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Article

Ensemble Deep Learning for Intelligent Ingredient Detection and Personalized Recipe Recommendation

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Abstract: Making meals and dishes that promote a healthy lifestyle is a challenge for many people these days. This project makes cooking easier with an AI-powered system that uses photos to identify ingredients and suggests customized recipes. Users upload a picture of the ingredients they have on hand, and the system uses an ensemble model that combines Faster R-CNN and YOLOv8 to accurately identify them. The system guarantees accurate ingredient detection by combining the detections from both models using NMS Fusion and the IoU metric.Additionally, it takes into account preparation time, dietary restrictions, and allergies, customizing recipe suggestions to suit personal preferences. This automatic method, which learns user preferences over time to provide even better choices, saves time and effort compared to traditional recipe searches.Combining ingredients wisely increases meal possibilities, minimizes food waste, and encourages better eating practices.Future developments might include voice assistants, linguistic assistance, and smart kitchen connectivity, which would make the system even more user-friendly and accessible for home cooks everywhere.

Keywords: IoU Metric, Ensemble Model, YOLOv8, Faster R-CNN, NMS Fusion, Ingredient Detection, Recipe Recommendation.

1. Introduction

In order to address these issues, we propose an Ingredient Detection and Recipe Recommendation System that uses deep learning and AI to automatically identify ingredients from images and recommend the corresponding recipes [1]. Many users find it difficult to identify vegetables, especially if they are unfamiliar with certain kinds. Additionally, finding suitable recipes from the given ingredients takes a significant amount of time and effort. Most recipe suggestion applications currently on the market require users to input ingredient names, which may be a time-consuming process. It also takes a lot of time and effort to find suitable recipes using the provided ingredients. Most recipe recommendation apps now available on the market need users to enter the names of ingredients, which can be a laborious procedure. We propose an Ingredient Detection and Recipe Recommendation System that employs AI and

deep learning to automatically identify items from photos and suggest recipes in order to address these issues [1].

There are two primary functions offered by the system. First, it uses advanced deep learning models like Yolov8 and Faster R-CNN to identify ingredients from an uploaded image. These models efficiently identify several Components in a picture, and an ensemble approach that combines the advantages of both models is employed to improve accuracy [2]. While Faster R-CNN guarantees greater precision in difficult circumstances, YOLOv8 provides real-time detection. Only the most reliable bounding boxes are kept after redundant detections are eliminated using Non- Maximum Suppression (NMS). Second, after the ingredients have been recognized, the Ingredients that were manually entered. This data is analyzed by AI to offer customized recipe suggestions based on the ingredients available. The system is sensitive to a variety of nutritional needs, and can tailor recipe recommendations to dietary restrictions, such as low-sugar, high-protein, vegetarian or gluten free options. The system is very user-friendly and flexible; the user can choose their favorite cuisines and also how many recipes they want to see [3].The system improves cooking efficiency by providing fast and smart recipe suggestions without manual input of the ingredient information. It cuts down on food waste, incentivizing users to maximize existing supplies by identifying vegetables on hand and suggesting suitable recipes. It also encourages healthy eating by giving diet-friendly recipes according to individual preferences.

The research is improving cooking with deep learning, ensemble model [7], AI based picture recognition and smart recipe suggestions, making it more convenient, accessible and eco- friendly

2. Literature Survey:

The [1] system recognizes ingredients with ResNet-50 and finds recipes with the Edamam API to reduce food waste. It does however have some problems including excessive latencies, the need of external APIs and single ingredient identification. In addition, the system lacks personalized dietary recommendations and uses real-time ingredient recognition, which may cause delays. Despite its capabilities, its reliance on third-party APIs limits its scalability and customizability.

The method in [2] uses YOLOv8 to detect ingredients, enabling automatic meal preparation using computer vision and machine learning.

The method simplifies the identification of items but has less flexibility as it does not provide options for manual input, cuisine or personalized diet programs.

The proposed system in [3] is a lightweight content-based recipe recommender. It uses OpenCV for grey level processing and histogram-based ingredient detection. Identification is not as good as deep learning based models, so it is not suitable for complex photos, but suitable for a casual user. The app's absence of manual ingredient input, cuisine selection, and diet filtering limits user agency and prevents customisation. It also does not provide AI-powered customisation or adjust for the available ingredient stock, which may limit the applicability of its recommendations.

In [4] sentiment analysis and Non-Negative Matrix Factorization (NMF) are used to generate recipe recommendations using content-based and collaborative filtering. The application is based on a Python-Flask-MongoDB backend, so it does not use automatic ingredient identification, but human input. Moreover, sentiment-based comment feedback can introduce biases that can jeopardize recommendation accuracy. Meal planning flexibility is constrained by its lack of ability to dynamically respond to personalized diet requirements or current ingredient availability, even as efficient as it could be.

The method in [5] employs NLP and cosine similarity for simple ingredient- based suggestions but does not employ deep learning, real-time adaptability, and multi-ingredient identification.

The method in [6] improves recipe recommendations using Word2Vec, TF- IDF, and cosine similarity but does not have automated ingredient detection and depends on user input, which may be prone to errors. In contrast, our method uses deep learning for automatic vegetable detection with optional user input for ingredients, cuisine, and dietary requirements. Non-Maximum Suppression (NMS) for precise multi- ingredient detection and AI-powered real-time recipe recommendations, it provides higher efficiency, accuracy, and user interaction.

The classification of diabetic retinopathy was improved by implementing ensemble deep-learning techniques on preprocessed images and models such as Xception and EfficientNetB4 to achieve better accuracies. However, real-time applications of this methodology are limited because of high computational requirements and low-quality images in the used dataset [7]. Such improvements in ingredient detection can be achieved using these small concepts of improving image quality and applying ensemble learning or lightweight models. Improvements in these areas will increase the flexibility, scalability and applicability of our system to real world scenarios.

They designed a Vision-Based Intelligent Recipe Recommendation System for real-time recipe suggestions using YOLOv7 for object recognition. It accurately identifies vegetables with an accuracy of 88.2%, while the other components such as Non-Maximum Suppression and Ajax optimize the overall performance of the system [7]. Object recognition constitutes the working principle in recognizing vegetables and thus intends to do a dataset upgrade and modify the UI.

This method [8] introduces the Vision Based Intelligent Recipe Recommendation System (VBIRRS), aimed at helping users select recipes based on available vegetables. It addresses the needs of individuals living away from home, such as students and professionals. The system uses YOLO for object detection to recognize vegetables and recommends Indian recipes accordingly. It also personalizes suggestions by remembering user preferences. The system achieves over 81.6% classification accuracy. Performance is optimized by skipping bounding box redraws and using AJAX for faster dynamic data updates.

The method in [9] presents a mobile- based cooking recipe recommendation system that utilizes real-time visual object recognition to identify food ingredients. By pointing a smartphone camera at ingredients, users receive instant recipe suggestions. The system aims to assist in recipe decision-making at grocery stores or in kitchens. It supports recognition of 30 ingredients with a quick response time of 0.15 seconds. This model attains a recognition rate of 83.93% for the top six results. User testing is conducted to validate the applicability of the suggested system. Furthermore, it makes the process easy and convenient for the user since there is no need for manual input.

3. System Architecture:

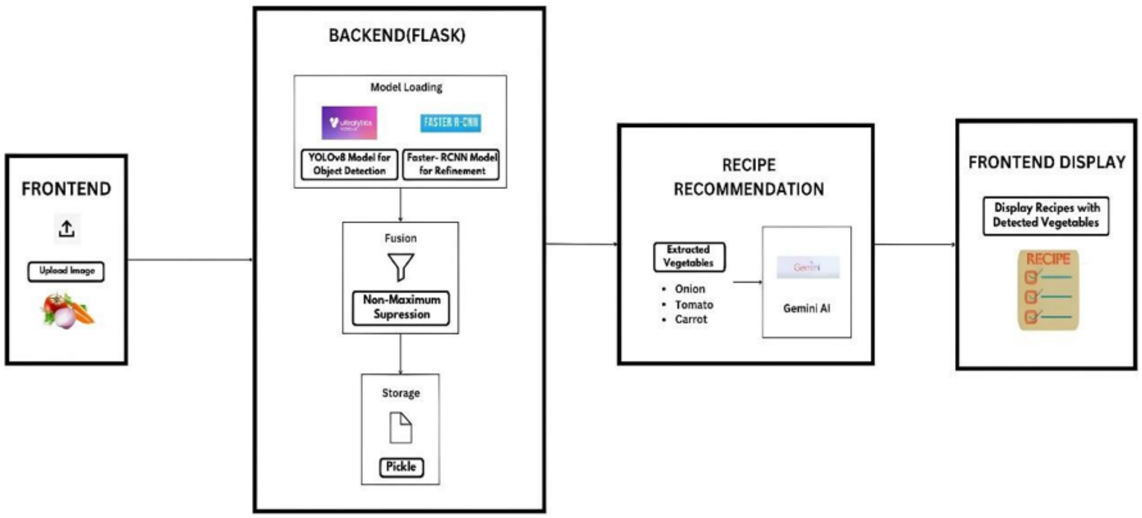


Fig.1 System Architecture

The architecture design of the system includes three main components that work together to offer users a customized cooking experience, which include the frontend, backend, and recipe recommendation modules. The frontend provides users with an opportunity to input ingredients using either the camera or manually. Afterward, the given data undergoes a process where the picture uploaded by the user is processed using a deep learning model using both the YOLOv8 and Faster R-CNN algorithms, after which the NMS algorithm removes duplicate objects. Finally, the ingredients are saved on a Pickle file.

Ingredients are sent from the database to the Recipe Recommendation module where Google Gemini AI recommends personalized recipes according to the user’s needs and preferences. Users get an entire recipe description that includes preparation instructions, preparation time, and nutrition. Recipes recommendations are shown to users through the frontend application.

This solution architecture will make meal planning easier for users while minimizing waste food and encouraging healthier habits. This is an architecture that is scalable in the future. Future improvements may include user authentication and a grocery service addition.

4. Proposed System:

The Vegetable Detection and Recipe Recommendation System aims to make cooking easier using AI and deep learning to recognize vegetables and suggest suitable recipes. This is contrary to the normal recipe app where the user is required to type in the name of ingredients in order to be offered a meal recommendation.

Key Features and Functionalities:

4.1. Automatic Vegetable Detection

Users can upload a photo with vegetables. The system processes the image using complex deep learning models to identify multiple vegetables with high accuracy. Non-Maximum Suppression (NMS) is used to remove duplicate detections for accurate recognition. The model trained is saved as a Pickle file so processing is faster and more efficient than in the case of traditional models.

4.2.AI-Fueled Recipe Suggestion

Once the machine recognizes the vegetables, it will automatically forward the names of the ingredients, as well as manually entered ingredients, to a suggestion mechanism powered by AI. This uses the ingredients available to suggest relevant recipes that people can prepare. There is room for personalization depending on diet preferences.

4.3. User-Friendly Interface

A minimal and interactive UI enables users to: Upload images of vegetables, See the recognized vegetables, navigate through suggested recipes based on recognized ingredients, and filter results based on dietary preferences.

4.4. Efficient Processing & Seamless Performance

The combination of YOLOv8 and Faster R-CNN provides a well-balanced solution in terms of speed and accuracy in detecting the ingredients. IoU is used along with Non-Maximum Suppression (NMS) to improve accuracy by eliminating false positives and removing duplicative predictions. This improves the speed and effectiveness of detection to ensure that our clientele get the best recipe recommendations possible.

Strengths of the Suggested System:

• Avoids manual entry of ingredients – reduces time and effort.

• Offers instant recipe recommendations according to available vegetables.

• Customized meal suggestions adapt to various dietary requirements.

• Averts wastage of food by proposing meals based on available ingredients.

• Quick and effective processing improves user experience.

5. Methodology:

The methodology used in our Recipe Suggestion System consists of collecting data, pre-processing data, creating dataset, detecting ingredients, user interaction, recommending recipes, and managing recipes. Using this methodology, we ensure that our system stays efficient, precise, and user-friendly.

5.1. Data Collection

Designing a well-structured dataset is the first step in developing an ingredient detection system. Due to the fact that public datasets usually do not contain real- world variation, we constructed a custom dataset with frequently used vegetables in daily cooking. The pictures were captured at different lighting conditions and using different cameras so as to simulate real-life situations of the kitchen environment. The vegetables were captured in their entirety, as well as in pieces and blended form so as to create variability within the dataset. All the pictures were annotated with bounding boxes to ensure accuracy during the training process.

5.2. Pre-Processing

To ensure consistency throughout the dataset, Resizing of the images was the only pre-processing done on the images. All images were resized to a uniform size that is suitable for training a deep learning model, keeping in view that all important attributes of the ingredients in the images would remain intact after resizing. This process of pre-processing did not involve any distortion or quality loss of the images.

5.3. Dataset Preparation

After preprocessing, the data set was systematically divided into training, validation, and testing parts for generalization of the model effectively. All the images had their ingredients marked using bounding boxes. This data was then divided as follows: 70% used for training where the model learns its weights, 15% was reserved for validation, and another 15% for testing Since the data set has been structured in the COCO format, it becomes easier to use it with any major deep learning framework.

5.4. Modules Explanation

5.4.1 Data Preprocessing Module

Image Uniformity Module It ensures that all the images are uniform when fed into the model. This module resizes all images to a uniform resolution such that it can fit into the input layer of the model without changing its aspect ratio, ensuring there is no distortion or loss of characteristics of the images. Minimal image preprocessing will ensure the system is light and low-cost without losing its ingredient recognition accuracy.

5.4.2 User Interaction Module

The User Interaction Module offers a user-friendly, interface through which the users can customize their recipe recommendation according to their ingredients and their food preferences. Users have the ability to either upload pictures of their ingredients or take pictures, rectify any mistakes regarding the detection of the item, and inform the system about their dietary restrictions, which may include veganism, gluten-free meals, diabetic friendly or heart-healthy food options. In addition, users have the option to select the cuisine that suits their tastes (for example Indian, Chinese or Italian), and choose the number of recipes they need.

• **Upload Ingredient Images:**

Users can capture or upload pictures of available ingredients.

• Confirm & Edit Detected Ingredients:

Users can verify and • Revise identified components for precision.

• **Enter Dietary Preferences & Restrictions:**

Users can input dietary restrictions and health-related limitations.

• **Choose Cuisine Type:**

Customers will choose a favourite cuisine, such as Chinese, Indian or Italian.

• **Enter Number of Recipes Wanted:**

Users can indicate the number of recipe ideas they require.

• **View Personalized Recipe Suggestions:**

The system creates and shows recipes based on the ingredients detected, user preferences and dietary needs.

5.4.3 Ingredient Detection Module

The Ingredient Detection Module is responsible for accurately detecting ingredients from images uploaded by the user. It employs an ensemble model combining YOLOv8 and Faster R-CNN for better performance. YOLOv8 provides high-speed detection in real-time, whereas Faster R-CNN is more accurate, particularly in complex conditions. Since both models may produce multiple bounding boxes for the same object, a fusion approach is applied to merge overlapping detections. This method employs Non-Maximum Suppression (NMS) and Intersection over Union (IoU) to eliminate duplicates and retain the most confident bounding box. When the IoU is larger than 0.5, NMS only retains the highest-scoring detections, thus improving detection precision.

- YOLOv8 is fast and real-time detection.
- Improved accuracy of complex cases with Faster R-CNN.
- NMS and IoU for overlapping bounding boxes.

5.4.4 Recipe Recommendation Module

Once the ingredients have been identified, the Recipe Recommendation Module generates customized and relevant recipe suggestions. It recalls user habits like dietary limitations and past choices and cross-references the identified ingredients with a handpicked recipe database. The final recipes are filtered by relevance, time to cook and ease, so the recommendations are not only tailored but also practical. This allows users to get relevant and personal recipe suggestions based on live ingredient recognition.

6. Results:

Fig. 2: To identify the ingredients, users share photos that are passed to an ensemble model.

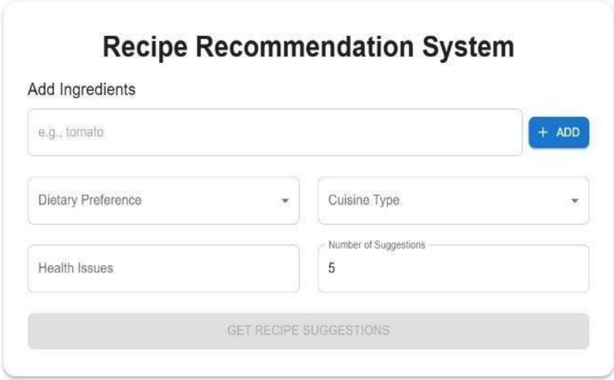


Fig. 3: A system for recommending recipes that lets users customize it.

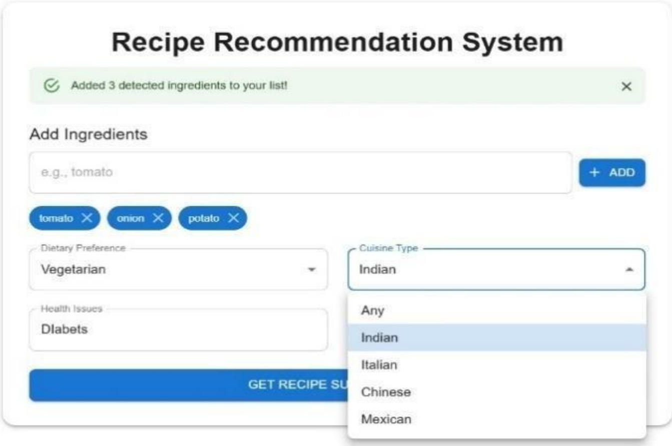


Figure 4: Include ingredients in the Recipe Recommender System so that consumers can customize their tastes

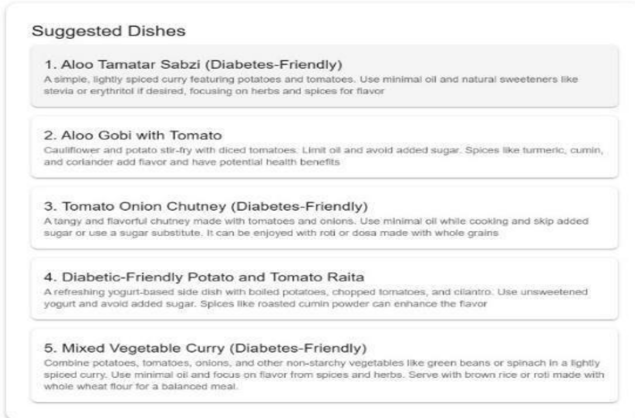
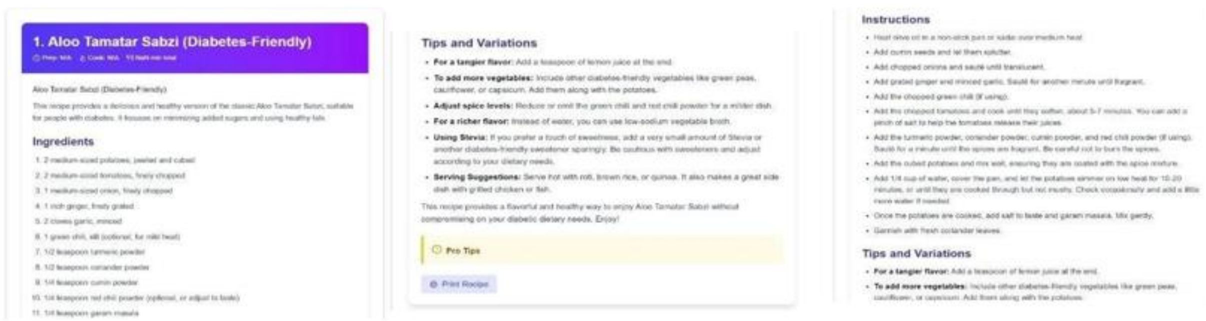


Fig. 5: The interface will show the suggested recipes



Figures 6, 7, and 8: Detailed instructions and the process (along with suggestions) for the selected recipe

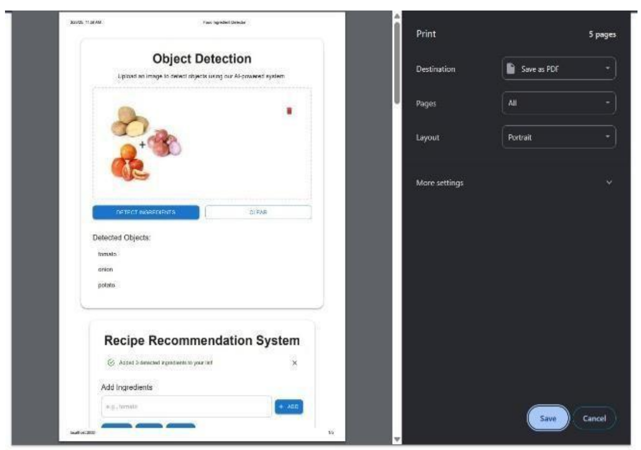
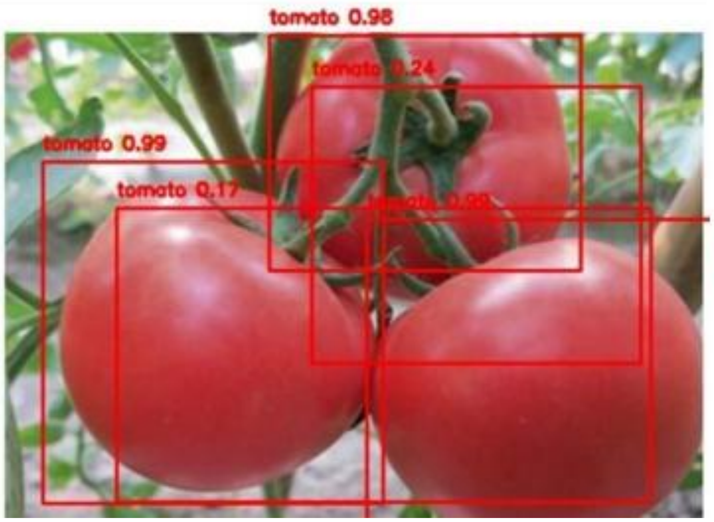
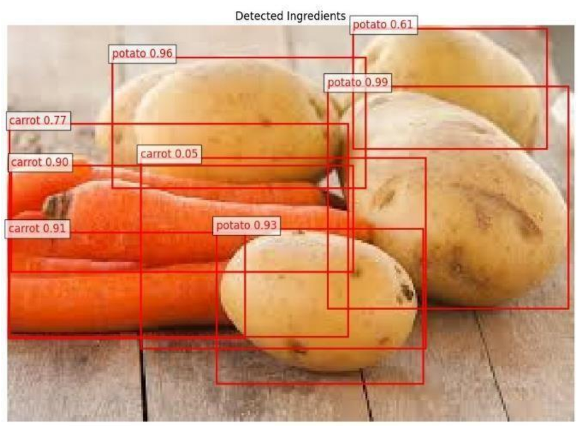


Fig.9: The print of the recipe




```
✅ Detection Results:
==========================================
Unique ingredients found:
1. tomato
```

Fig. 10, 11: Tomatoes identified from the picture and the special ingredients printed in a Python file




```
Detection Results:
All items: ['potato', 'potato', 'potato', 'carrot', 'carrot', 'carrot', 'potato', 'carrot']
Unique items: ['potato', 'carrot']
Confidence scores: [0.988069474697113, 0.9620305299758911, 0.9344714283943176, 0.9085783958435059, 0.8991029262542725
```

Fig. 12: The unique ingredients reported in the Python file and the ingredients identified from the image

7. Challenges and Limitations

Despite being a cutting-edge method of ingredient automation, our vegetable detection and Recipe Recommendation system has many drawbacks and restrictions.

- **Limited Training Data** – The quality and richness of the dataset determine how well the model performs. The model won't correctly identify unusual or local product if it isn't present in the dataset.
- **Computational Requirements**–Deep learning models are computationally demanding, especially when it Come to real-time detection. Low-end gadgets, such as low-end smartphones, may experience performance issues or become sluggish.
- **Storage and Model Update** –New veggies and methods for detecting changes must occasionally be added to the model. The system will become outdated and inefficient if the model is not updated

- **Multilingual and Regional Issues** – Recipe recommendations can be language-specific; therefore unless the system is bilingual, it could be difficult to provide localized recipes for users depending on different locations.
- **Internet Dependency:** The internet-based recipe recommendation tool is limited in its use when offline because it requires an online connection.

8. Conclusion:

This method significantly improves cooking by cooking by merging AI-driven recipe ideas with deep learning techniques like YOLOv8, Faster-RCNN, and NMS fusion. It eliminates the need for users to manually type in ingredients, but it still gives them the choice to do so if necessary. By selecting different cuisines, adding more recipes, and implementing dietary restrictions like low-sugar or high-protein options, users may further customize their experience. In addition to being convenient, it promotes healthier eating, reduces food waste by making the best use of ingredients, and enables consumers to discover new vegetables. This approach simplifies cooking while meeting various nutritional needs, whether it is used in private kitchens or supermarkets long-lasting.

With greater customization and smart kitchen integration, the system can enhance user experience even more as it develops, making cooking more sustainable and user-friendly.

9. Future Scope:

There is a lot of room for future improvements and broader uses for the Recipe recommendation system. The system can be improved in the following ways by implementing more recent AI and machine learning techniques:

- **Improved Vegetable Detection Accuracy** – The Future models may employ self-supervised learn in transformer-based architectures (such as Vision Transformers) to improve detection accuracy even in low light or when ingredients are partially ***visible.***
- **Support for Packaged and Processed Ingredients** – Recipe recommendations will be more inclusive if the system is expanded to include packaged foods, grains, dairy, and spices.
- **Offline Functionality** – For users in areas with inadequate internet connectivity, including an offline mode for vegetable identification and basic recipe recommendations will enhance usage.
- **Voice and Speech Recognition** – Adding voice commands will enable users to control the system without using their hands, making cooking more convenient.
- **Personalized Meal Planning** – By considering user preferences, dietary requirements, and health goals (e.g., weight loss, diabetes control), the system can become a personalized nutrition guide. AI-powered meal planning tools might provide weekly meal plans based on available ingredients and **Integration with smart kitchen appliances–for** real-time recipe recommendations and ingredient-level monitoring, the system can be coupled with smart refrigerators, kitchen scales, and culinary appliances.
- **Augmented Reality (AR) for Cooking Guidance** – Future updates may add AR-based instructions, superimposing step-by- step cooking operations over a user's camera view, boosting recipe performance as an interactive experience.
- **Multi-Language and Regional Recipe Support** – The method will be applicable globally and accommodate multicultural eating habits if recipe recommendations are scaled to different languages and cuisines.
- **Crowdsourced Recipe Contributions** – Users would be able to submit their recipes, adding community contributions and user submissions to the System database.
- **E-commerce Integration** – Cooking could be made more convenient by the system's ability to recommend missing supplies and allow users to place online shopping orders.

By adding these improvements, the Vegetable Detection and **Recipe Recommendation System** can transform into a whole AI-based cooking assistant that facilitates meal planning, ingredient management, and healthy consumption more efficiently and simply.

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