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

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Presentation Outline

- Motivation
- Objectives
- Scope of Project
- Proposed Methodology
- Dataset Availability
- Expected Results
- Project Applications
- Tentative Timeline
- Estimated Project Budget
- 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

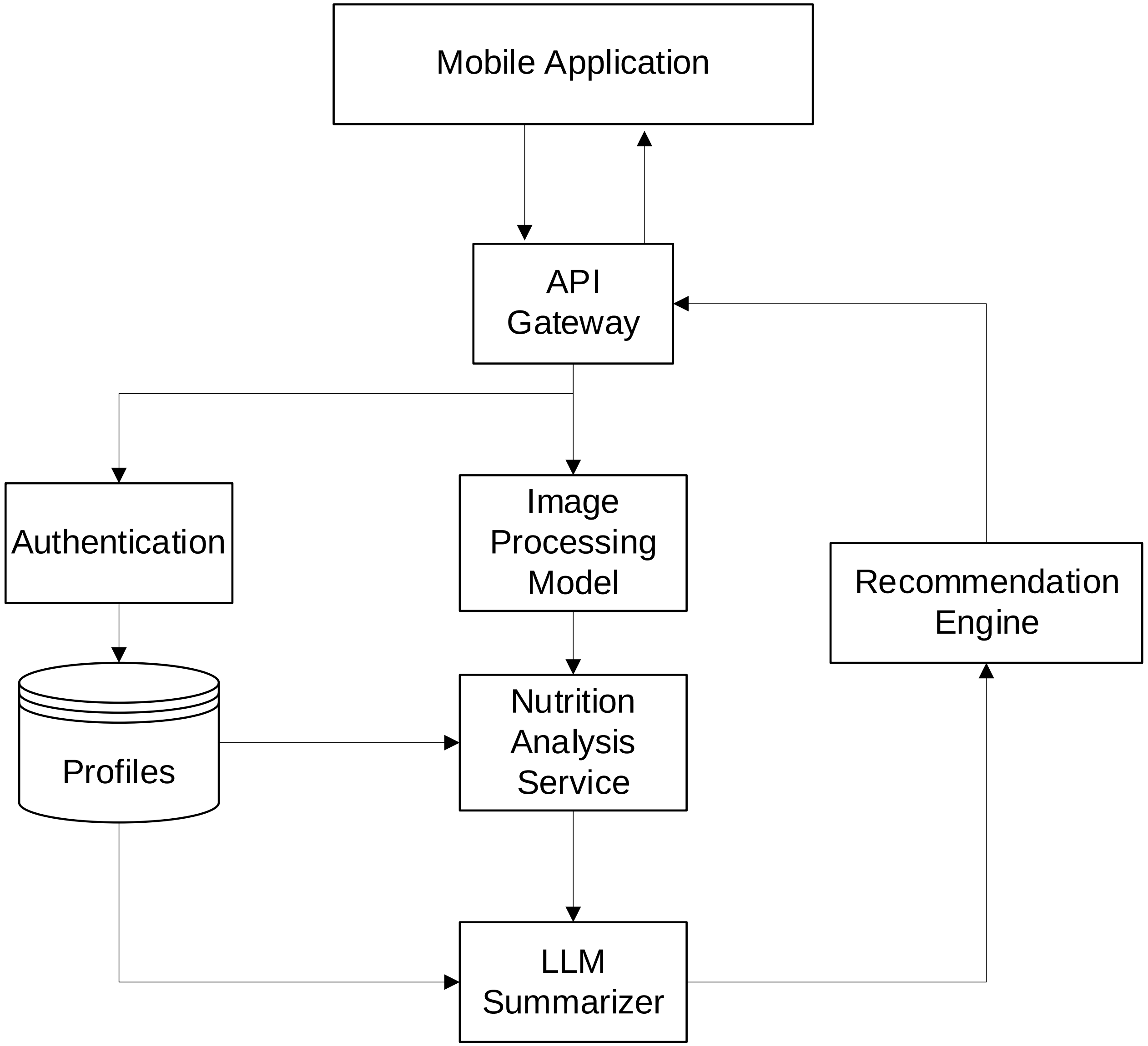
Objectives

- 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.

Methodology - [1]
(System Architecture)



Methodology - [2] (Mobile Application)

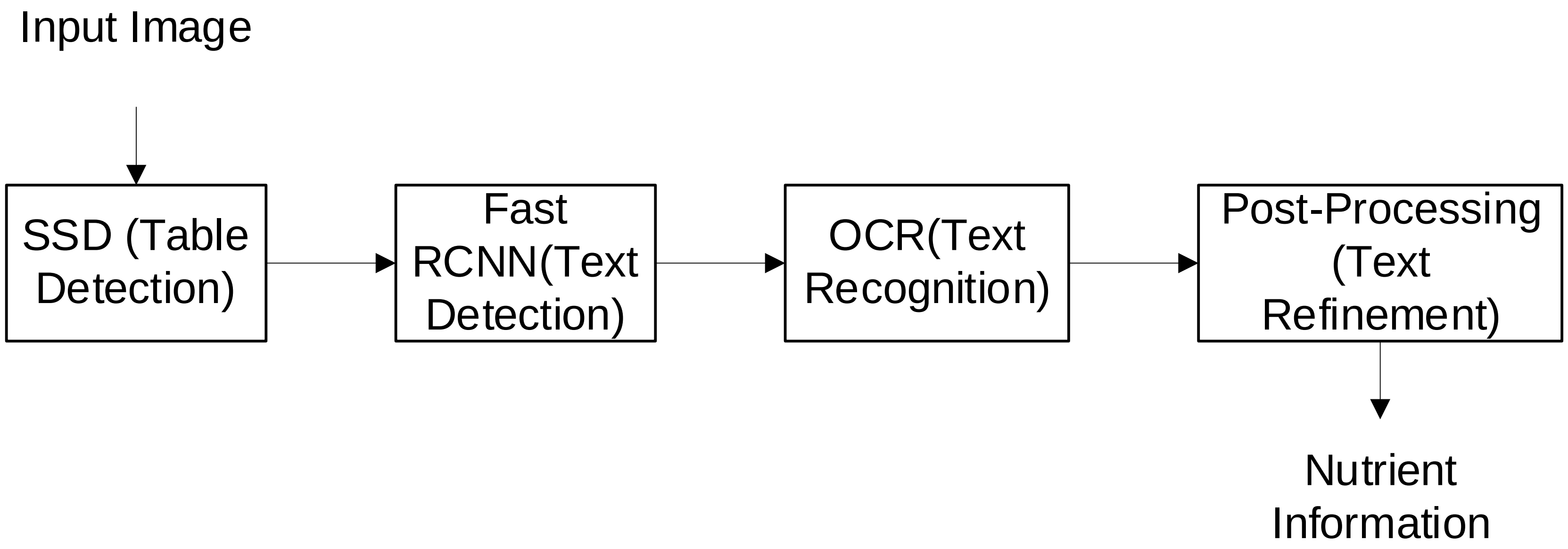
❑Purpose

- User-friendly interface for personalized diabetic profiles
- Input health data and scan food items easily
- Receive personalized dietary recommendations in real-time

❑Development method

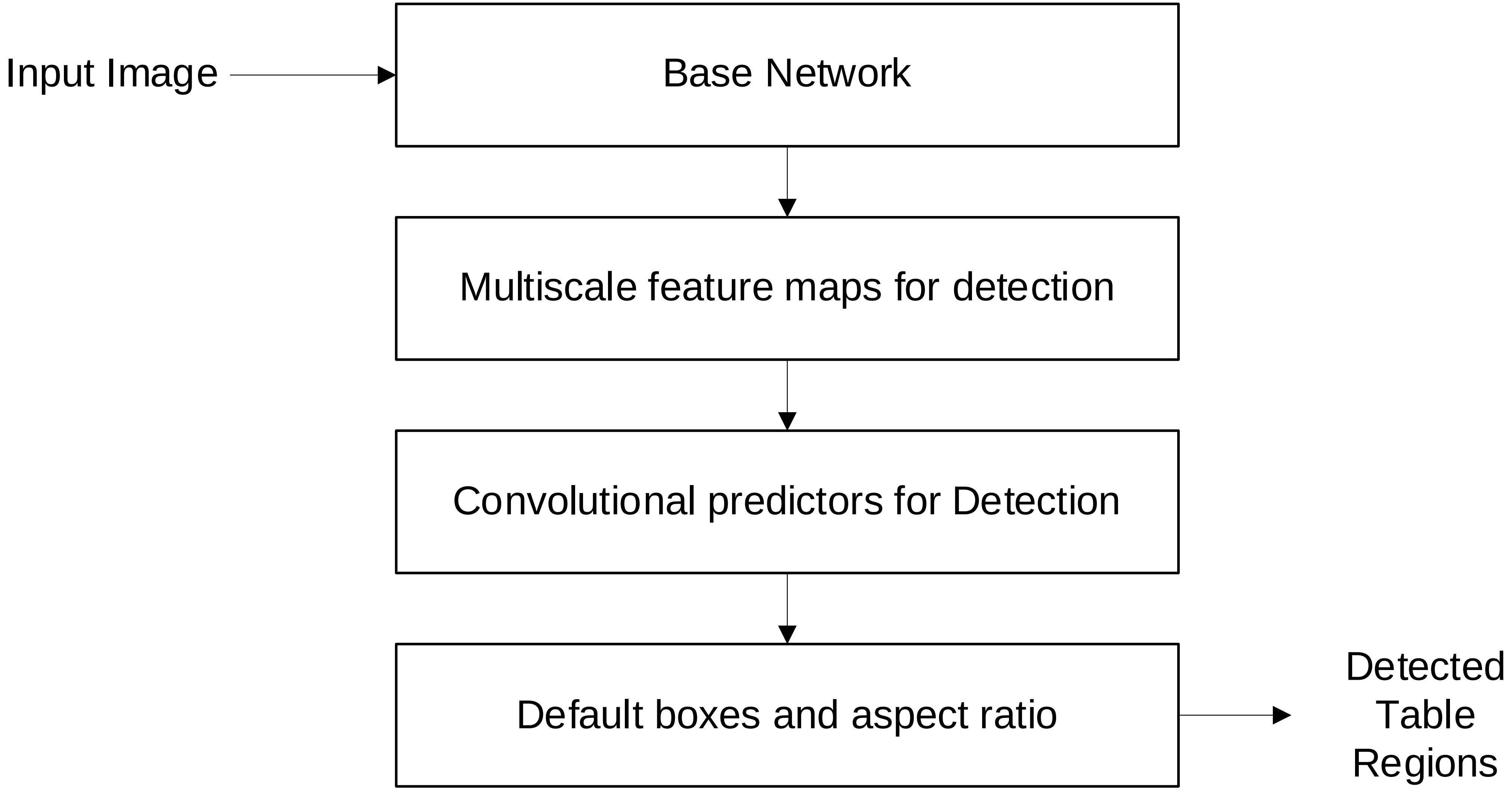
- Using cross-platform frameworks for compatibility, like Flutter or React Native
- Integrate user authentication for secure login, data storage
- Communicate with backend APIs for nutritional analysis display

Methodology - [3]
(Image Processing Model)



- Goal: Detect and extract nutrient labels from product packaging.
- Stages: SSD for table detection, Fast RCNN for text detection, OCR for text recognition.
- Outcome: Accurate extraction of nutritional information for personalized dietary recommendations.

Methodology - [4]
Single Shot Multibox Detector (SSD)



Methodology - [5]
Single Shot Multibox Detector (SSD)

- Base Network
  - Typically uses VGG-16 or ResNet as the base network.
  - Responsible for extracting high-level features from the input image.
  - Consists of several convolutional and pooling layers.
  - The output feature maps serve as the foundation for subsequent layers.
- Multiscale Feature Maps for Detection
  - Additional convolutional layers are added on top of the base network.
  - These layers generate feature maps at multiple scales.
  - Enables the detection of objects (tables) of various sizes.
  - Helps in handling small and large objects effectively.

Methodology - [6]
Single Shot Multibox Detector (SSD)

❑ Convolutional Predictors for Detection

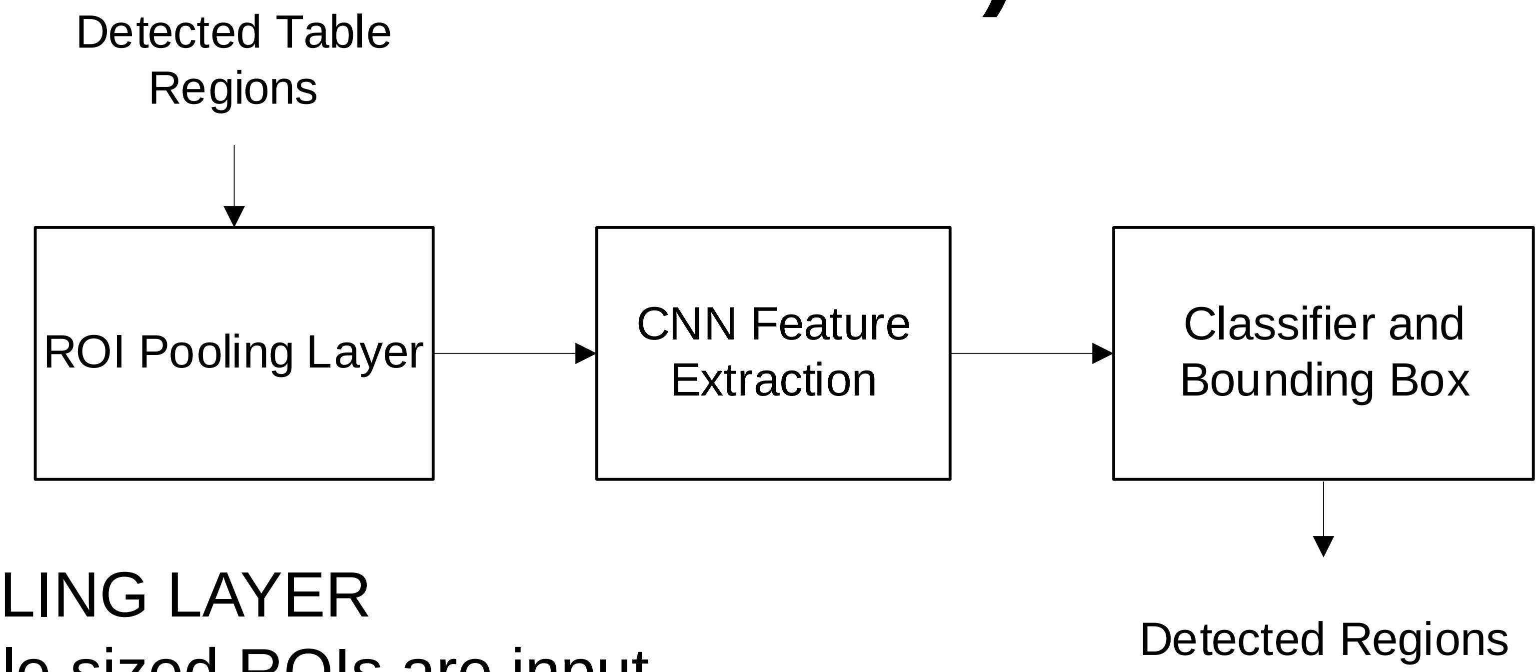
- Uses convolutional predictors to generate predictions from the feature maps.
- For each location in the feature map, predicts:
  - ➢ Class scores (probability of different object classes).
  - ➢ Bounding box offsets (coordinates of the detected objects).
- Convolutional predictors are applied to each feature map scale.

Methodology - [7]
Single Shot Multibox Detector (SSD)

- Default Boxes and Aspect Ratios
  - A set of default boxes with different aspect ratios and scales are used.
  - Each default box predicts both class scores and bounding box offsets.
  - Allows SSD to handle objects of various shapes and sizes.
  - Default boxes are refined based on the predictions.

- Detected Table Regions
  - Involves applying Non-Maximum Suppression to filter out redundant boxes.
  - Remaining boxes represent the detected table regions on the product packaging.
  - Detected regions are then passed to the Fast RCNN for further text detection.

Methodology - [8]
Fast RCNN (Region-based Convolutional Neural Network)



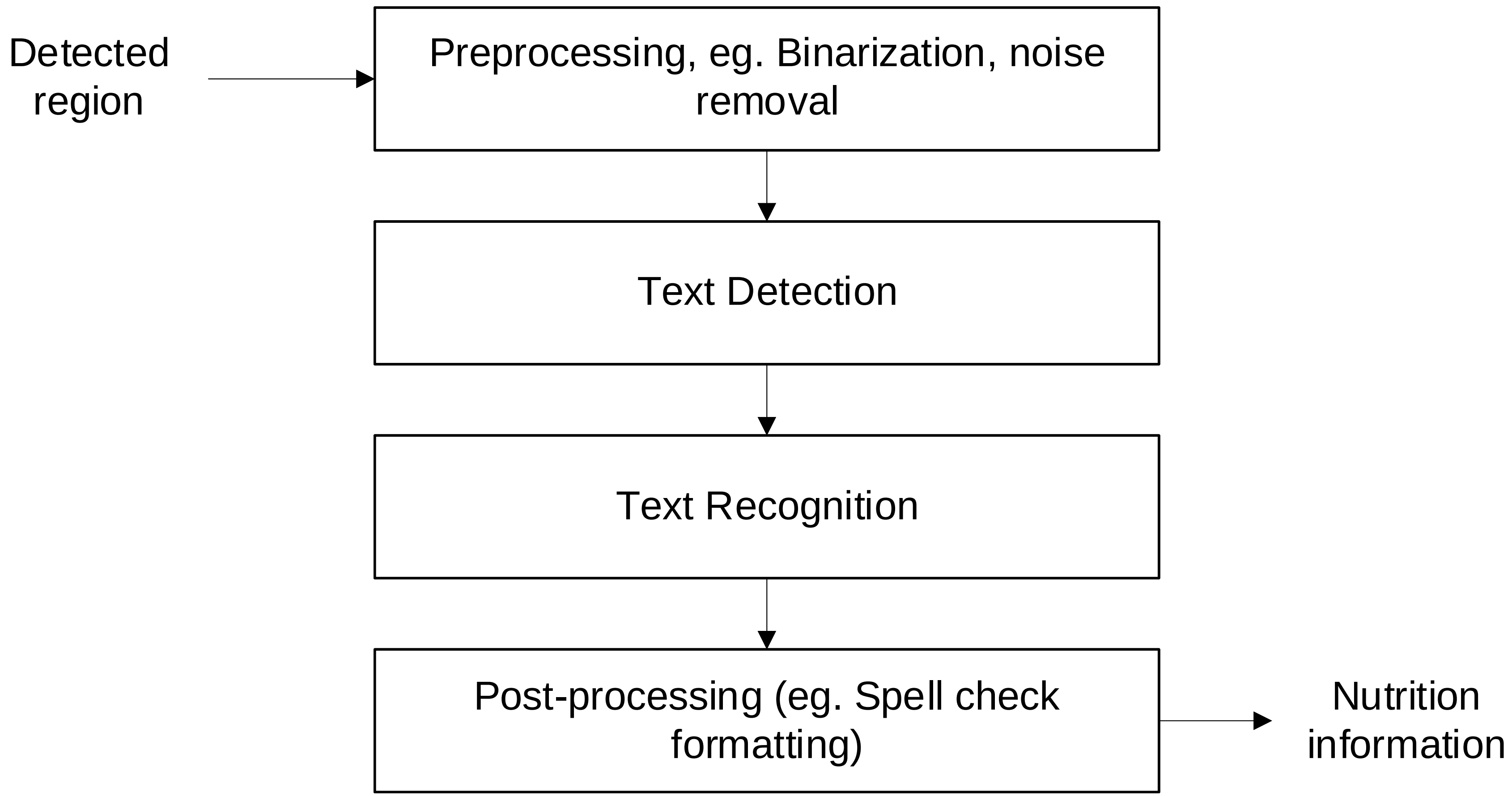
❑ROI POOLING LAYER
- Variable sized ROIs are input
- Extracts Fixed size feature maps from input ROIs
- Divides ROIs into equal-sized sub-regions
- Applies max-pooling to each sub-region
- Outputs fixed sized feature maps for each ROI

Methodology - [9]
Fast RCNN (Region-based Convolutional Neural Network)

- CNN Feature extraction
  - Raw input image
  - Extracts visual features
  - Utilizes Pretrained CNN (VGG-16, ResNet)
  - High dimensional feature maps representing image content

- Classifier and Bounding Box
  - Takes fixed-size feature maps from ROI pooling as input
  - Utilizes fully connected layers for further processing
  - Computes probability scores for each class (e.g., text or non-text)
  - Refines and adjusts bounding box coordinates for each ROI
  - Outputs class scores and adjusted bounding box coordinates for each ROI

Methodology - [10]
Tesseract OCR (Optical Character Recognition)



Methodology - [11]
Tesseract OCR (Optical Character Recognition)

- Preprocessing
  - Enhances the quality of the text regions for better recognition.
  - Common steps include:
    - Binarization: Converts the image to black and white, making text more distinct.
    - Noise Removal: Eliminates background noise to improve text clarity.
  - Prepares the text regions for accurate OCR.

- Text Detection:
  - Identifies the precise location of text within the preprocessed regions.
  - Involves algorithms that can distinguish text from non-text elements.
  - Ensures that only the relevant text areas are sent for recognition

Methodology - [12]
Tesseract OCR (Optical Character Recognition)

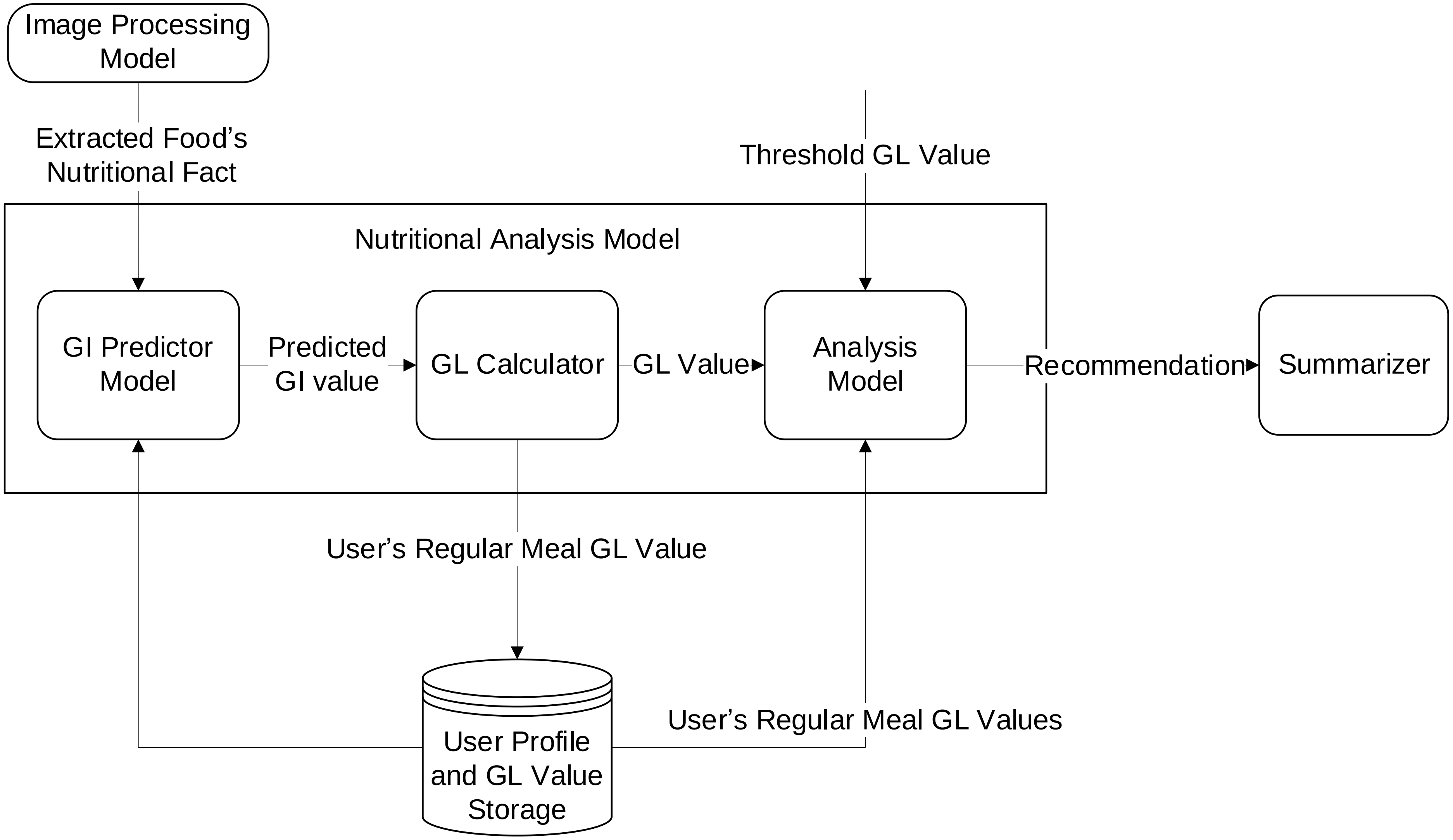
- Text Recognition:
  - The core OCR engine, such as Tesseract, processes the detected text regions.
  - Recognizes individual characters and words, converting them from images to digital text.
  - Utilizes character recognition models trained on various fonts and styles to improve accuracy.

- Post-Processing
  - Post-processing refines the recognized text for usability.
  - Steps include:
    - Spell Check: Corrects any OCR errors in the recognized text.
    - Formatting: Adjusts the text format to match the expected output structure.
  - Ensures the final text is accurate and properly formatted.

Methodology - [13]
Tesseract OCR (Optical Character Recognition)

- Nutrition Information:
  - The final output is the extracted and processed nutritional information from the product packaging.
  - This information is used to assess the product's suitability for individuals with diabetes and hypertension.
  - The extracted text is then analyzed to provide personalized dietary recommendations.

Methodology - [14]
(Nutritional Analysis Model)



Methodology - [15]
(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 - [16]
(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 - [17]
(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 - [18]
(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 - [19] (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 - [20]
(XGBoost - Algorithm)

- XGBoost is an efficient and scalable implementation of the gradient boosting framework that builds an ensemble of decision trees, each correcting the errors of the previous ones.

It operates through the following key steps:

I. **Initialization:** Start with initial prediction, usually target mean.

II. **Iterative Improvement:** Build trees to predict residuals (prediction errors).

III. **Tree Building:** Construct trees to correct previous model errors.

IV. **Model Update:** Combine new tree predictions with existing model.

V. **Regularization:** Prevent overfitting using regularization terms in objective.

Methodology - [21] (XGBoost – Predicted Output)

- Every tree is learning from the residuals of all previous trees.

Predicted output of XGBoost is the sum of all the results given as,

$$\hat{y}_i = \sum_{k=1}^{n} f_k(x_i), \qquad f_k \in F$$

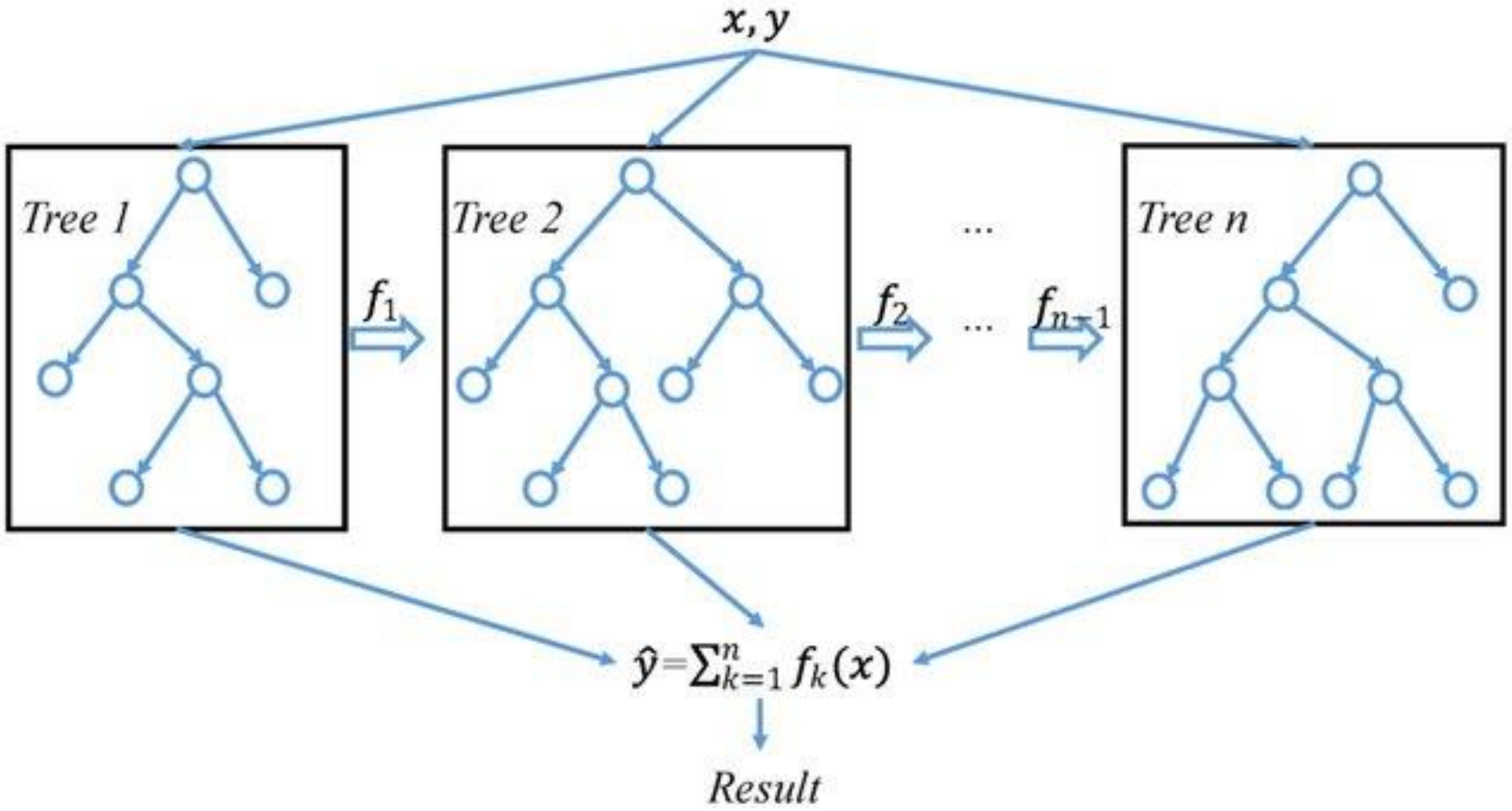
Where:

F means the space of regression trees

f_k corresponds to a tree, so f_k is the result of tree k

$\hat{y}_i$ is the predicted value of $i-th$ instance x_i

Methodology - [22] (XGBoost – Tree visualization)



Methodology - [23]
(XGBoost – Objective Function)

- Objective function is used to minimize the prediction error while controlling model complexity to avoid overfitting.

$$\mathrm{Obj} = \sum_{i=1}^{n} \mathcal{L}(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k)$$

Where:

$\mathcal{L}$ represents the loss function, such as mean squared error for regression tasks

Ω denotes the regularization term for each tree f_k

y_i and $\hat{y}_i$ are the actual and predicted values, respectively.

Methodology - [24] (XGBoost – Regularization)

- Regularization function avoids overfitting by adding a penalty for models with too many parameters or overly complex structures.

$$\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} {w_j}^2$$

Where:

T is the number of leaves in the tree

w_j is the weight of leaf j

γ and λ are regularization parameters that control the penalty

Methodology - [25]
(XGBoost – Application)

- XGBoost can be effectively utilized to predict the GI and GL values of food items based on their nutritional information.

Steps involved:

I. **Data Collection:** Gather dataset with nutritional, GI, and GL values.

II. **Feature Engineering:** Extract and preprocess relevant nutritional features for modeling.

III. **Model Training:** Train XGBoost with nutritional features predicting GI or GL.

IV. **Model Validation:** Cross-validate to ensure robust performance on new data.

V. **Prediction:** Apply model to predict GI or GL for new foods.

Methodology - [26]
(XGBoost – Accuracy Calculation)

- Accuracy of the trained nutritional analysis model can be evaluated as the Coefficient of Determination (R^2).
- It measures how much of the target variable's variance (GL or GI) is explained by the input features.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

Where:

y_i represents the actual value of the target variable for the $i-th$ observation.

$\hat{y}_i$ represents the predicted value of the target variable for the $i-th$ observation.

$\bar{y}$ is the mean of the actual values of the target variable.

n is the total number of observations.

Datasets - [1]
(USDA FoodData Central)

Attribute	Details
Dataset	FoodData Central Nutritional Information
Quantity	Over 7,000 commonly consumed foods in the United States
Volume	Around 16 columns with nutrient content for each food item
Origin	Compiled by the FoodData Central, a project of the US Department of Agriculture (USDA)
Description	Consist of following information: • Unique Identifier • Nutrients: Calories, Protein, Total Fat, Carbohydrates, Cholesterol, Sodium, Vitamins, Minerals, Water content, Fatty acid, Amino acid, Sugars, Serving size information.

Datasets - [2]
(Open Food Facts)

Attribute	Details
Dataset Name	Open Food Facts
Data Type	Food Product Information
Source	Primarily User-Contributed
Size	Over 3 million food products
Label Information	• Ingredients • Allergens • Nutritional Values
Product Identification	• Barcode of the food product • Photo of the product
Description	A comprehensive resource of user-contributed data typically found on food labels.

Nutrition facts	As sold for 100 g / 100 ml
Energy	1,971 kj (471 kcal)
Fat	21 g
Saturated fat	9.4 g
Carbohydrates	61 g
Sugars	1.8 g
Fiber	5.2 g
Proteins	10 g
Salt	3.2 g

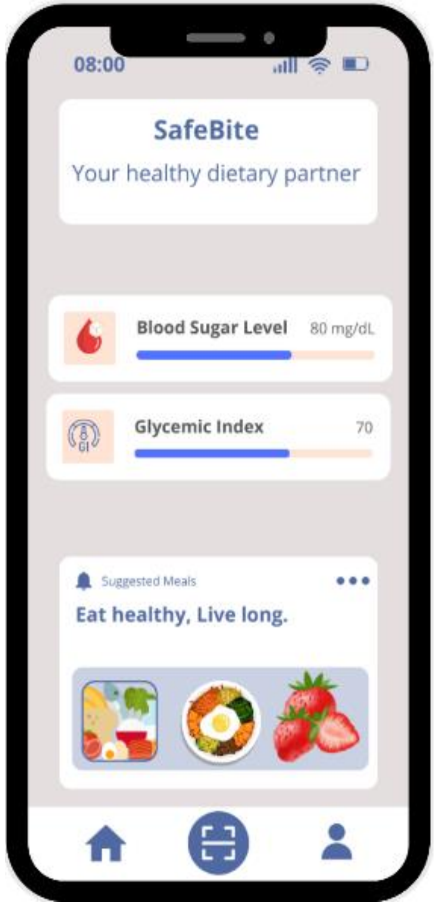
Datasets - [3]
(GI & GL Dataset)

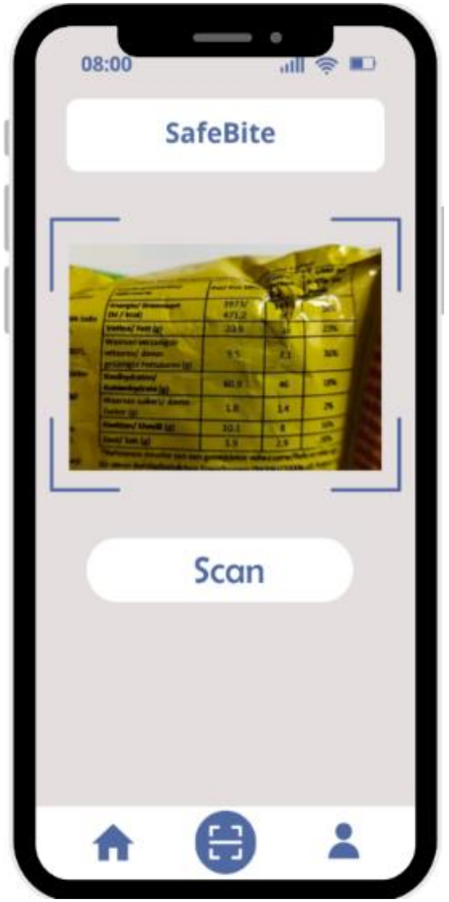
Food Item	Carbohydrates (g)	Fats (g)	Proteins (g)	Fiber (g)	Sugars (g)	Sodium (mg)	Serving Size (g)	GI	GL
Apple	25	0.3	0.5	4.4	19	1	100	40	5
White Bread	50	1.2	8	2.6	5	300	70	70	35
Brown Rice	23	1.8	2.6	1.8	0.5	2	100	68	15
Carrot	9	0.2	0.9	2.8	5	69	100	35	3

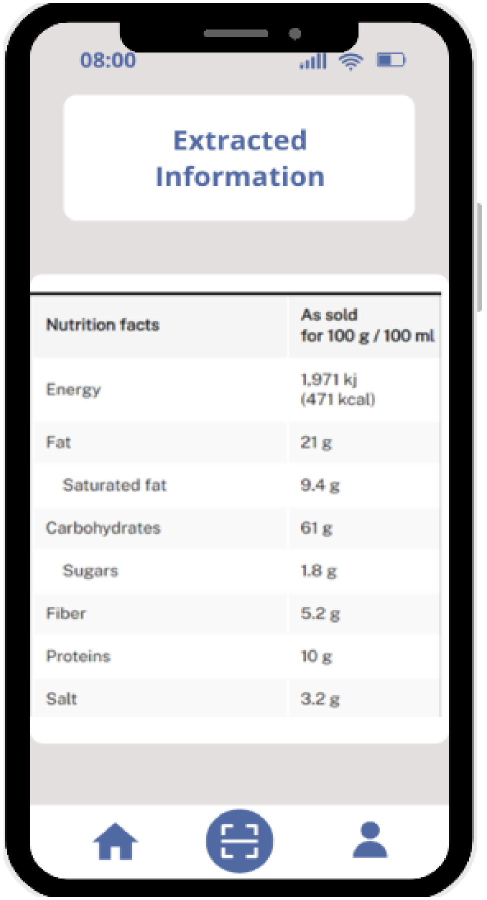
How will it be prepared?

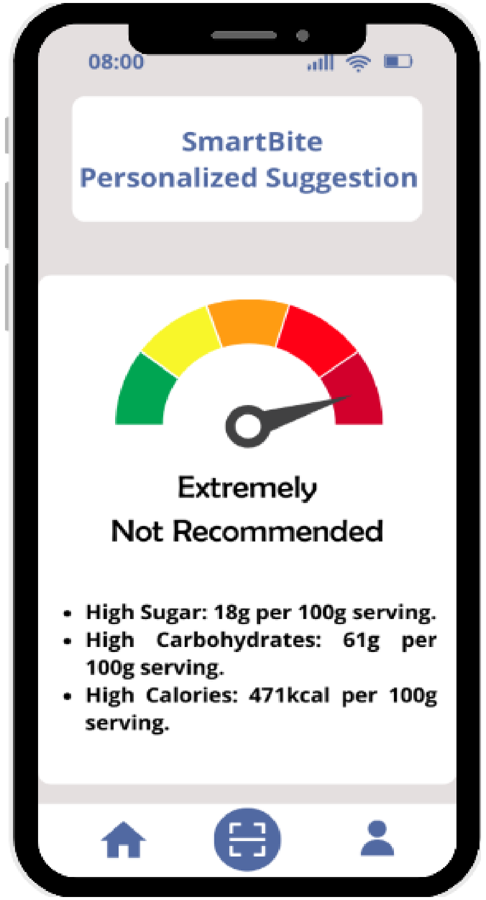
- Scrape nutritional data from reputable nutrition websites.
- Annotate each food item with its GI value.
- Gather additional nutritional components for each food.
- Compute GL using GI and carbohydrate content.

Expected Results





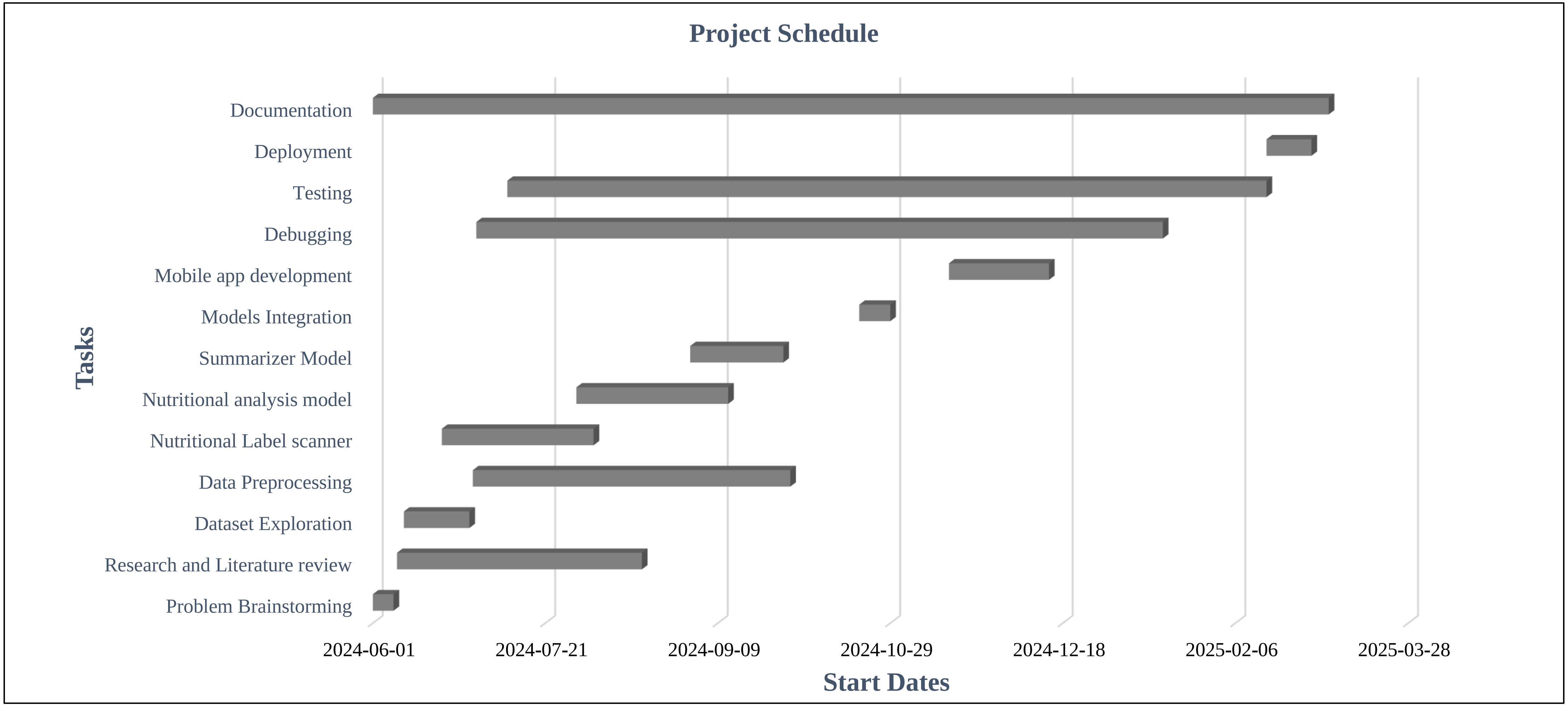




Project Application

- ❑ Personalized Health Profiles
  - Create profiles with blood sugar, medications, recommendations
- ❑ Nutritional Label Scanner
  - Uses 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

Tentative Timeline



Estimated Project Budget

S.N.	Particulars	Price (Rs.)	Quantity	Total Price (Rs.)
1	Printing	300	20	6000/-
2	Cloud Services	5000	1	5000/-
3	Miscellaneous	2500	1	2500/-
TOTAL				13,500/-

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THANK YOU