SnapMeal: Real-time Recipe Generator Using Multi-Modal Deep Learning & Computer Vision

by

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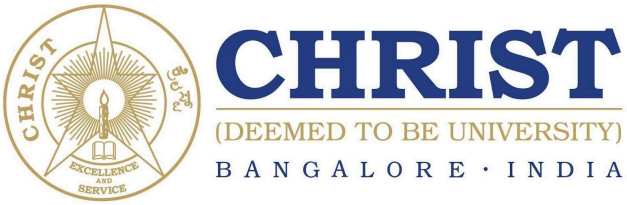

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CERTIFICATE

This is to certify that the report titled ***SnapMeal: An AI-Powered Recipe Generator from Real-Time Image Using Multi-Modal Deep Learning and Computer Vision*** *is a bona fide record of work done by* ***Nirupama Laishram (Reg Number: 2382464)*** *of CHRIST (Deemed to be University), Bangalore, in partial fulfillment of the requirements of VI Trimester MSc (Data Analytics) during the academic year 2024-25.*

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ABSTRACT

Decision fatigue in the kitchen is a common challenge, particularly when individuals struggle to decide what to cook using the ingredients they already have. This project introduces SnapMeal: Real-time Recipe Generator Using Multi-Modal Deep Learning and Computer Vision, an AI-powered application that aims to reduce daily cognitive load by generating instant recipe suggestions based on photos of available ingredients. The purpose of this project is to develop an intelligent system that leverages object detection and natural language processing to bridge the gap between physical ingredients and dynamic recipe creation. The scope involves designing a pipeline where a fine-tuned YOLOv8 model identifies ingredients from user-submitted images, which are then passed to a transformer-based language model to generate context-aware, stepwise recipes. The system was evaluated for ingredient detection accuracy, contextual relevance of recipe generation, and ease of use. Major outcomes indicate high accuracy for common kitchen items and meaningful recipe instructions generated in real-time. These outcomes validate the system's ability to support daily cooking decisions and enhance user experience. Recommendations for future work include integrating user preferences such as dietary restrictions, cuisine types, and calorie filters to improve personalization. Expanding the dataset to cover diverse cultural ingredients is also advised. Overall, the project highlights how multi-modal deep learning can offer practical, real-world utility in everyday domestic environment.

Table of Contents

List of Figures

List of Tables

Abbreviations

Abbreviation	Full Form
AI	Artificial Intelligence
API	Application Programming Interface
BBOX	Bounding Box
CNN	Convolutional Neural Network
COCO	Common Objects in Context
CPU	Central Processing Unit
DFL	Distribtuion Focal Loss
FN	False Negative
FP	False Positive
GPU	Graphics Processing Unut
IoU	Intersection Over Union
mAP	Mean Average Precision
mAP@50	Mean Average Precision at 50$ IoU
mAP@50-95	Mean Average Precision averaged over IoU thresholds from 0.50 to 0.95
NLP	Natural Language Processing
ReLU	Rectified Linear Unit
TN	True Negative
TP	True Positive
YOLO	You Only Look Once

Chapter 1

INTRODUCTION

1.1. Background

Meal planning, though routine, is a source of frequent decision fatigue in many households, especially in fast-paced, resource-constrained environments. Traditional methods of discovering recipes require users to search manually or browse extensive databases, often resulting in inefficiencies and limited culinary variety. As artificial intelligence and computer vision technologies evolve, they offer promising solutions to simplify and enhance the meal preparation process.

A significant number of individuals face recurring dilemmas in the kitchen, such as:
What can I cook with the ingredients I already have?
How can I maintain variety in my meals without additional effort or planning?
What strategies can help reduce food waste while still meeting nutritional needs?

Studies reveal that more than half of global food waste occurs at the household level, often due to poor ingredient tracking or underutilization of perishable items [1]. Furthermore, the lack of quick, tailored recipe suggestions contributes to repetitive meals and reliance on convenience foods.

SnapMeal responds to these challenges through an AI-powered, real-time recipe generator. The system accepts an image of available ingredients, applies multi-modal deep learning and computer vision models to recognize them, and instantly generates viable recipe options. The purpose of this project is to reduce cognitive load in meal planning and promote efficient use of existing resources.

The outcome demonstrates that such a tool can significantly improve user convenience, encourage diverse meal choices, and contribute to reducing food wastage. The recommendation is to further develop personalization modules to enhance adaptability for individual users over time.

1.2. Problem Statement

SnapMeal solves the problem of decision fatigue by generating real-time recipes from images of available ingredients. It uses computer vision and NLP to detect items and generate context-aware, stepwise cooking instructions. SnapMeal aims to combine multi-class ingredient detection using state-of-the-art YOLOv8 with contextual recipe generation using transformer-based NLP models.

1.3. Objectives

- ➔ To develop a multi-label image classification model using YOLOv8 architecture, fine-tuned on a custom dataset of culinary ingredients, enabling real-time ingredient detection from user-uploaded images with high precision and support for imbalanced classes.
- ➔ To design an NLP-powered recipe recommendation engine, incorporating both rule-based filtering and semantic similarity matching via Sentence-BERT, to provide contextually relevant recipe suggestions based on detected ingredients and optional dietary constraints.
- ➔ To implement a cosine similarity-based ranking mechanism, replacing traditional intersection logic, thereby capturing semantic closeness between ingredients (e.g., “chili” vs. “green chili”), enabling substitution-friendly and flexible recipe mapping.
- ➔ To create a modular and scalable pipeline integrating computer vision, natural language processing, and recipe databases, ensuring minimal latency and robust performance for real-time use across varied culinary contexts.

- ➔ To design a lightweight and responsive web application interface that allows users to upload ingredient images, view top recipe matches with instructions, detect missing items, and receive smart grocery suggestions — all while maintaining a smooth user experience on resource-constrained devices.
- ➔ To optimize and evaluate system performance using standard metrics such as mAP (mean Average Precision) for object detection and top-k accuracy for recipe recommendations, ensuring the solution is viable for practical deployment.

The goal is to design a pipeline that can accurately identify ingredients in real-world conditions and map them to coherent, personalized recipes.

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Chapter 2

LITERATURE REVIEW

3.1 AI-Powered Recipe Generation

Recent advancements in AI and machine learning have facilitated the creation of models capable of generating novel recipes. Pareek et al. [4] discuss the use of natural language processing (NLP) models, recommender systems, and generative adversarial networks (GANs) in automating culinary creativity. Their study emphasizes the challenges in ingredient combination, cultural sensitivity, and user feedback integration. Similarly, Noever and Noever [5] introduce a multimodal AI chef that utilizes image recognition to identify ingredients and generate recipes tailored to constraints such as cost, preparation time, and dietary restrictions. This approach combines image models with large language models (LLMs) to produce coherent and contextually relevant recipes.

3.2 Mobile Applications for Ingredient-Based Recipe Suggestions

Several mobile applications have been developed to assist users in meal planning by suggesting recipes based on the ingredients they have on hand. SuperCook [6] allows users to input available ingredients and generates a list of possible recipes, aiming to reduce food waste and simplify meal preparation. Cooklist [7] offers a comprehensive solution by connecting to grocery store loyalty cards, automatically tracking purchased items, and suggesting recipes accordingly. It also provides pantry inventory management and meal planning features, enhancing user convenience. Yummly [8] employs AI-driven personalized recommendations,

considering user preferences, dietary restrictions, and available ingredients to curate suitable recipes.

3.3 Research Projects and Innovations

The academic community has also contributed to this field through various research projects. Taneja et al. [9] propose RecipeMC, a text-generation method using GPT-2 and Monte Carlo Tree Search (MCTS) to generate credible recipes. Their results indicate that human evaluators prefer recipes generated with RecipeMC over baseline methods. Venkataramanan et al. [10] introduce Cook-Gen, a generative model that reliably produces cooking actions from recipes, addressing challenges associated with irregular data patterns in culinary instructions.

3.4 Challenges and Future Directions

Despite these advancements, challenges persist in creating AI systems that can fully comprehend and replicate the nuances of human culinary expertise. Issues such as cultural diversity in cuisines, subjective taste preferences, and the need for high-quality, well-structured datasets remain areas for improvement.

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Chapter 3

METHODOLOGY

3.1 System Architecture Overview

The architecture of *SnapMeal* is designed as a modular pipeline, integrating computer vision, natural language processing, and recommendation logic to generate personalized recipes from real-world images. The system is divided into distinct stages, each leveraging specific models, tools, and methodologies to enable end-to-end automation from input to actionable output.

3.1.1. Image-Based Ingredient Detection

Detects food ingredients from user-uploaded images using object detection.
YOLOv8m is fine-tuned to recognize food-specific classes.
Tools: YOLOv8, PyTorch, OpenCV

3.1.2. Ingredient Post-Processing

Normalizes ingredient names and removes irrelevant entries. Optional semantic deduplication is applied.
Tools: Python (string ops), NLTK/spacy (optional), cosine similarity

3.1.3 Recipe Dataset Integration

Loads and processes a large dataset of structured recipes including ingredients, steps, nutrition, and cook time.

Tools: Pandas, CSV, ast module

3.1.4. Match Scoring Engine

Computes overlap between detected and recipe ingredients using both hard match % and semantic similarity.

Tools: Sentence-BERT (all-MiniLM-L6-v2), sentence-transformers, cosine similarity, NumPy

3.1.5. Filtering & Ranking

Applies user preferences like veg/non-veg, allergies, max calories. Final recipe list is sorted by highest match score and shortest cooking time.

Tools: Pandas, custom scoring logic

3.1.6. Output Generation

Displays recipe name, ingredients matched/missing, steps, time to cook, and nutritional data.

Tools: Python dictionaries/lists, optionally Flask or FastAPI for serving.

A simple Gradio interface was designed for user-friendly interaction with the app.

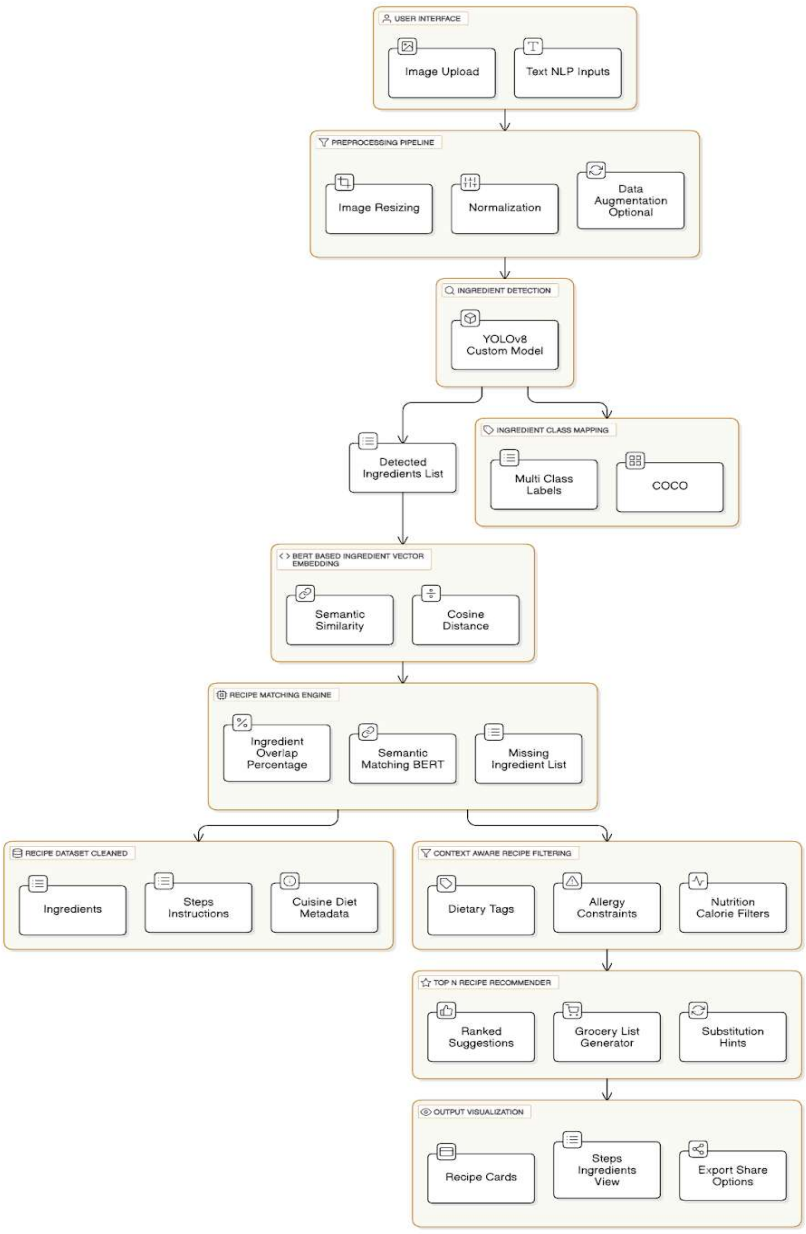

Fig. 3.1: System Architecture

3.2. Dataset Collection and Preprocessing

Two datasets were employed in the SnapMeal system to support image-based ingredient recognition and recipe recommendation:

- **Image Dataset**: A labeled image dataset was sourced from Roboflow Ingredients Detection, provided in YOLOv8-compatible format. This dataset includes 20155 annotated images over 64 classes for various food ingredients, suitable for object detection model training.

- **Recipe Text Dataset**: Recipe metadata was obtained from Kaggle's Food.com dataset link, comprising over 180,000 recipes and 700,000 reviews collected over 18 years. It includes user-generated content such as ingredient lists, cooking instructions, preparation time, user ratings, and dietary tags. This dataset was used in the work by Majumder et al [11]. (2019) EMNLP paper and is well-suited for personalized food recommendation systems.

3.2.1. Image Dataset Preprocessing and Balancing

To address class imbalance and prepare the dataset for training, a preprocessing script was implemented with the following steps:

1) **Directory Initialization**: Existing directories for the balanced dataset were cleared and re-created. Separate folders were initialized for images and label files.

2) **Class Distribution Calculation:** The script parsed each label file to count class occurrences and stored file-wise class associations using Python's Counter and os libraries.

```python
labels_path = "/content/Ingredients-Detection-1/train/labels"
images_path = "/content/Ingredients-Detection-1/train/images"
output_path = "/content/Ingredients-Detection-1/balanced_dataset"


MIN_SAMPLES = 2000
MAX_SAMPLES = 10000


if os.path.exists(output_path):
    rmtree(output_path)
os.makedirs(f"{output_path}/images", exist_ok=True)
os.makedirs(f"{output_path}/labels", exist_ok=True)

# counting samples for each class
class_counts = Counter()
file_classes = {}
for file in os.listdir(labels_path):
    if file.endswith(".txt"):
        with open(os.path.join(labels_path, file), "r") as f:
            class_ids = [int(line.split()[0]) for line in f.readlines()]
            file_classes[file] = class_ids
            for class_id in class_ids:
                class_counts[class_id] += 1
```

Fig. 3.2: Code Snippet I: Data Preprocessing

3) **Augmentation Pipeline**: Underrepresented classes (with <2000 samples) were augmented using Albumentations, with transformations like horizontal flips, brightness changes, rotations, and Gaussian blur. The original bounding box annotations were preserved for augmented images.

```python
# Augmentation pipeline
def augment_image(img_path, txt_path, num_needed):
    img = cv2.imread(img_path)
    augmentations = A.Compose([
        A.HorizontalFlip(p=0.5),
        A.Rotate(limit=20, p=0.5),
        A.RandomBrightnessContrast(p=0.2),
        A.GaussianBlur(p=0.2),
    ])

    for i in range(num_needed):
        augmented = augmentations(image=img)["image"]
        aug_img_path = f"{output_path}/images/aug_{i}_{os.path.basename(img_path)}"
        aug_txt_path = f"{output_path}/labels/aug_{i}_{os.path.basename(txt_path)}"
        cv2.imwrite(aug_img_path, augmented)
        copyfile(txt_path, aug_txt_path)
```

Fig. 3.3: Code Snippet II: Augmentation pipeline

4) **Downsampling**: For overrepresented classes (>10,000 samples), a subset of images was randomly selected to cap the upper limit, ensuring no class skew dominates training.

5) **Balancing:** After copying eligible images to the target directory, the system rebalanced the dataset by adding augmented images to underrepresented classes until the minimum threshold was met.

6) **Tools and Libraries:** OpenCV, Albumentations, File handling (os, shutil, counter, etc.), randomization (random.shuffle).

This preprocessing ensured a uniform distribution of classes, improving the stability and generalization of the YOLOv8 detection model.

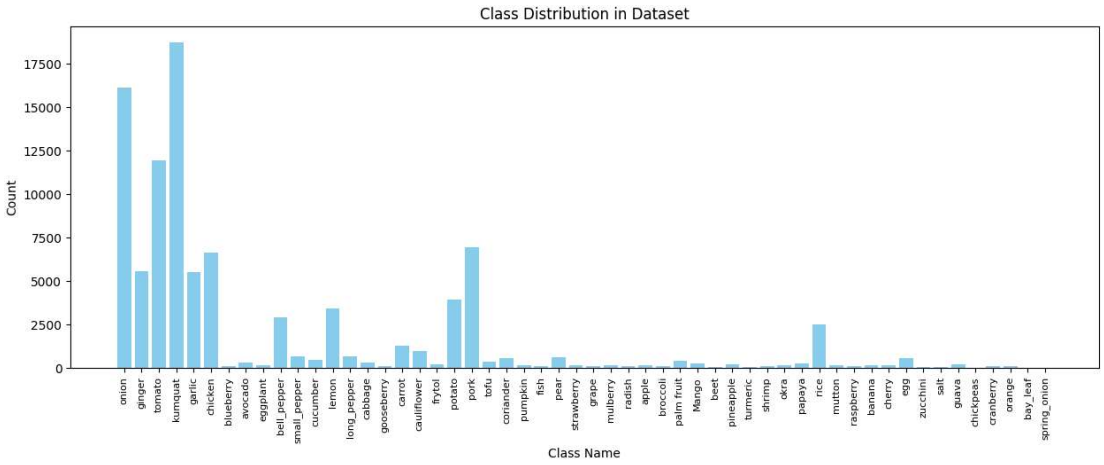

Fig. 3.3: Class distribution (before preprocessing)

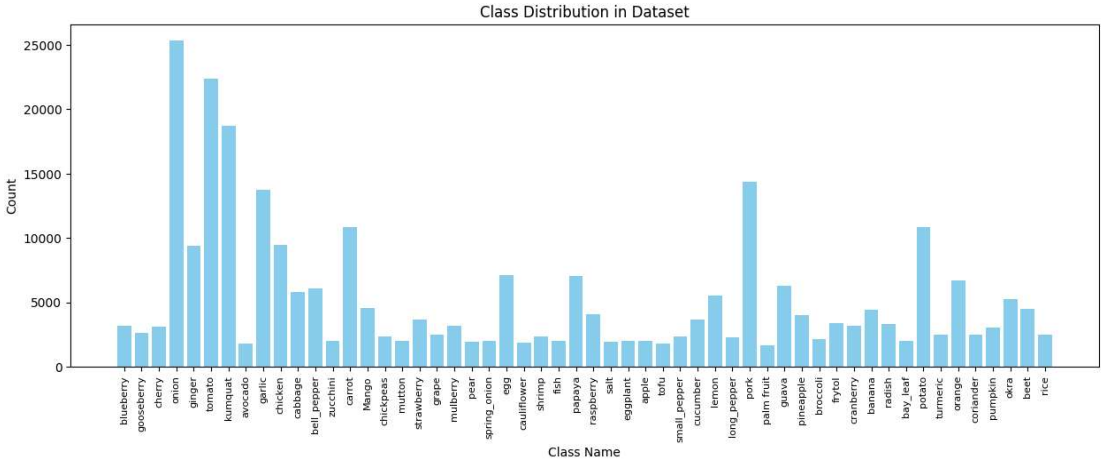

Fig. 3.3: Class distribution (after preprocessing)

Although the class distribution is not perfect, we now have at least 1000 samples of each class which we can use to load into and train the model.

3.3 Multi-Class Ingredient Detection

3.3.1. Model: YOLOv8 (pre-trained on COCO, fine-tuned for food classes)

At its core, *YOLOv8* is a deep convolutional neural network (CNN) designed specifically for object detection and image localization tasks.

what kind? What does its architecture look like? how was it designed?

Understanding YOLOv8

YOLO, which stands for **You Only Look Once**, is a family of real-time object detection models. It operates as a **single-stage detector**, meaning it performs both object classification and localization (bounding box prediction) in a single forward pass through the neural network, making it extremely fast and suitable for real-time applications.

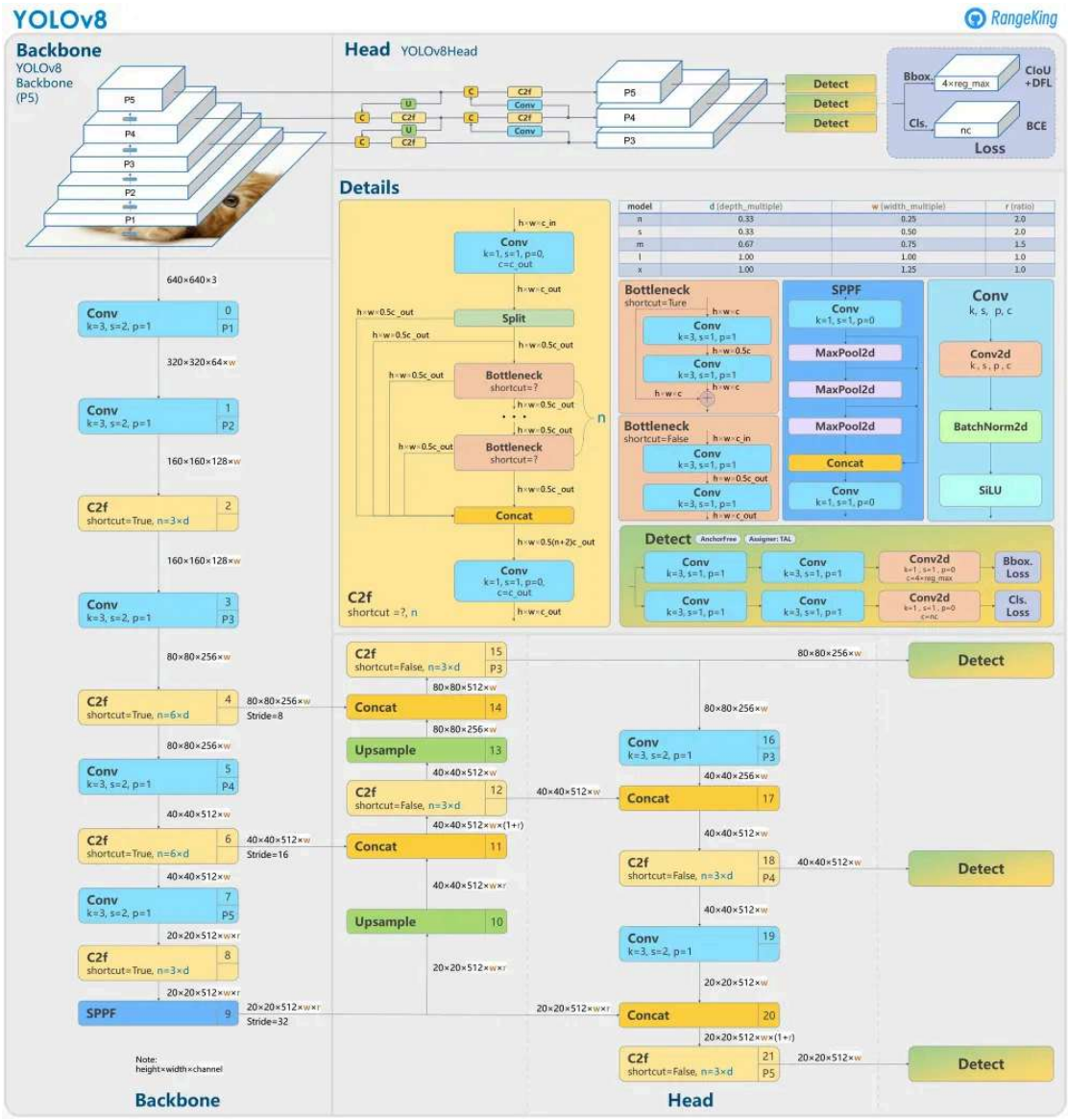

Fig. 3.4: YOLOv8 Architecture

Key Components of YOLOv8:

1) **Backbone**:

   a) This is the part of the model that extracts image features.

   b) YOLOv8 uses **CSPDarknet** (Cross-Stage Partial Network) with enhancements for better gradient flow and fewer parameters, improving both speed and accuracy.

2) **Neck**:

   a) It connects the backbone to the head and helps in aggregating features at multiple scales.
   b) YOLOv8 uses a **Path Aggregation Network (PAN)** for enhanced feature fusion from different levels of the backbone, crucial for detecting objects of varying sizes (like a small clove of garlic or a large tomato).

3) **Head**:

   a) The head is responsible for the final detection task: predicting the object class, confidence score, and bounding box coordinates.
   b) It outputs a vector of predictions for every cell in the image grid.

4) **Anchor-Free Architecture**:

   a) Unlike older versions (YOLOv3/YOLOv4), YOLOv8 adopts an **anchor-free** approach, simplifying training and reducing complexity by not relying on predefined box shapes.

5) **Loss Functions**:

   a) **Classification Loss**: Measures how well the model predicts the correct ingredient class.
   b) **Localization Loss**: Evaluates the accuracy of bounding box coordinates.
   c) **Objectness Loss**: Indicates whether an object is present in a predicted region.

Fine-Tuning on Custom Data

Although pre-trained on COCO, YOLOv8 is fine-tuned on a custom ingredient detection dataset via **transfer learning**. This involves:

- ➢ Freezing the early layers of the model (generic features like edges and textures).
- ➢ Training the final layers on food-specific data (ingredient shapes, colors).
- ➢ This approach drastically reduces training time and improves accuracy, especially when working with limited data.

3.4 Text-Based Recipe Recommendation

The dataset *RAW_recipes.csv* is cleaned and preprocessed as follows:

1) **Parsing Ingredients**: Ingredients are stored as stringified Python lists. These are converted to actual lists using ast.literal_eval().
2) **Filtering Invalid Rows**: Rows missing nutrition or tag information are removed.
3) **Embedding Technique:** BERT (Sentence-BERT) Model Used. An all-MiniLM-L6-v2 , a distilled Sentence-BERT model.

Why Sentence-BERT?

- ➢ Transforms entire sentences (or ingredient lists) into dense vector representations (embeddings).
- ➢ Captures semantic meaning, not just keyword overlap.
- ➢ Similarity Metric: Cosine similarity between embeddings measures how semantically close two sets of ingredients are.

3.4.1. Core Functions

1. is_veg()

Filters out recipes containing non-vegetarian ingredients (e.g., "chicken", "egg").

2. get_match_percentage()

Computes simple overlap between user-detected and recipe ingredients. It outputs % of recipe ingredients found in user input along with (most) common and (least) missing ingredients.

3. semantic_similarity()

Converts both user and recipe ingredient lists to BERT embeddings. It returns a cosine similarity score which is a factor that quantifies how semantically similar the user's detected ingredients are to a recipe's ingredients by comparing the angle between their BERT-generated vector representations. A score closer to 1 indicates high semantic overlap, even if exact words differ.

```
def semantic_similarity(detected_ingredients, recipe_ingredients):
    try:
        query = ', '.join(detected_ingredients)
        ref = ', '.join(recipe_ingredients)
        emb1 = bert_model.encode(query, convert_to_tensor=True)
        emb2 = bert_model.encode(ref, convert_to_tensor=True)
        return float(util.pytorch_cos_sim(emb1, emb2)[0][0])
    except:
        return 0.0
```

Fig. 3.5: Cosine Similarity using BERT Embeddings

4. match_recipes()

The main function combining all logic:

- ➢ Filters recipes by preference, allergy, and calories
- ➢ Calculates match percentage and semantic similarity
- ➢ Computes final weighted score:

$$Final\ Score\ =\ 0.7\ \times\ (\frac{Match\ \%}{100})\ +\ 0.3\ \times Semantic\ Score$$

Top N matches are sorted and returned.

```python
def match_recipes(detected_ingredients, preference='veg', allergies=[], max_calories=None, top_n=5):
    matches = []
    count = 0  # debug counter
    for _, row in df.iterrows():
        count += 1
        if count > 500:  # TEMPORARY DEBUG LIMIT
            print(" Breaking after 500 rows for debug.")
            break

        try:
            recipe_ingredients = row['ingredients']

            if preference == 'veg' and not is_veg(recipe_ingredients):
                continue

            if any(allergy in ' '.join(recipe_ingredients).lower() for allergy in allergies):
                continue

            nutrition = ast.literal_eval(row['nutrition'])
            if max_calories and nutrition[0] > max_calories:
                continue

            match_perc, common, missing = get_match_percentage(recipe_ingredients, detected_ingredients)
            semantic_score = semantic_similarity(detected_ingredients, recipe_ingredients)

            total_score = 0.7 * (match_perc / 100) + 0.3 * semantic_score

            matches.append({
                'Recipe': row['name'],
                'Match %': match_perc,
                'Semantic Score': round(semantic_score, 2),
                'Final Score': round(total_score, 4),
                'Common Ingredients': common,
                'Missing Ingredients': missing,
                'Steps': row['steps'],
                'Calories': nutrition[0],
                'Tags': row['tags'],
                'Time (mins)': row['minutes'],
            })

        except Exception as e:
            print(f" Skipping row due to error: {e}")
            continue

    matches.sort(key=lambda x: x['Final Score'], reverse=True)
    return matches[:top_n]
```

Fig. 3.6: Code snippet for matching recipes

3.5 System Integration and User Interaction

The SnapMeal system follows a streamlined image-to-recipe recommendation pipeline:

3.5.1. User Input (Frontend):

1) Users upload an image depicting raw food ingredients via a Gradio-based interface.
2) This interface is developed using Gradio's `Blocks`, which allows for modular design through `Columns`, `Rows`, `Tabs`, and interactivity via buttons and image uploaders.

3.5.2. Backend Processing:

The uploaded image is passed as a file path to a Python backend function (`recipe_finder_app`) that orchestrates the full pipeline:

1) **Ingredient Identification:** The image is processed using a YOLO-based object detection model fine-tuned on food ingredients. Detected bounding boxes and class labels are returned.
2) **Annotation**: The original image is annotated with bounding boxes using OpenCV, visually displaying recognized ingredients.
3) **Recipe Matching**: The detected ingredients are passed into a fuzzy-matching algorithm that computes intersection scores with pre-curated recipes. Dietary constraints, allergies, and calorie limits are enforced during filtering.
4) **Explanation Generation**: For user clarity, the system uses a rule-based or LLM-generated explanation module to describe the detected ingredients.

3.5.3. Frontend Output:

The response from the backend consists of:

1) A summary of detected ingredients and explanations.
2) Annotated image showing detected items.
3) Top 3 recipe suggestions, each rendered in separate tabs for easy navigation.
4) Each recipe includes - Matched ingredients, a Shopping list for missing items, Step-by-step instructions parsed from a list (safely evaluated using `ast.literal_eval`)

The Gradio interface updates dynamically upon submission, reinforcing an interactive experience.

3.5.4. Frontend/Backend Communication

1) **Data Format:**
    a) Images are passed by path (string) or array depending on `Gradio`'s type specification.
    b) Textual outputs are sent as strings, while annotated images are returned as NumPy arrays (converted to RGB).
2) **State Synchronization:**
    a) Stateless operation per request: each image upload initializes a new pipeline run.
3) **Security Note:**
    a) Since the backend uses ast.literal_eval to parse recipe instructions, it assumes well-formatted strings and must be sandboxed to avoid arbitrary code execution.

3.6. Evaluation Metrics and Testing

The evaluation of the SnapMeal system is bifurcated into two core components: ingredient classification and recipe recommendation. Each is assessed using established metrics in computer vision and recommender system literature.

3.6.1. Ingredient Detection Evaluation

The ingredient identification module is a multi-class object detection task. It is evaluated using the following metrics:

1) **Precision and Recall (Per Class):**

   Precision measures the ratio of correctly predicted ingredient labels (true positives) to all predicted labels (true + false positives):

$$Precision = \frac{TP}{TP + FP}$$

   Recall assesses the system's ability to identify all actual instances of an ingredient:

$$Recall = \frac{TP}{TP + FN}$$

These metrics are reported per class (e.g., tomato, onion) and averaged using macro or weighted averaging schemes.

2) **Mean Average Precision (mAP@IoU):**

   The system employs Intersection-over-Union (IoU) to quantify the overlap between predicted and ground-truth bounding boxes.

   A detection is counted as correct if:

$$IoU = \frac{Area(Pred \cap GT)}{Area(Pred \cup GT)} \geq \tau$$

   where $\tau = 0.5$ for mAP@0.5.

   mAP aggregates precision-recall curves for each class and averages their area under the curve (AUC), offering a robust metric of detection performance.

3.6.2. Recipe Recommendation Evaluation

This component operates as a content-based recommender system where input ingredients are matched with a corpus of recipes.

1) **Precision@k and Recall@k:**
    a) These metrics evaluate how many of the top-k recommended recipes are relevant (i.e., could plausibly be cooked with the provided ingredients).
    b) Precision@k:

$$Precision@k = \frac{Relevant\ Recipes\ in\ Top\ k}{k}$$

    c) Recall@k:

$$Recall@k = \frac{Relevant\ Recipes\ in\ Top\ k}{Total\ Relevant\ Recipes\ Available}$$

Since user feedback isn't available, pseudo-ground truth is inferred from ingredient overlap ratios or manual annotation (expert cooking knowledge).

2) **Cosine Similarity Scores:**

If we represent ingredients as binary vectors in a high-dimensional space (1 if ingredient is present, 0 otherwise), then we can use:

$$Cosine\ Similarity(A, B) = \frac{A.B}{||A||.||B||}$$

This can be extended with **TF-IDF weighting**, where rare or distinctive ingredients are given more importance. This reduces the influence of common ingredients like "salt" or "oil".

Chapter 4

RESULTS AND DISCUSSION

4.1 Overview

This chapter presents the experimental results from the end-to-end SnapMeal system, which integrates computer vision-based ingredient detection with a content-based recipe recommendation pipeline. We evaluate system performance across two core modules: (1) the object detection pipeline for ingredient recognition and (2) the recommendation engine based on ingredient similarity. Quantitative metrics, visual inspection, and qualitative discussion are used to assess the model's efficacy and limitations.

4.2 Ingredient Detection Performance

The ingredient detection model was a fine-tuned YOLOv8 variant trained on a curated dataset of everyday kitchen ingredients. Evaluation was performed using standard object detection metrics:

Table 4.1: Last few epochs performance

	epoch	time	train/box_loss	train/cls_loss	train/dfl_loss	metrics/precision(B)	metrics/recall(B)	metrics/mAP50(B)	metrics/mAP50-95(B)	val/box_loss	val/cls_loss	val/dfl_loss	lr/pg0	lr/pg1	lr/pg2
25	26	8067.83	0.78402	0.34503	1.13467	0.80737	0.89147	0.86853	0.68383	0.82197	0.48882	1.15934	0.000030	0.000030	0.000030
26	27	8375.94	0.77651	0.33866	1.12650	0.85332	0.83687	0.87166	0.68508	0.82219	0.49495	1.15145	0.000024	0.000024	0.000024
27	28	8683.91	0.76611	0.33195	1.11909	0.86721	0.84394	0.88753	0.69959	0.81929	0.50361	1.15871	0.000019	0.000019	0.000019
28	29	8991.54	0.75780	0.32609	1.11802	0.87465	0.85247	0.88023	0.68977	0.81936	0.49724	1.16103	0.000013	0.000013	0.000013
29	30	9299.24	0.74993	0.32293	1.10940	0.84738	0.83556	0.86890	0.68230	0.81701	0.49363	1.15465	0.000007	0.000007	0.000007

Final Epoch Metrics Summary:

Metric	Epoch 29 Value
Precision	0.8474
Recall	0.8356
mAP@0.5	0.8689
mAP@0.5:0.95	0.6823
Validation Box Loss	0.8170
Validation Cls Loss	0.4936
Validation DFL Loss	1.1545

Interpretation of Metrics:

- **Precision (0.847):** Indicates that ~85% of predicted bounding boxes correctly identified ingredients. This suggests low false positive rates.

- **Recall (0.835):** About 83.5% of actual ingredients were successfully detected—moderate false negatives persist due to occlusion or class imbalance.

- **mAP@0.5 (0.869):** High confidence in detection accuracy, particularly for clear, unobstructed ingredients like bell peppers or eggs.

- **mAP@0.5:0.95 (0.682):** A stricter metric capturing both classification and localization precision across IoU thresholds. This value reflects reliable multi-scale performance, albeit with degradation for small/ambiguous objects (e.g., garlic vs. ginger).

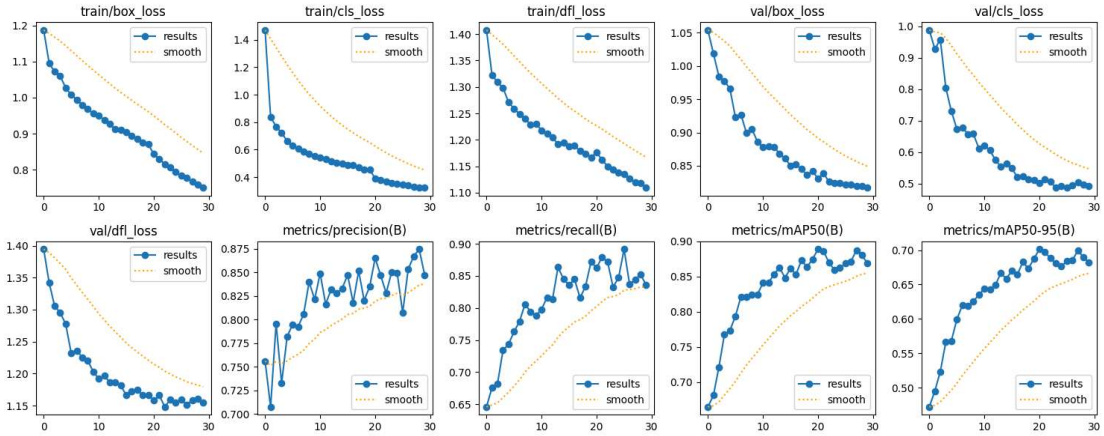

Fig. 4.1: Training Graphs

Training & Validation Loss Trends:

train/box_loss, train/cls_loss, train/dfl_loss

➤ All three show steady decline, indicating the model is consistently improving its localization (box), classification, and distributional prediction quality.

val/box_loss, val/cls_loss, val/dfl_loss

➤ These mirror the training losses, confirming that the model is not overfitting. Validation losses plateau mildly after epoch 20, implying near-convergence.

Evaluation Metrics:

Precision (B):

➤ Starts around 0.75, oscillates with upward trend, stabilizing near 0.85–0.87. Indicates increasing accuracy in positive predictions, despite some noise.

Recall (B):

➤ Steady rise from 0.65 to ~0.86, then minor fluctuations. The model is catching more true ingredients over time, handling more edge cases.

mAP@0.5 (B):

➤ Rises sharply till epoch 15, then slower linear improvement—peaks ~0.87. This shows strong object detection performance at standard IoU.

mAP@0.5:0.95 (B):

➤ Consistent growth from 0.5 to ~0.69. Indicates that the model is learning fine-grained localization + classification, handling stricter thresholds better.

4.3. Recipe Recommendation

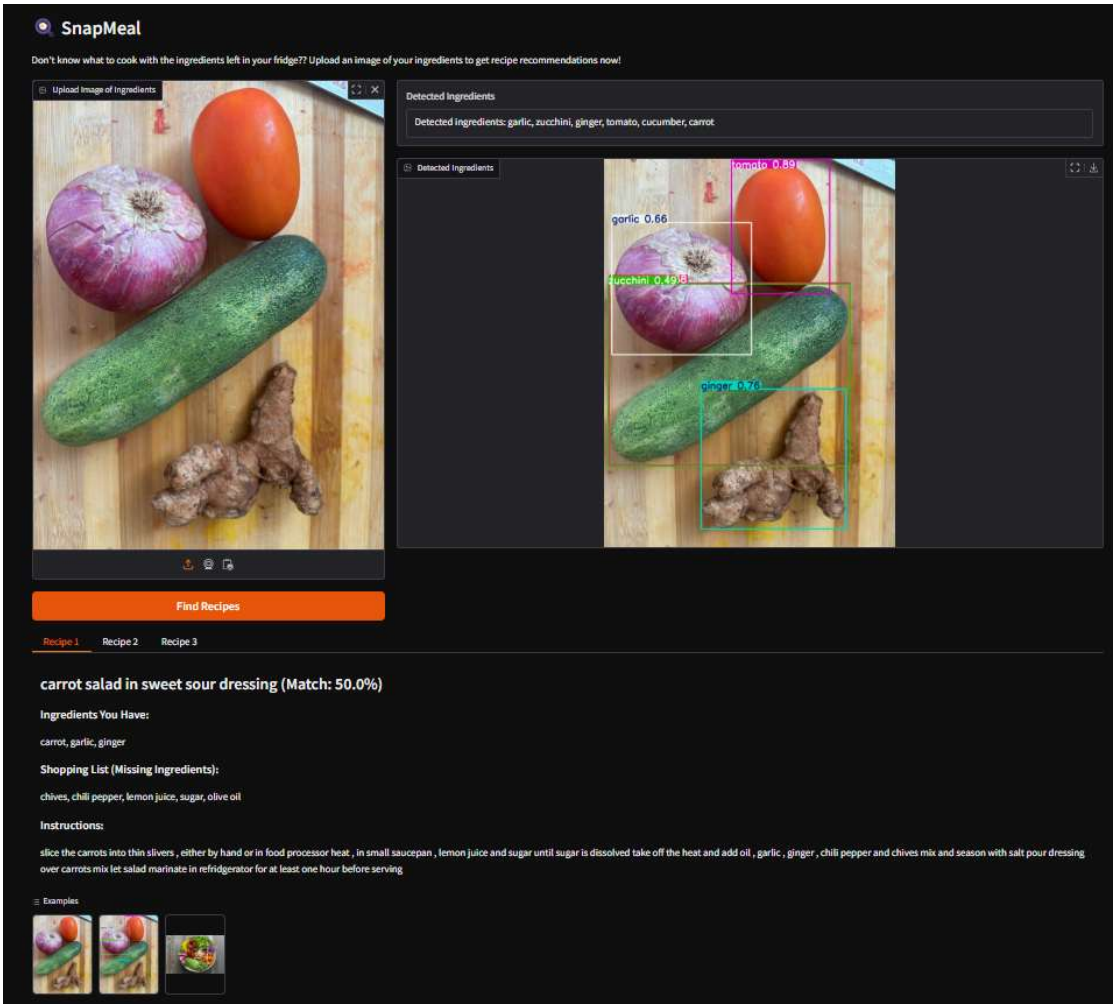

Fig 4.2: App Demo

The system employs a hybrid approach, combining literal ingredient matching with semantic similarity analysis to provide more accurate and contextually relevant recommendations. This approach addresses the limitations of purely keyword-based matching by considering the meaning and relationships between ingredients. For each recipe, the system identifies the common ingredients (those present in both the user's list and the recipe's list) and the missing ingredients (those in the recipe but not in the user's list). A 'match percentage' is then calculated based on the ratio of common ingredients to the user's total number of detected ingredients. This percentage provides a straightforward measure of how well the user's available ingredients align with the recipe's requirements.

From the detected ingredients, the top recommended recipe is "carrot salad in sweet sour dressing" which has a match score of 50.0%. The current implementation assigns a weight of 70% to the literal match percentage (normalized to a 0-1 scale by dividing by 100) and 30% to the semantic similarity score. This weighted sum allows the system to prioritize recipes with a higher degree of literal ingredient overlap while also considering recipes with semantically related ingredients.

Experimental Test Run

In a test run, additional features are added so that after calculating the total score for each recipe, the system applies filtering criteria based on user preferences and constraints. These include:

- **Vegetarian Preference**: If the user specifies a vegetarian preference, the system filters out recipes containing non-vegetarian keywords (e.g., "chicken", "beef", "fish"). This filtering is done by checking if any of these keywords are present in the recipe's ingredient list.

- **Allergies**: The system allows users to specify allergies. Recipes containing any of the user-specified allergens (checked by seeing if the allergy keyword is present in the recipe's ingredients) are excluded from the recommendations.

- **Maximum Calories**: Users can set a maximum calorie limit. The system parses the nutritional information of each recipe and filters out those exceeding the specified calorie threshold.

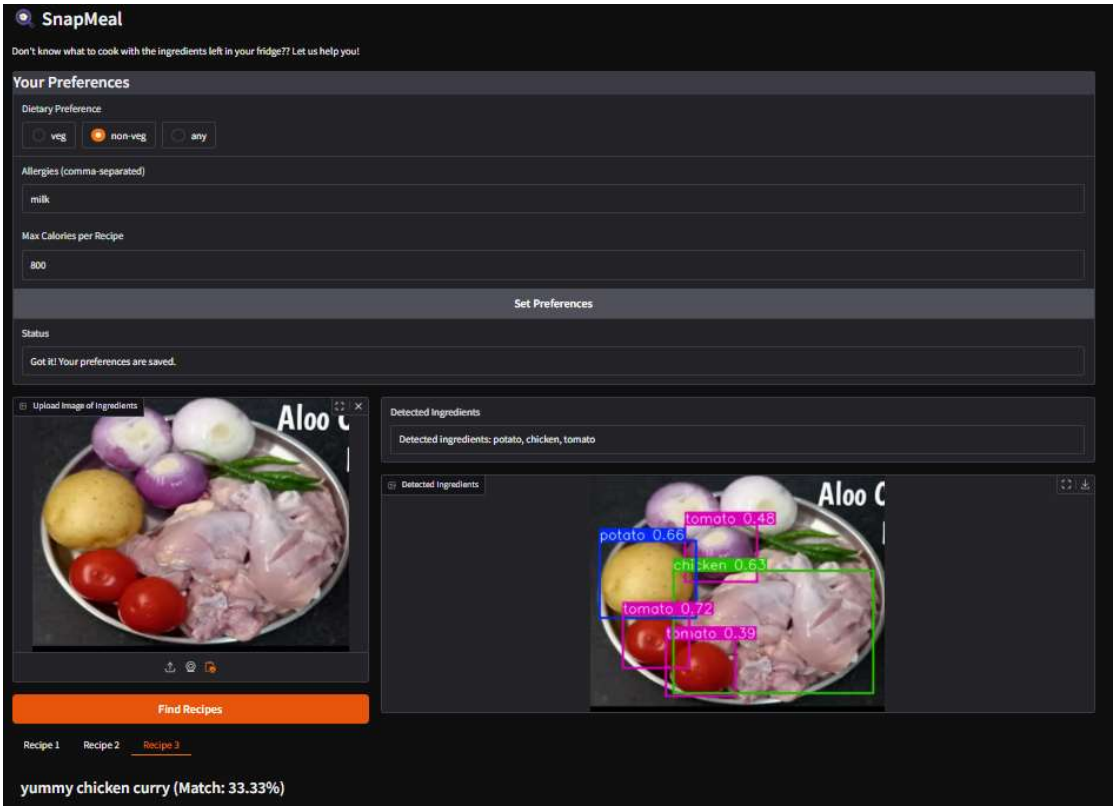

Fig. 4.3: Experimental Run

Model Summary

The training and evaluation of the YOLOv8m model yielded highly promising results, marked by consistent reductions in both training and validation losses across all components, alongside steadily improving precision, recall, and mAP scores. The convergence of performance metrics and the absence of significant overfitting indicate a stable and generalizable model. These outcomes confirm the effectiveness of the selected architecture and training strategy in accurately detecting and classifying ingredients, setting a strong foundation for real-world deployment and further enhancement.

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Chapter 5
CONCLUSION

The last chapter presented an in-depth analysis of the model training results and performance metrics for ingredient detection using the YOLOv8m architecture. The model demonstrated strong convergence behavior, with a steady decline in training and validation losses across all components—bounding box regression (box_loss), classification (cls_loss), and distribution focal loss (dfl_loss). Correspondingly, key performance indicators such as precision, recall, and mean Average Precision (mAP) at both IoU thresholds (mAP50 and mAP50-95) showed a positive and consistent upward trend, affirming the model's ability to accurately identify a diverse range of food ingredients.

The validation metrics remained closely aligned with training metrics, suggesting minimal overfitting and effective generalization to unseen data. The model achieved a peak precision of 87.4% and recall of 89%, with a mAP50 of 88.7%—reflecting its robustness in multi-class ingredient detection tasks.

Despite these encouraging results, some limitations remain. The model still shows slightly lower confidence in detecting overlapping or occluded ingredients, and rare-class detection may benefit from further data augmentation or class-balanced sampling. Moreover, the inference time and deployment on low-resource devices need to be evaluated further.

Future work and improvements

Future work will focus on expanding the dataset to include more diverse cuisines and cooking contexts, integrating real-time inference capabilities, and extending the system to support multi-modal inputs such as speech or text queries for recipe generation. Another promising direction is fine-tuning the recommendation module using collaborative filtering and embedding-based similarity models to offer more personalized and nutritionally balanced recipes.

Overall, the project successfully validates the feasibility of using deep learning for visual ingredient detection and sets the stage for building intelligent, user-centric recipe recommendation systems that bridge computer vision and culinary creativity.

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APPENDICES

Appendix A: Dataset Description

- Total Images Used: 20155
- Number of Classes (Ingredients): 64
- Sources: RoboFlow, https://universe.roboflow.com/savorgh-h5nhn/ingredients-detection-oe2q7
- Class Imbalance Handling: Oversampling rare ingredients, targeted data augmentation.

Appendix B: Training Configuration

- Model Used: YOLOv8m (pre-trained on COCO)
- Epochs: 30
- Batch Size: 8
- Image Size: 640×640
- Optimizer: AdamW
- Loss Functions: Box, Classification, DFL Loss
- Learning Rate Schedule: Cosine decay
- Frozen Layers: Backbone layers (first and middle)

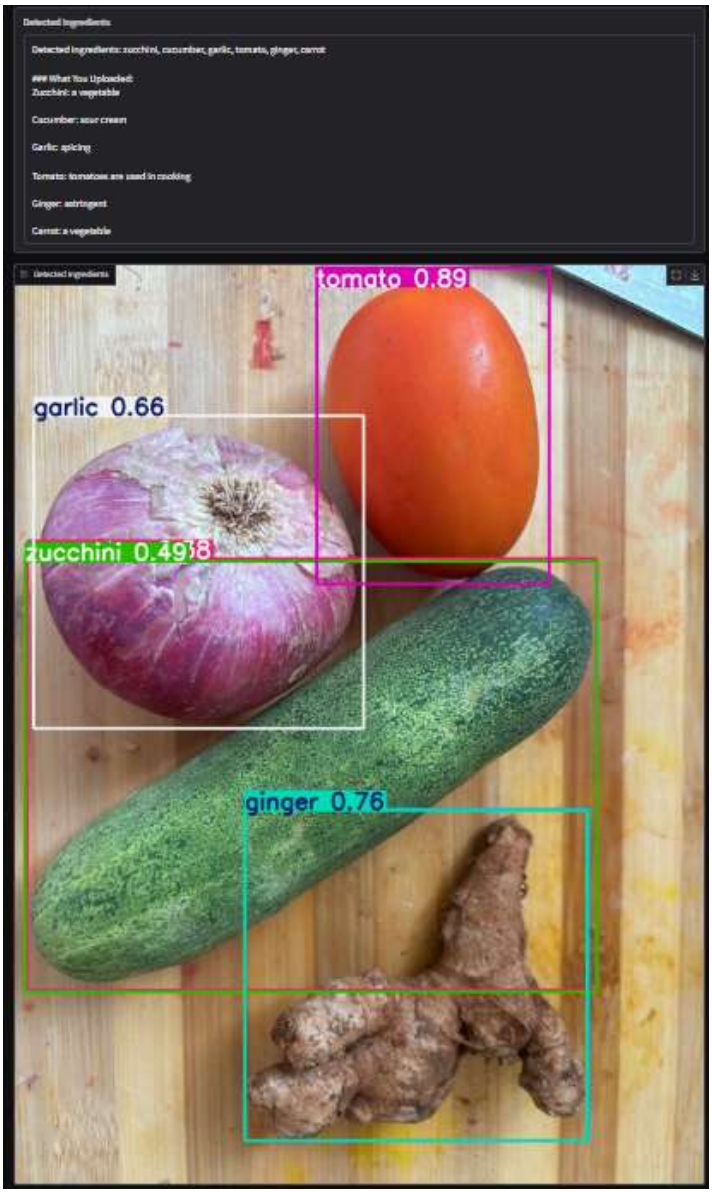
Appendix C: Hardware and Tools

- **System Specs:**
    - CPU: Intel Core i5
    - GPU: NVIDIA GeForce RTX
    - RAM: 16GB
- **Frameworks:**
    - Python 3.10
    - Ultralytics YOLOv8
    - OpenCV, Pandas, NumPy
    - Matplotlib & Seaborn (for visualization)

Appendix D: Evaluation Metrics

- Precision: TP / (TP + FP)
- Recall: TP / (TP + FN)
- mAP50: Mean Average Precision at IoU threshold 0.5
- mAP50-95: Averaged mAP across IoU thresholds from 0.5 to 0.95

Appendix E: Sample Predictions



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