‘SafeBite’
AI-Enhanced Nutritional Label Extraction and Diabetic Health Assessment

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22nd July, 2024

Presentation Outline

- Motivation
- Objectives
- Scope of Project
- Project Applications
- Methodology
- Results
- Results Analysis
- Remaining Tasks
- References

Motivation

- Empower individuals with diabetes to make informed dietary decisions
- Improve blood glucose management through personalized food recommendations
- Leverage advanced technology for accurate glycemic index predictions
- Enhance user quality of life with healthier choices

Objectives

- To create a user-friendly mobile application where users can input their recent blood sugar levels and current medications
- To develop a nutritional label scanner and analysis model that provides users with insights into whether the scanned foods are suitable for them based on their profile information

Scope of Project

❑Project Capabilities

- Provides personalized nutritional advice for diabetes management.
- Simplifies understanding of food labels and nutrition details.
- Offers a user-friendly platform for health management.

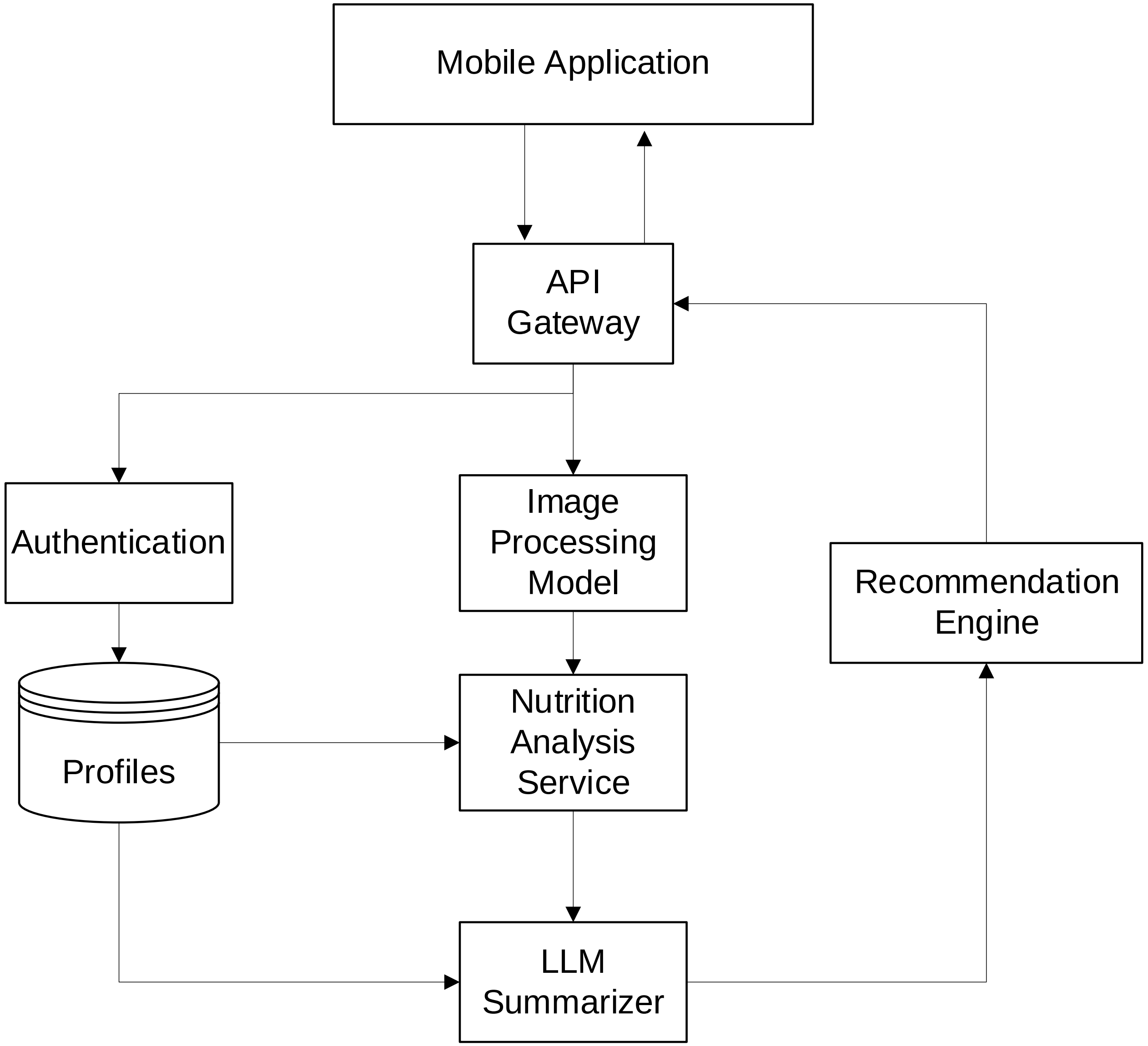
❑Project Limitations

- May not cover all health conditions or restrictions.
- Dietary advice can vary between regions and cultures.

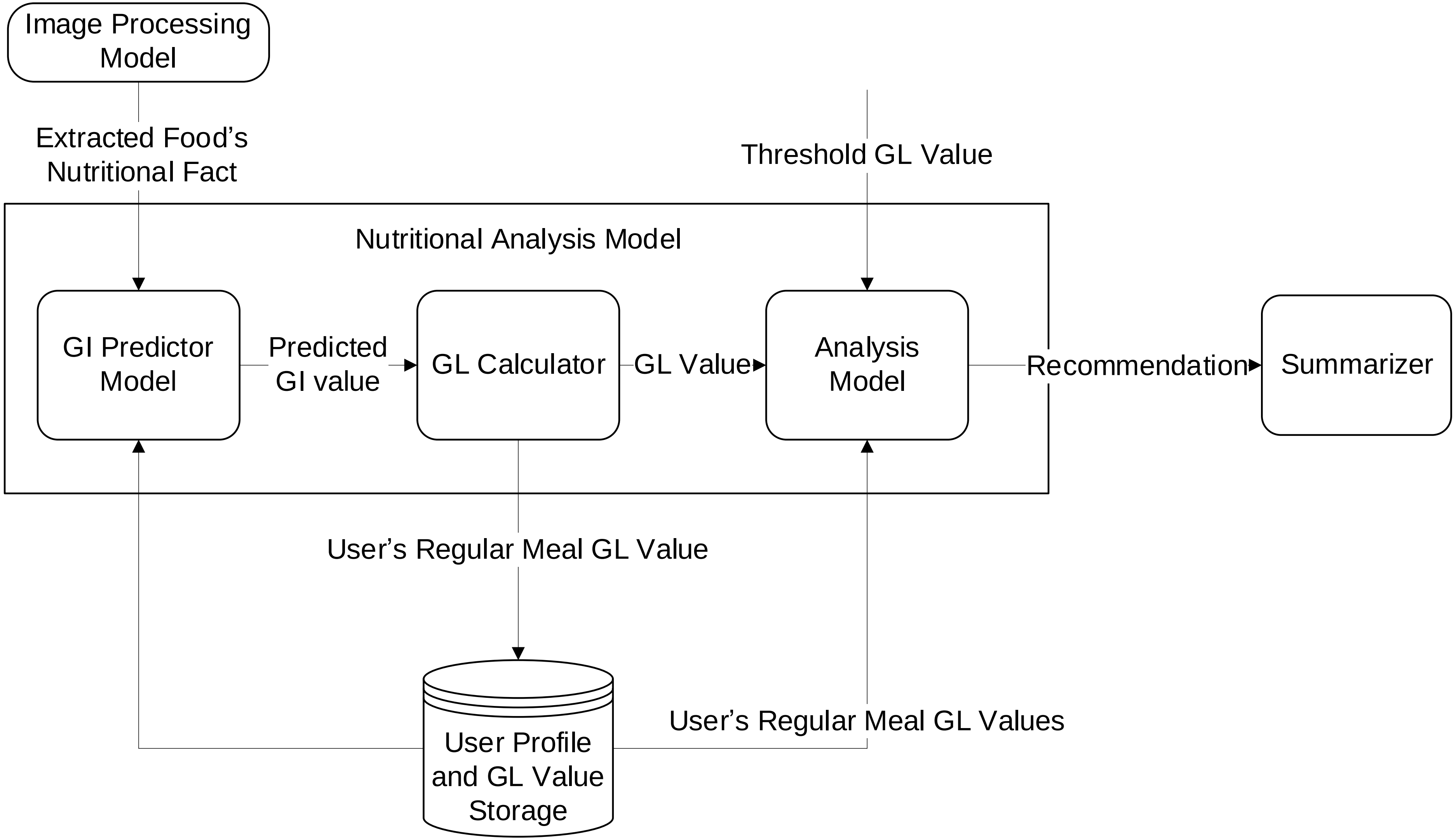
Project Application

- Personalized Health Profiles
  - Create profiles with blood sugar, medications, recommendations
- Nutritional Label Scanner
  - Uses YOLO & OCR to extract nutritional information from labels
- Machine Learning-Driven Recommendation
  - Analyzes data to generate personalized dietary recommendations
- User Empowerment
  - Provides insights and tools for informed health decisions

Methodology - [1] (System Architecture)



Methodology - [2]
(Nutritional Analysis Model)



Methodology - [3]
(Nutritional Analysis Model)

❑ GI Predictor Model

- Scanned food’s nutritional information which is extracted by image processing model is passed as input to this model.

- Trained on dataset with features as nutritional facts and target variable as Glycemic Index(GI) value.

- It predicts GI value for scanned food.

- Glycemic Index (GI) of a food is a numerical value (0-100) which represents how quickly the food raises blood glucose levels after consumption.

Methodology - [4] (Nutritional Analysis Model)

❑ GL Calculator

- Glycemic load (GL) is a measure that assesses the impact of carbohydrate consumption on blood sugar levels.
- It combines both the Glycemic Index and quantity of carbohydrates in a food.
- This calculator calculates the GL value from the predicted GI value by the below given formula:

$$\text{Gly}cemic\ Load = \frac{Glycemic\ Index * amount\ of\ carbohydrate\ in\ gram}{100}$$

Methodology - [5]
(Nutritional Analysis Model)

❑ Interpretation of GL Values

- **Low GL (10 or less)**: Foods with a low glycemic load have a minimal impact on blood sugar levels.

- **Medium GL (11-19)**: Foods with a medium glycemic load have a moderate impact on blood sugar levels. These can be included in a balanced diet but should be consumed in moderation, especially by those sensitive to changes in blood sugar.

- **High GL (20 or more)**: Foods with a high glycemic load can cause significant spikes in blood sugar levels. These should be limited, particularly for individuals with diabetes.

Methodology - [6]
(Nutritional Analysis Model)

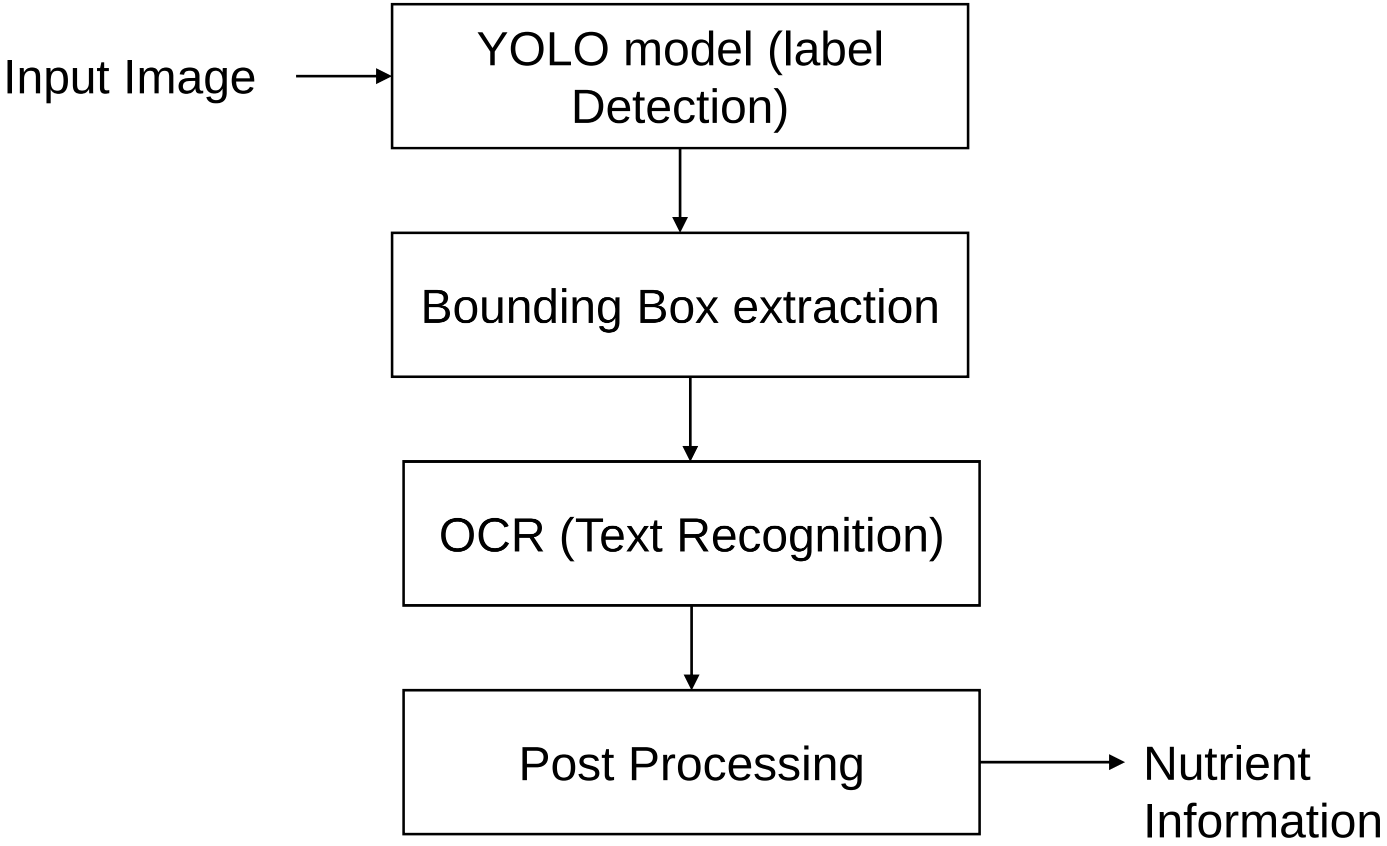
❑ Analysis model

- Receives Glycemic Load(GL) value stored in the database and threshold GL value as input.
- Compares total sum of GL value of previous foods and scanned food from the database with threshold value.
- If the total GL value of the user is less than or equal to the threshold value, then the food is recommended to consume otherwise not.
- This information is passed as an output to the summarizer model for further processing.

Methodology - [7] (Summarizer)

- Summarizer
  - Uses Large Language Models (LLMs) like Llama or Mistral to generate summaries.
  - Processes detailed nutritional information, GL calculations, and comparison results.
  - Produces clear summaries indicating whether a food item is suitable for consumption.
  - Includes detailed explanations to ensure users understand the reasoning behind the recommendations.

Methodology - [8]
(Nutritional Label Extraction)



Methodology - [9]
(Nutritional Label Extraction)

The process starts with an input image containing the nutritional label.

❑ YOLO Model (Label Detection):

- Trained specifically for detecting nutritional labels,
- Processes the input image and outputs bounding boxes around the detected text regions.

❑ Bounding Box Extraction:

- Extract the bounding box coordinates from the YOLO model's output.
- Use these coordinates to crop the detected regions from the original image.

Methodology - [10]
(Nutritional Label Extraction)

❑ OCR (Text Recognition):

- Apply OCR on the cropped regions to extract the text within the bounding boxes.
- Tesseract OCR is a commonly used library for this purpose.

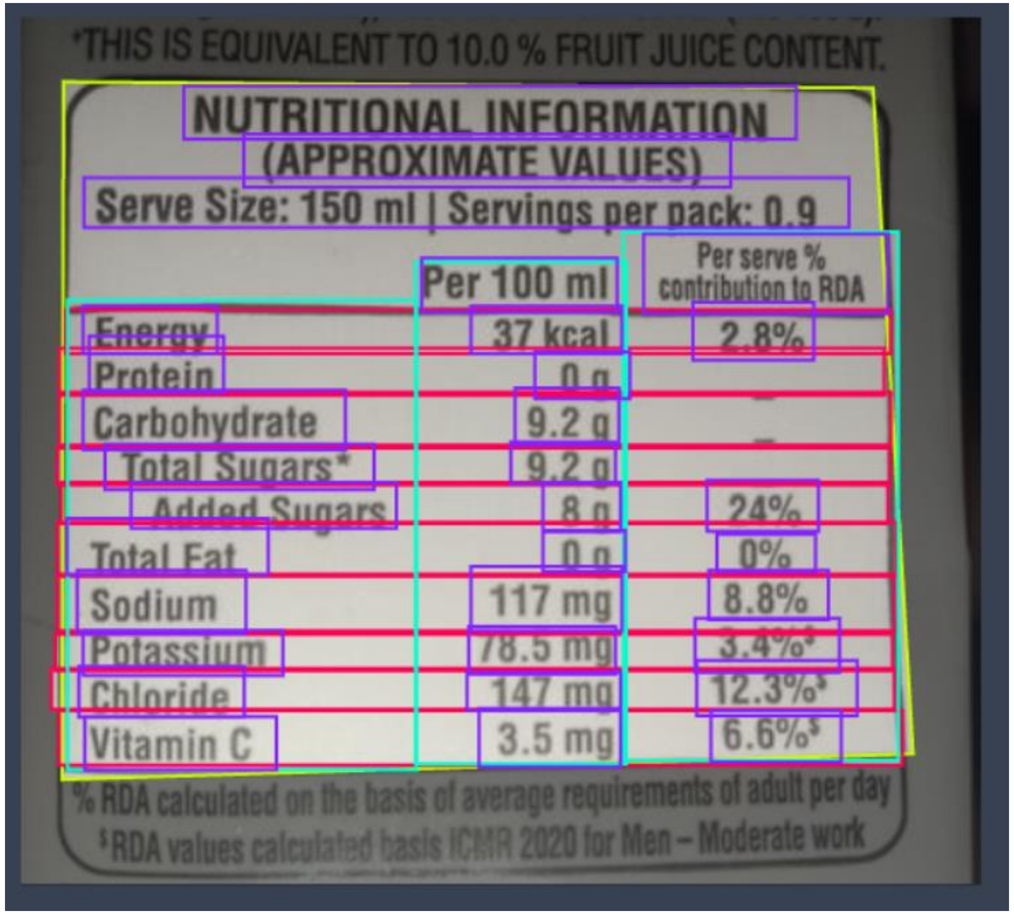
❑ Post-Processing (Text Refinement):

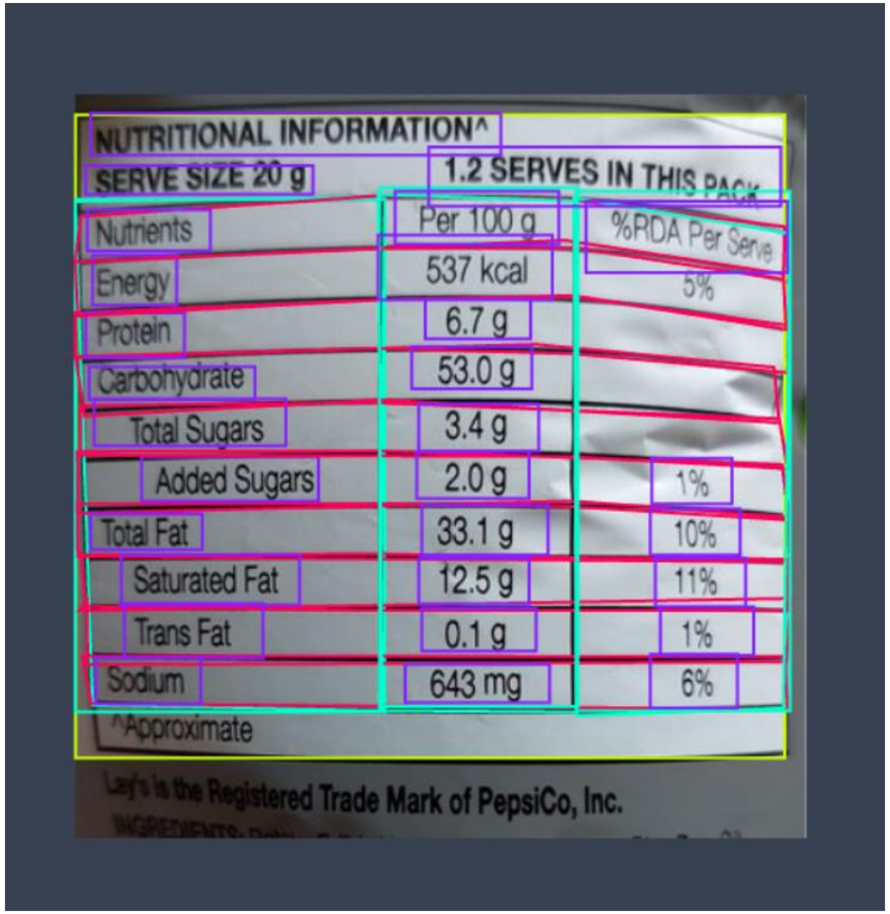
- Post-process the OCR results to refine and format the extracted text.
- It includes correcting OCR errors, structuring the text in tabular format, and parsing the text into nutrient information.

❑ Nutrient Information:

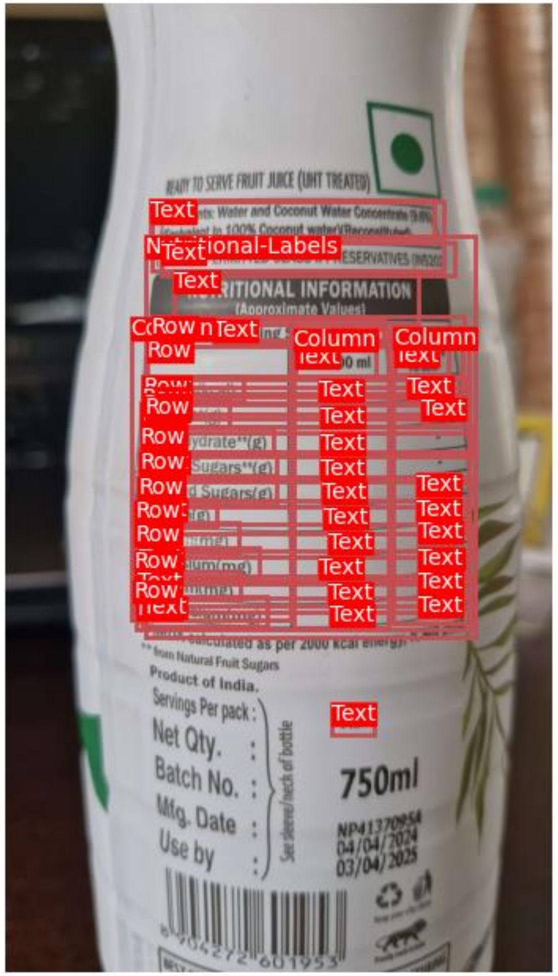
- The final structured and refined text is then stored as nutrient information.

Methodology - [11]
(Dataset Annotation)





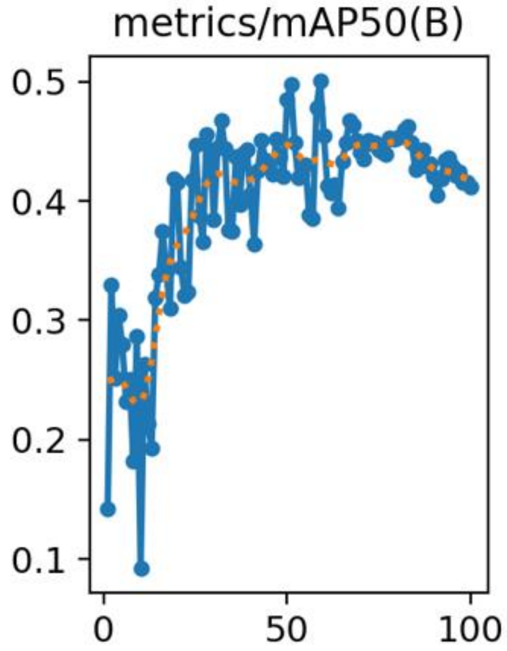
Results

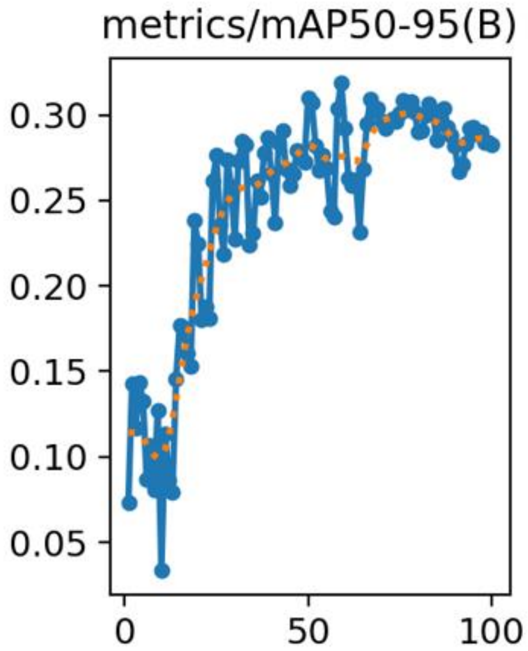


Nutritional-Labels
Column
Row
Text
NUTRITIONAL INFORMATION
(Approximate Values)
Product of India.
Servings Per pack :
Net Qty. :
Batch No. :
Mfg. Date :
Use by :
750ml
NP41370954
04/04/2024
03/04/2025

Nutritional-Labels
Row
Text
Column
Nutritional Facts
Serving Size
(330mL)
Calories
12
%RDA* per serve
Energy 12 (kcal)
Protein 0.08 g
Carbohydrate 2.5 g
Dietary Fiber 0 g
0%
Total Sugars 2.5 g
Added Sugars 2.5 g
5%
Total Fat 0.2 g
0.26%
Saturated Fat 0 g
Trans Fat 0 g
Sodium 0.63 mg

Results Analysis – [1]
(Mean Average Precision)

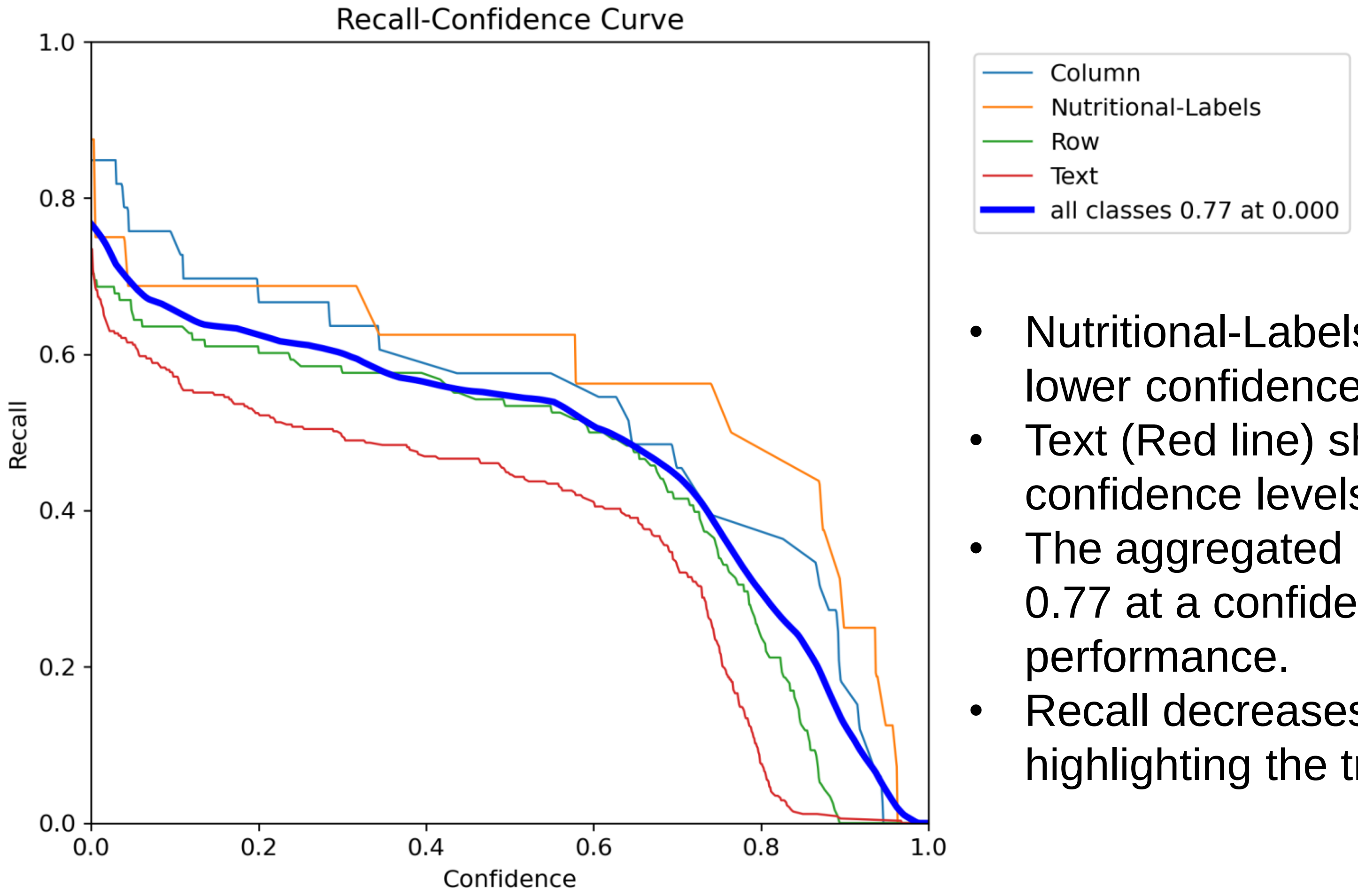




- mAP50 starts at approximately 0.1 and increases to around 0.5 as training progresses.
- There is significant fluctuation initially, but it stabilizes after about 50 epochs.
- Orange dotted line represents a smoothed trend, showing a clear upward trajectory.

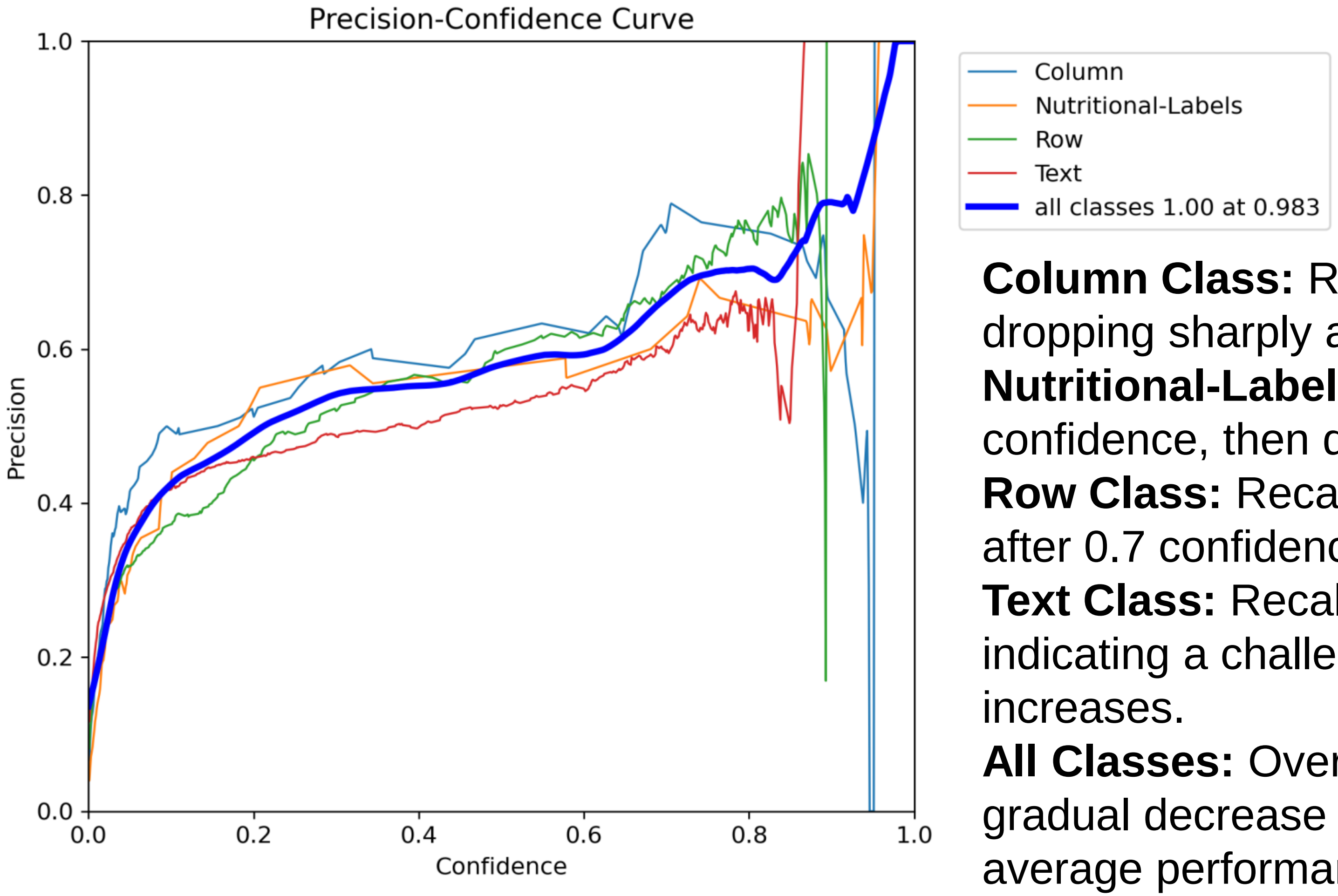
- mAP50-95 starts at around 0.05 and increases to approximately 0.3.
- There is considerable fluctuation initially, with stabilization occurring after about 50 epochs.
- The orange dotted line again represents a smoothed trend, showing a steady increase.

Result Analysis – [2] (Recall-Confidence Curves)



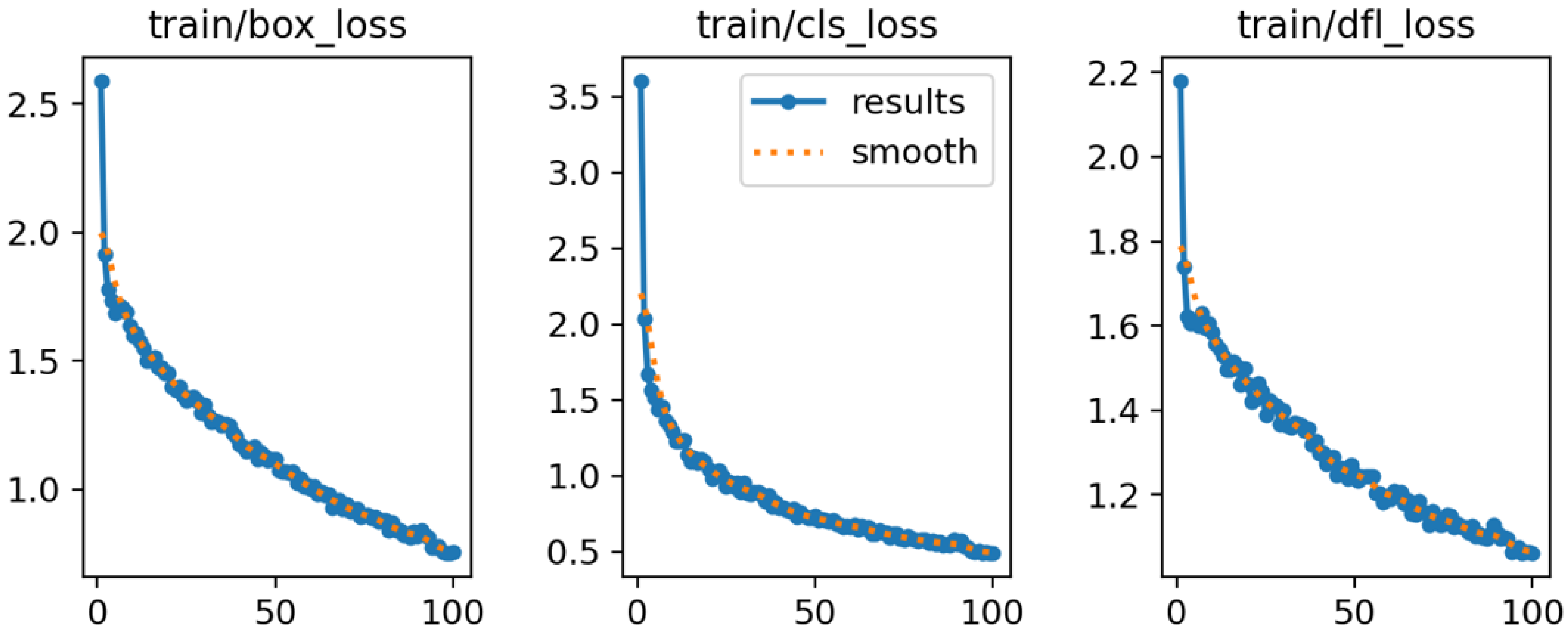
- Nutritional-Labels (Orange line) maintains higher recall at lower confidence levels compared to other classes.
- Text (Red line) shows the lowest recall across most confidence levels.
- The aggregated performance (Thick Blue line) has a recall of 0.77 at a confidence level of 0.000, indicating overall model performance.
- Recall decreases for all classes as confidence increases, highlighting the trade-off between recall and confidence.

Result Analysis – [3]
(Precision-Confidence Curves)



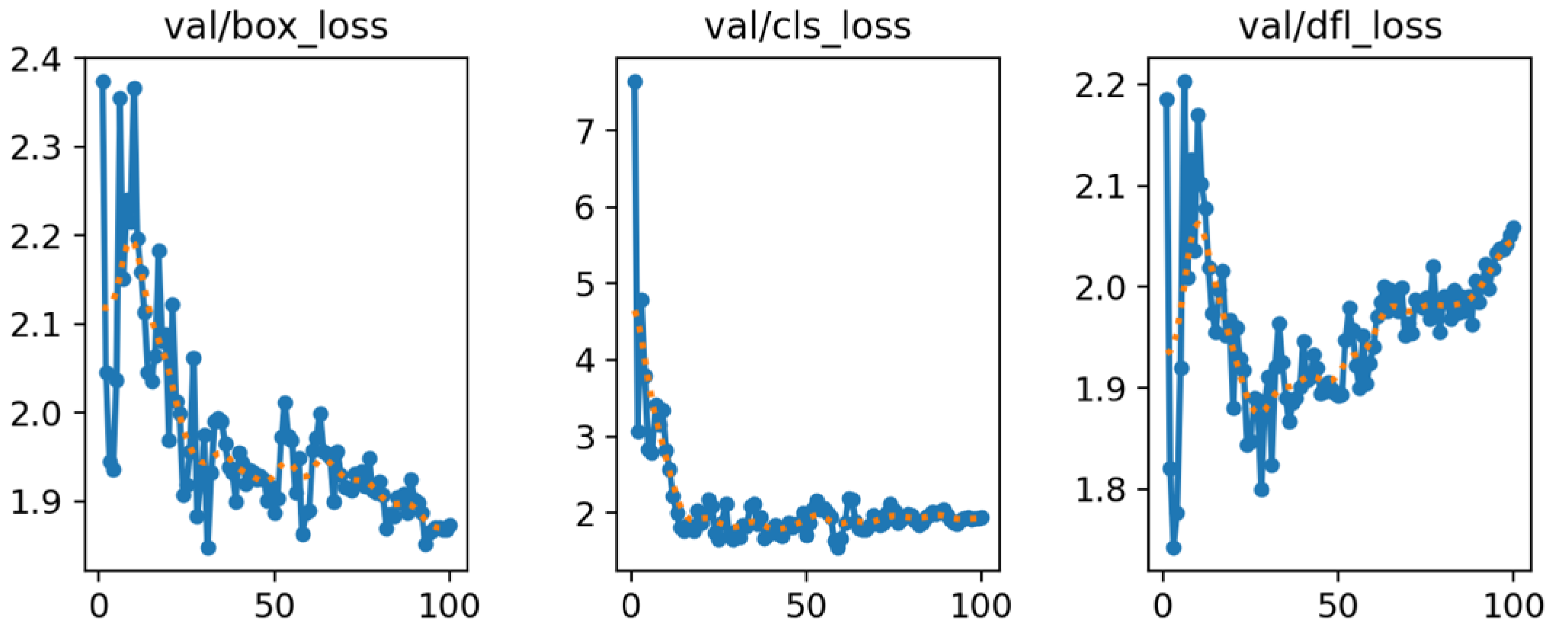
Column Class: Recall starts high and decreases gradually, dropping sharply after 0.5 confidence.
Nutritional-Labels Class: Recall remains high up to 0.7 confidence, then drops sharply.
Row Class: Recall decreases gradually, with a significant drop after 0.7 confidence.
Text Class: Recall drops steeply compared to other classes, indicating a challenge in maintaining high recall as confidence increases.
All Classes: Overall recall is 0.77 at 0.0 confidence, with a gradual decrease as confidence increases, representing average performance across all classes.

Results Analysis – [4] (Training Loss)



- **Box Loss:** Rapid initial decrease, then gradual decline, stabilizing around 1.0 after 100 epochs.
- **Classification Loss:** Sharp drop initially, followed by a steady decrease, approaching 0.5 by 100 epochs.
- **DFL Loss:** Fast initial reduction, then consistent decrease, stabilizing near 1.0 towards the end.

Result Analysis – [5] (Validation Losses)



- **Box Loss:** Starts above 2.5, rapidly decreases, and stabilizes around 1.0 after 100 epochs.
- **Classification Loss:** Begins at 3.5, sharply drops, and gradually declines to about 0.5 by 100 epochs.
- **DFL Loss:** Initially over 2.2, quickly reduces, and levels off near 1.0 by 100 epochs.

Remaining Tasks

- Implementation of OCR on the output given by the YOLO model
- Post processing the extracted text into usable format
- Exploration of the dataset for calculation of GI values
- Training a model for GI value prediction
- Exploration of the summarizer model
- Mobile Application development
- Integration of all the models

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THANK YOU