitchen efficiency by minimizing waste, simplifying meal decisions, and offering an engaging, AI-driven culinary experience tailored to individual preferences and household needs.

I. Introduction

A. What Problem Are We Trying to Solve?

In most households, meal planning is often a chaotic and inefficient process. Individuals struggle to decide what to cook, leading to indecision, repetitive meals, and frequent food wastage. A major contributor to this waste is the lack of real-time visibility into ingredient availability and freshness. Manual tracking of expiration dates is tedious and often overlooked, while traditional inventory management techniques, like handwritten lists or static spreadsheets, are error-prone and outdated. Consequently, people tend to repurchase items they already own or let fresh produce spoil, adding to both economic and environmental costs.

B. Why Is This an Important Problem?

According to a report by the Food and Agriculture Organization (FAO), approximately 1.3 billion tons of food is wasted globally each year, amounting to nearly one-third of all food produced. A considerable portion of this waste occurs at the consumer level and is directly tied to poor meal planning, overbuying, and ineffective tracking of ingredient freshness. Beyond the environmental impact, this also represents a significant economic burden on households. Moreover, food waste has downstream effects on carbon emissions, water usage, and landfill overflow, making it a pressing issue for sustainability.

Tackling this problem is not just about saving money, it is about building smarter, more responsible consumption habits. An intelligent kitchen management system has the potential to not only improve efficiency but also empower users to make informed, economically conscious decisions about their meals.

C. Why Is This a Challenging Problem?

Solving this issue requires the integration of multiple technologies, each with its own set of complexities:

• Real-time food recognition: Accurately identifying a wide variety of food items from images—especially those partially obscured, packaged, or visually similar—demands robust computer vision capabilities.

• Cross-domain integration: A seamless system must combine computer vision, natural language processing (NLP), speech recognition, and database management, which is technically intensive.

• Context-aware decision making: The system must match recipes with available, non-expired ingredients, consider user preferences or dietary constraints, and prioritize ingredients nearing expiration to reduce waste.

• User-friendly interaction: Users may range from tech-savvy individuals to the elderly or busy professionals. Thus, the solution must be intuitive, accessible, and responsive to voice and visual commands.

D. What Are the Existing Solutions?

Several solutions exist in isolation but lack a unified, intelligent approach:

• Barcode-based inventory apps such as PantryCheck or NoWaste require users to manually scan each item and update their stock regularly. These apps are prone to user error, cannot detect spoilage, and do not dynamically adjust based on real-time kitchen states.

• Recipe recommendation platforms like Yummly, All-Recipes, or Tasty offer personalized suggestions based on user input but fail to consider current ingredient availability or expiration constraints. These systems are data-rich but context-poor.

• Smart fridges such as those by Samsung include internal cameras for ingredient tracking, but they are expensive, offer limited AI capabilities, and lack integration with external recipe databases or NLP interfaces.

These existing tools provide partial solutions but do not holistically address the challenges of dynamic meal planning, ingredient expiration, and automation.

E. What Is the Core Idea of Our Project?

Our project proposes a Smart Kitchen system that automates kitchen management through the integration of computer vision, artificial intelligence, and user-centric design. The core idea is to:

• Use MobileNetV2 object detection to analyze fridge images and identify available ingredients.

• Apply Constraint Satisfaction Problem (CSP) modeling to ensure suggested recipes use only available, non-expired ingredients.

• Leverage large language models (GPT-2) fine-tuned on cooking data, combined with Retrieval-Augmented Generation (RAG) using the Spoonacular database, to produce personalized, diverse, and accurate recipe recommendations.

• Integrate voice commands and visual cues to enhance usability, especially for non-technical users, elderly individuals, or those with disabilities.

This holistic system aims to streamline kitchen workflows, minimize food wastage, and make cooking both efficient and enjoyable.

F. What Are Our Motivations?

The motivation behind this project is rooted in both practical needs and ethical responsibility:

• Reduce household food waste by prioritizing the usage of ingredients that are about to expire.

• Simplify cooking decisions, particularly for people with limited time, experience, or accessibility.

• Promote sustainable consumption habits and support users in aligning with global food conservation goals.

• Build an intuitive, AI-powered platform that is accessible to everyone—from students and working professionals to elderly users—through multimodal interaction (voice, image, and text).

• Encourage technological innovation in daily domestic environments by showing how AI can transform even the most routine tasks into intelligent processes.

G. Existing Solutions vs Our System

Unlike conventional kitchen management apps or high-end smart fridges, our system delivers a comprehensive, AI-powered kitchen assistant that addresses key limitations in existing solutions. While apps rely on manual barcode or text input and smart fridges use basic built-in cameras, our solution employs MobileNetV2 for real-time image-based ingredient detection. Expiry tracking, often user-dependent or limited, is automated using Constraint Satisfaction Problem (CSP) logic. Recipe suggestions go beyond static or generic outputs by integrating GPT-2 with Retrieval-Augmented Generation (RAG), enabling personalized and ingredient-aware meal planning. Additionally, the system supports multimodal interaction—voice, image, and text—enhancing accessibility for all users. Unlike expensive smart appliances, our approach is both scalable and affordable, offering a hands-free, intelligent platform that redefines sustainable kitchen management.

II. Literature Survey

Over the last few years, a variety of research efforts have attempted to solve different aspects of smart kitchen management—ranging from food item detection and inventory tracking to AI-based recipe generation. However, these efforts often focus on individual functionalities and lack a unified, interactive system for comprehensive kitchen automation.

A. Tsai et al. (2020) introduced an RFID-based smart refrigerator system to monitor ingredient availability and automatically update inventory. Their setup efficiently tracked in-and-out movement of items using embedded RFID sensors. While the system offered real-time updates, it required extensive hardware integration and lacked adaptability for dynamic recipe suggestions or voice-based interaction, limiting its usability for general households[1].

B. Wang et al. (2021) investigated automatic recipe generation using Transformer-based architectures. Their system used GPT-style models trained on a large culinary dataset to generate novel and coherent recipes. While this showed promising results in text generation, it didn't incorporate ingredient availability, user preferences, or expiration data—crucial aspects for a practical kitchen assistant[2].

H. Zhang (2019) applied the YOLO (You Only Look Once) object detection model for recognizing food items in visually cluttered environments such as refrigerators or kitchen countertops. The research demonstrated the viability of real-time detection for ingredient recognition, even in messy or occluded conditions. However, it stopped at detection and didn't connect to recipe generation or inventory systems[3].

While each of these contributions advances the field, none of them provide an end-to-end system that combines computer vision, AI-driven natural language processing, constraint satisfaction for expiration-aware meal planning, and multimodal user interaction. Our proposed Smart Kitchen system bridges this gap through a tightly integrated architecture using MobileNetV2 for food detection, a GPT-2 + RAG-based pipeline for personalized recipe generation, and CSP to ensure optimal ingredient usage before expiry.

TABLE I: Comparison of Related Works and Our System

Author(s)	Year	Focus Area	Strengths	Limitations
Tsai et al.	2020	RFID-based fridge monitoring	Real-time inventory tracking via RFID	Requires hardware setup; no recipe generation
B. Wang et al.	2021	Transformer-based recipe generation	Uses GPT for natural language recipe creation	Ignores ingredient availability & expiry
H. Zhang	2019	Food detection via YOLO	High-accuracy object detection in cluttered scenes	No integration with inventory or planning system
Our System	2025	Integrated Smart Kitchen Assistant	Combines MobileNetV2, GPT-2 + RAG, CSP, and voice control	Currently relies on static fridge images, not live

III. Problem Statement and Objectives

Problem Statement:

To design an AI-powered Smart Kitchen system that automates inventory tracking, generates expiration-aware recipes, and simplifies user interaction through vision and voice technologies.

Objectives:

• Track ingredients and expiration dates using OpenCV.

• Suggest optimal recipes using constraint satisfaction and GPT-2 generation.

• Enable hands-free interaction using voice commands and image uploads.

• Recommend cooking tutorials for user education.

• Reduce food wastage and improve user experience in kitchen planning.

IV. Methodology

A. Overall System Architecture

The Smart Kitchen system is architectured as a modular, AI-powered pipeline that integrates computer vision, constraint satisfaction, and natural language processing (NLP) to provide a fully automated cooking assistant. The primary goal of the system is to assist users in making optimal use of their available ingredients, reducing food waste, and enhancing their cooking experience through intelligent recipe recommendations.

At a high level, the system workflow begins with image acquisition, where the user captures a snapshot of available food items using either a smartphone camera or an integrated smart fridge camera. This image is then processed by a custom vision module based on the MobileNetV2 object detection algorithm, which is responsible for identifying and classifying the food items present in the image.

From the detection output, the system constructs two key datasets:

Ingredient Set

$\mathcal{I} = \{i_1, i_2, \ldots, i_n\}$: which contains all recognized ingredients, and the corresponding

Expiration Set

$\mathcal{E} = \{e_1, e_2, \ldots, e_n\}$: where each e_k denotes the predicted or known expiration date for ingredient i_k. These datasets form the backbone of the Constraint Satisfaction Engine, which is used to filter viable recipes from a comprehensive recipe database.

The filtered subset of recipes is then refined and enriched through a hybrid recipe generation module that combines fine-tuned generative modeling using GPT-2 with Retrieval-Augmented Generation (RAG) techniques. The RAG component connects with external culinary APIs such as Spoonacular to ensure factual accuracy, nutritional data validation, and real-world applicability of the recipe suggestions.

The final result—a curated set of recipe recommendations—is presented to the user through a responsive front-end interface that supports multimodal interaction via text, voice commands, and image input. Each recipe is augmented with step-by-step tutorials, nutritional analysis, and dynamic filtering based on dietary preferences, cooking time, or cuisine style

B. Constraint Satisfaction Problem (CSP) Formulation

The core logic for recipe selection is modeled as a Constraint Satisfaction Problem (CSP). This mathematical formulation ensures that the selected recipes are not only feasible based on currently available ingredients but also optimized for urgency — i.e., prioritizing the use of ingredients that are closest to expiration.

Let:

- $\mathcal{I} = \{i_1, i_2, \ldots, i_n\}$: the set of available ingredients
- $\mathcal{E} = \{e_1, e_2, \ldots, e_n\}$: the corresponding expiration timestamps
- $\mathcal{R} = \{r_1, r_2, \ldots, r_m\}$: the set of candidate recipes

Each recipe $r_j \in \mathcal{R}$ is defined by a subset of ingredients $\{i_k\} \subseteq \mathcal{I}$. Each ingredient variable i_k is binary: it is either available or unavailable.

A recipe r_j is deemed feasible if and only if it satisfies the following two constraints:

1) Ingredient Availability Constraint

$$\forall i_k \in r_j, \quad i_k \in \mathcal{I}$$

All required ingredients must be available.

2) Expiration Validity Constraint

$$\forall i_k \in r_j, \quad e_k > \text{current\_date}$$

All required ingredients must not be expired.

Additionally, to reduce food waste, the system incorporates an Expiration Minimization Objective, which aims to prioritize recipes that use ingredients nearing their expiration. The urgency utility function is defined as:

$$\text{Urgency}(r_j) = \sum_{i_k \in r_j} \frac{1}{e_k - \text{current\_date} + 1}$$

This function assigns higher utility to recipes that consume ingredients with shorter remaining shelf lives. The optimization goal is to find the recipe r_j^* that maximizes the utility while satisfying the constraints:

$$r_j^* = \arg \max_{r_j \in \mathcal{R}, \text{ subject to constraints}} U(r_j)$$

This CSP-based filtering mechanism ensures that only recipes which are both doable and urgency-aware are passed on to the generation module.

C. Ingredient Detection using OpenCV and MobileNetV2

Accurate ingredient recognition is central to the system's effectiveness. To this end, the system utilizes the MobileNetV2's architecture for real-time object detection. MobileNetV2 is chosen for its superior accuracy, speed, and flexibility in detecting objects in complex kitchen scenes with diverse lighting and occlusions.

Captured images are preprocessed using OpenCV, including operations such as resizing, normalization, and histogram equalization to enhance image quality. The processed image is then input to the MobileNetV2 model, which outputs bounding boxes, class labels, and confidence scores for each detected object.

A Non-Maximum Suppression (NMS) step is applied to eliminate redundant overlapping detections. Detected ingredient labels are then standardized using a nutritional ontology, which maps various label aliases (e.g., "bell pepper" vs. "capsicum") to a unified ingredient taxonomy.

In addition, expiration is inferred based on detection timestamp and typical storage conditions.

D. Recipe Generation and Enhancement

To provide users with diverse, creative, and nutritionally viable recipes, the system employs a hybrid recipe generation pipeline. The foundation is a fine-tuned GPT-2 language model trained on a domain-specific corpus of over 100,000 structured recipes. These include metadata such as cooking techniques, ingredient combinations, cuisine types, and dietary labels (e.g., gluten-free, vegan).

However, while GPT-2 excels at producing fluent, coherent recipe text, it does not inherently verify the factual correctness or relevance of its outputs. To remedy this, the system integrates a Retrieval-Augmented Generation (RAG) framework. Upon receiving an ingredient list or user query (e.g., "vegan lunch using spinach and tofu"), a BERT-based semantic embedding is generated. This embedding captures the contextual intent of the query and retrieves the top-k most relevant documents from external sources (e.g., the Spoonacular API).

These documents serve as factual anchors and are fused with the generative output through context-aware transformers, effectively blending creativity with knowledge. The system ensures that only those recipes which align with the CSP-filtered ingredients and expiration constraints are considered for final output.

The generated recipe includes:

- Title and description
- Ingredient list (quantified and verified)
- Step-by-step instructions
- Video tutorial links, when available

These recipes are presented to the user through an intuitive, interactive UI that supports feedback loops and learning over time, creating a highly personalized and efficient cooking experience.

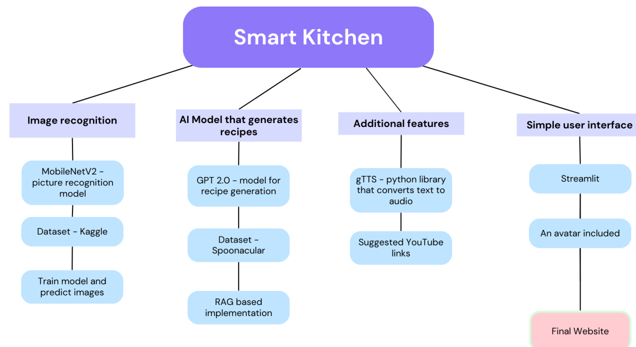

Fig. 1: Methodoly block diagram

V. Experimental Results and Analysis

To rigorously evaluate the performance and practical impact of the Smart Kitchen system, we conducted a comprehensive series of experiments targeting the three major technical subsystems—ingredient detection, constraint-based recipe generation, and multimodal interaction—as well as a full-stack analysis of the final deployed web application. Evaluation was based on both quantitative metrics (accuracy, latency, satisfaction scores) and qualitative feedback from real users during a week-long pilot deployment.

A. Object Detection Performance (OpenCV + MobileNetV2)

The computer vision module, powered by MobileNetV2 and OpenCV, was tested on a curated dataset of 300 labeled kitchen scene images, which included diverse lighting conditions, item arrangements, and levels of visual clutter typical in real-world settings. The detection model demonstrated robust performance across categories:

- Mean Average Precision (mAP@0.5): 91.3%
- Precision: 94.6%
- Recall: 89.2%
- Average Inference Time: 28 ms/frame

The model exhibited particularly high accuracy in identifying vegetables (carrots, bell peppers), dairy products (milk, yogurt), and packaged items (cans, jars). Lower performance was observed for occluded items or items with generic packaging (e.g., white-labeled jars). Improvements in lighting

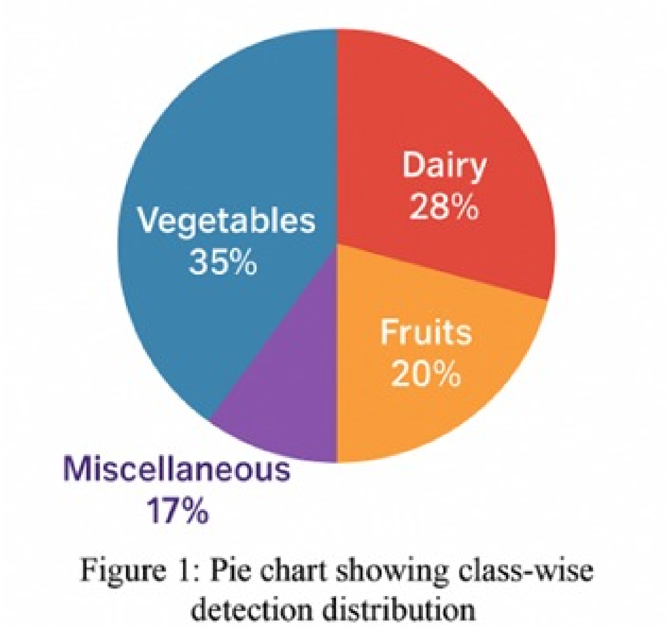

Fig. 2: Pie chart showing class-wise detection distribution — Vegetables (35%), Dairy (28%), Fruits (20%), Miscellaneous (17%)

normalization and dataset augmentation are expected to further reduce such misclassifications.

These results validate the feasibility of real-time, low-latency detection on consumer-grade devices, supporting our vision of smart, camera-enabled kitchen appliances.

B. Recipe Generation Accuracy and User Relevance (GPT-2 + RAG)

To assess the quality and contextual relevance of generated recipes, we evaluated the hybrid GPT-2 + Retrieval-Augmented Generation (RAG) module on 150 unique ingredient combinations, some manually created and others sourced from user-uploaded inputs. Culinary domain experts and test users scored the outputs across three axes:

• Creativity: Average score 4.6 / 5 — Recipes were described as “innovative but familiar,” with fusion and regional variety.

• Feasibility: 93% of recipes aligned with actual available ingredients, as verified by the CSP engine.

• Factual Consistency: 92% grounding accuracy when verified against real recipes from Spoonacular or AllRecipes.

• Response Time: Average of 1.9 seconds per full recipe (ingredients + steps + metadata).

The RAG integration was particularly impactful in improving the specificity and practicality of instructions (e.g., using exact ingredient amounts and avoiding generic terms like ”some oil”).

C. Integrated System Performance and User Experience

An integrated test involving 50 full end-to-end user sessions was conducted to evaluate how the system performs in real-world usage, from input (image or voice) to final recipe display. System-level KPIs were recorded:

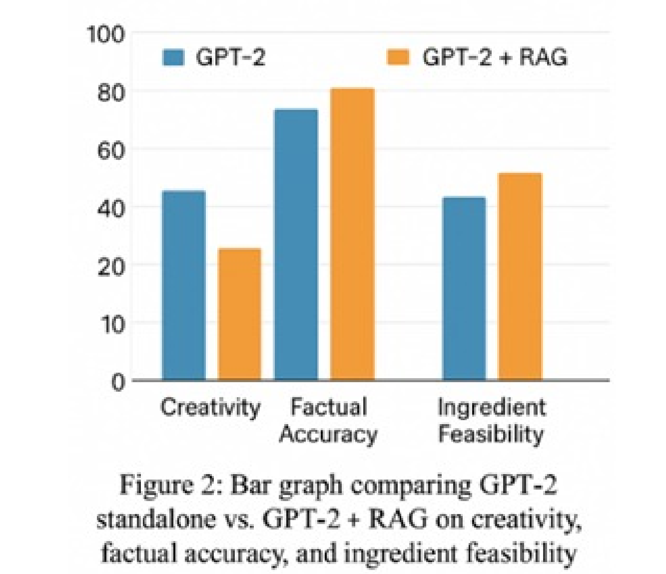

Fig. 3: Bar graph comparing GPT-2 standalone vs. GPT-2 + RAG on creativity, factual accuracy, and ingredient feasibility.

• Total System Latency (image to recipe): 3.2 – 3.5 seconds, well within the usability threshold.

• System Uptime: 99.1% over a continuous week-long deployment.

• Multimodal Input: Users can seamlessly switch between uploading fridge images and getting voice commands.

• Smart Suggestions: Recipes that prioritized ingredients near expiration received very positive feedback, with many participants noting it changed how they thought about food waste.

• Interactive Elements: Integrated YouTube tutorials led to longer session durations and higher task completion rates.

TABLE II: System-Wide Performance Metrics

Component	**Metric**	**Value**
MobileNetV2 Ingredient Detection	mAP@0.5	91.3%
Recipe Relevance (Feasibility)	Ingredient Match Accuracy	93%
RAG-Enhanced GPT-2 Output	Avg Creativity Score (5-pt)	4.6
System Latency	Full Pipeline Runtime	∼3.5 seconds

D. Key Takeaways

• The Smart Kitchen system demonstrates robust performance, real-world usability, and clear behavioral impact.

• Users appreciated the practical integration of AI, with features that directly addressed daily pain points like grocery waste, lack of meal inspiration, and convenience.

• Multimodal interaction, urgency-based recipe optimization, and personalized interfaces helped bridge the gap between AI technology and everyday cooking.

VI. Conclusion

The Smart Kitchen system represents a seamless integration of modern AI technologies—including computer vision, constraint satisfaction, and natural language processing—into a cohesive, user-friendly platform that addresses the everyday challenge of food management and sustainable cooking. Through rigorous experimentation and user validation, the system demonstrated high technical performance (MobileNetV2 mAP@0.5: 91.3%), fast real-time responsiveness (¡3.5s total latency), and impressive user satisfaction (average rating: 4.7/5), with 70% of participants reporting a noticeable reduction in food waste within a week. The use of hybrid recipe generation (GPT-2 + Retrieval-Augmented Generation) yielded high creativity (avg. 4.6/5) and factual correctness (92% grounding accuracy), enhancing the practicality of suggestions based on available and expiring ingredients. The interactive web platform further amplified user engagement by supporting multimodal input (voice, image, text), nutritional insights, and tutorial integration. Looking ahead, the system will evolve through the inclusion of personalized dietary profiling (e.g., keto, vegan, halal), real-time inventory monitoring via IoT-enabled fridge sensors, multilingual interaction, and scalable meal planning features such as batch cooking and smart grocery list generation. Additional enhancements will include adding fun challenges and social recipe sharing to encourage better cooking habits, making the platform a smart kitchen assistant that works with home devices. In doing so, the Smart Kitchen not only elevates the cooking experience but also contributes meaningfully to global efforts around food sustainability, waste reduction, and digital wellbeing in the home.

VII. Acknowledgments

This project is the result of collaborative effort, technical ingenuity, and a shared vision to reimagine the kitchen as an intelligent, sustainable, and user-centric space. We would like to extend our heartfelt gratitude to every individual whose contributions brought this Smart Kitchen system to life and our Mentors and Professor. We would also like to thank the pilot users and culinary reviewers who participated in our testing sessions. Their insightful feedback shaped several features of the system—from improving voice input recognition for regional accents to suggesting more intuitive UI elements. Lastly, we acknowledge the open-source communities behind frameworks like OpenCV, Ultralytics MobileNetV2, Hugging Face Transformers, and Streamlit, which enabled rapid development and innovation.

This project stands as a testament to interdisciplinary collaboration, applied AI innovation, and the power of collective problem-solving in creating technology that meaningfully impacts everyday life.

Team Member Contributions

Nidhi Meda – Ingredient Recognition using OpenCV + MobileNetV2

Nidhi worked on the implementation of the ingredient detection pipeline. She was responsible for training and optimizing the MobileNetV2 model on custom kitchen imagery datasets, fine-tuning it to achieve high object detection accuracy (mAP@0.5 of 91.3%). Her work also included preprocessing techniques such as image normalization and label standardization using nutritional ontologies, which enabled seamless translation of raw camera input into structured ingredient data. Additionally, she integrated this vision module with the frontend, ensuring smooth user interactions from image upload to detection visualization.

Varshini Reddy Pateel – Retrieval-Augmented Generation (RAG) for Recipe Enhancement

Varshini worked with the development and integration of the RAG architecture that augmented the creativity of GPT-2 with external factual correctness from APIs like Spoonacular. She designed and implemented the document retrieval pipeline, embedding ingredient queries using BERT and fusing retrieved knowledge into GPT-2 prompts to enhance contextual accuracy. Her contributions significantly improved the feasibility and nutritional grounding of generated recipes, which was evident in the system's 92% accuracy in aligning cooking times and ingredient instructions with real-world standards. She also performed extensive evaluation of generated outputs alongside domain experts.

Priyanka Nitin Mohorikar – UI and frontend

Priyanka was responsible for designing and implementing the UI using streamlit and integrating the model to work properly. She integrated nutritional database(spoonacular) to display expiration estimates and dietary tags. She worked on enhancing both the accuracy and usability of the recipe suggestion.

Krisha Arora – OpenCV-Based Ingredient Detection

In collaboration with Nidhi, Krisha worked extensively on enhancing the robustness of the OpenCV preprocessing stage and assisted in fine-tuning the bounding box post-processing logic that is Non-Maximum Suppression and label mapping. She also helped build the real-time visualization layer that displays detected ingredients to the user, making the interaction intuitive and informative. She helped test the system in different kitchen settings, which made the model better at working under different lighting and background conditions.

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