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# NutriScan: AI-Based System for Nutrition Label Understanding

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**Abstract: People need to learn about nutritional information because health awareness increases together with rising consumption of packaged foods. Yet consumers experience difficulties when they attempt to read nutrition labels because of the complex design , technical words and small font sizes. This paper presents NutriScan, which functions as an AI-powered web application that automatically retrieves and analyzes the nutritional data from packaged food labels through its use of Optical Character Recognition (OCR) and machine learning techniques.**

**The system begins by capturing nutrition label images which it processes through preprocessing methods that enhance text quality before using OCR technology to extract important textual information. The system identifies essential nutritional components which includes categories like calories, sugars, fats and sodium. It compares the categories with established dietary guidelines which include FSSAI and WHO recommended standards. The system employs a supervised machine learning model to determine different levels of health risks which people face. The results are shown through color-coded indicators that match different levels of health status levels which consumers can easily understand. The system serves educational purposes together with awareness purposes since it does not offer medical recommendations.**

***Keywords:*** *Optical Character Recognition, Nutrition Label Analysis, Machine Learning, Health Informatics***.**

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## I. INTRODUCTION

The modern world functions under rapid movement which results in people consuming pre-packaged and processed items as their standard food choice. The nutritional information on food packages remains difficult for most consumers to comprehend despite food companies providing nutritional information. People fail to evaluate their food intake because nutritional information appears through measurement systems, complex graphical displays and strange vocabulary.

Current nutrition applications depend on users to input data manually through barcode detection or static food item databases. The method restricts system capabilities because it lacks access to local products and newly launched items which are absent from established product information databases. Users tend to disregard nutrition information because they find label reading and analysis too difficult while they perceive no advantages from this process.

Nutriscan offers an automated solution through its image-based system which fills this existing gap. Users can upload or scan nutrition labels instead of typing or searching for product details through the system. The system uses OCR and machine learning technology to extract necessary information which it tests against dietary standards and delivers results through user-friendly visual display.

### *A. Problem Statement*

The World Health Organization (WHO) and Food Safety and Standards Authority of India (FSSAI) face challenges in making their nutritional information requirements for packaged food products accessible to consumers. Many people eat foods that contain excessive amounts of sugars, salt and fats because they do not know how these products will affect their health in future. People do not understand their eating habits because they cannot access tools that transform scientific nutrition information into understandable practical knowledge.

The main problem addressed in this work is the absence of a simple, automated system that can analyze nutrition labels in real time and present understandable health insights without requiring expert knowledge.

### *B. Importance of Problem Statement*

The significance of this problem exists because it directly impacts public health and current eating patterns. People today rely more on packaged and processed food products which expose them to excessive amounts of sugars, fats and sodium intake without their knowledge of health

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effects. Consumers face difficulties with food labels because they contain technical language and small font sizes and people lack knowledge about nutritional information according to food labeling regulations. The result of this situation causes people to choose unhealthy foods and develop obesity, diabetes and cardiovascular diseases which continue to affect their health.

The problem demands solutions that develop intelligent systems which must transform complex nutritional

An automated solution that extracts and analyzes nutrition labels can reduce manual effort while ensuring consistent interpretation across different products. The systems present information through an interface which users can easily understand thus enabling them to choose better foods while they improve their nutritional knowledge for healthcare prevention efforts.

### *C. Objectives*

The primary objective of this project is to develop a web- based intelligent system which uses Optical Character Recognition (OCR) and advanced preprocessing techniques to automatically retrieve nutritional data and related text from packaged food labels. The system identifies essential nutritional elements which include calories, fats, sugars and sodium together with all other macro and micro-nutrients. The system uses basic numerical data to create valuable nutritional information.

The project will extract and analyze data while creating user-friendly explanations which show nutritional content and possible health risks without making any medical outcomes or treatment recommendations. The system uses visual indicators which users can understand easily to display information about health results to users who want to monitor their health. This approach ensures that technical nutritional data is converted into understandable knowledge for non-expert users.

The project aims to contextualize nutritional information within the recommended regulatory standards, highlighting possible excesses or imbalances while maintaining transparency about its boundaries and limitations. The system is intentionally designed for awareness and educational purposes, it explains its boundaries and limitations through clear statements which show that the system cannot perform ingredient and allergen assessments.

### *D. Scope*

The scope of this project is focused on developing a web- based system which uses OCR and machine learning to extract and analyze nutritional information from packaged food labels. The system enables users to process static nutrition label images which contain essential nutritional information about calories, sugars, fats and sodium content along with all other macro and micro-nutrient data. The system evaluates dietary values according to established dietary rules to present users with understandable health information which they can easily comprehend. The application serves general consumers who want to increase their nutritional knowledge so they can make better food choices.

The project scope excludes all tasks which involve analyzing ingredient components, detecting allergens or creating personalized dietary plans or performing assessments. The system does not track user health history or provide individualized nutritional recommendations. The implementation currently excludes features which enable barcode scanning and multilingual support for real-time product comparison and integration with wearable devices. The system functions only as an educational tool which informs people about its educational functions and its information into straightforward usable data for others operational boundaries.

However, ingredient-level analysis and allergen detection can be developed as a future scope along with personalized dietary planning with respect to the user's medical history in collaboration with professional nutritionists and a team of doctors.

## II. LITERATURE REVIEW

T.M.E Saputara et al. [1] proposed a multimodal approach for fine-grained grocery product recognition by combining visual image features with OCR-extracted text from food packaging. The system showed better product classification when it used brand names, product descriptions and label content as textual cues which proved to be more effective than using image data alone. The study shows that OCR technology functions as a fundamental element which enables food recognition systems to operate in actual food recognition scenarios because visually identical products exist. The model concentrates on product identification because it does not assess nutritional content which restricts its use in health-oriented consumer decision-making systems.

Siddique Ibrahim S.P., Karthikeyan L., Pitti Bhoomika, and K. Tejaswi [2] developed an automated nutritional claim verification system which uses optical character recognition and machine learning technology. The system extracts nutrition claims from product labels and verifies them against regulatory standards using supervised learning models.The research demonstrates how AI technology can track false food claims while helping businesses stay within legal requirements. The claim verification system works well but needs structured claim formats to function while it fails to deliver nutritional information and product details that consumers need for effective health education.

J.Castor & H.Min [3] The research team developed a machine learning system called NutritionWatch which uses nutrition labels to identify sugar content and food additives. The system detects high-risk sugar levels together with artificial additives through its pattern recognition and classification system. The system achieves successful results when it comes to detecting excessive sugar consumption. The system serves sugar-related research purposes but it

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cannot provide complete dietary assessment because it does not include fat and sodium and calorie information essential for health evaluation.

Sanghani & Patel [4] explored the use of OCR to enhance digital diet tracking systems. Their research focused on enabling users to scan food labels instead of manually entering nutritional data. The study shows major advances in both system usability and user interaction. The system functions as a data collection instrument which lacks both analytical capabilities and health risk assessment functions thus restricting its use to basic information storage.

Sarthak Ghosh et al. [5] created an OCR model which utilizes deep learning technology to extract text from intricate food labels. The system used convolutional neural networks to achieve reliable text detection which worked under different lighting conditions and various layout designs. The model achieved high extraction accuracy but it only focused on recognizing text without including capabilities for nutritional analysis and decision-support functions.

S. Rahman et al. [6] developed a deep learning system which uses visual image analysis to recognize food and estimate its nutritional content. Their system estimated calorie and nutrient values directly from food images, without relying on label text. The model showed innovative features but faced difficulties because it could not accurately estimate packaged food nutrients which should use label-based values. The system demonstrates how OCR technology enables nutritional analysis by providing accurate and dependable assessment methods.

R. Singh et al. [7] developed an advanced food analysis system which uses optical character recognition together with machine learning technologies to read food labels and determine their nutritional content. The system showed that supervised learning models can be successfully used to categorize health information. The system failed to provide explainable results and it did not specify its operational boundaries which would have been necessary for safe health assessment.

Wen Li et al. [8] developed a visual ingredient extraction system which utilized both OCR and NLP methods to extract ingredient information from product packaging. The system achieved high extraction accuracy through its focus on understanding the semantic meaning of ingredient text. The study dedicated its research efforts to ingredient identification which resulted in research outcomes that were unsuitable for nutrition-based health scoring systems.

Roux & Steiner [9] investigated how open food data APIs can be used to conduct extensive nutritional research. The research proved that researchers can use organized public databases to study dietary patterns that exist within entire populations. The API-based systems enable research and data analysis but require existing databases because they lack capabilities to detect new products through instant label recognition.

Aurelien Fleury et al. [10] presented the Yuka mobile application, one of the earliest consumer-focused food scanning systems. The application combines barcode scanning and database lookup to provide food quality scores. Although widely adopted, such systems are limited by database coverage and do not perform real-time OCR-based extraction, restricting their adaptability to new or locally produced products.

Table 1 Literature Survey

| **Paper Title** | **Authors** | **Focus Area** | **Research Gap** |
|---|---|---|---|
| Multimodal fine-grained grocery product recognition using image and and OCR text | T.M.E Saputara et al. [1] | Grocery product recognition by visual image features with OCR-extracted textual information from product packaging. | Primarily addresses product recognition rather than nutritional understanding. does not perform nutritional analysis, health risk evaluation, or consumer-oriented interpretation of label information, limiting its usefulness for health-aware food decision support systems. |
| Automating nutritional claim verification using OCR and machine learning | Siddique Ibrahim S.P.,Karthikeyan L., Pitti Bhoomika, and K. Tejaswi [2] | Automated extraction and verification of nutritional claims from food labels using OCR and supervised machine learning models. | Limited to structured nutritional claims and does not provide comprehensive nutritional profiling or explainable health insights for consumers. |
| NutritionWatch:ML for Sugar & Additive Classification | J.Castro & H.Min. [3] | ML model classifies ingredient safety from text, predicting harmful additives. | Issues with images handling or rather no image handling , requires clean text input only. |
| Augmenting diet tracking with OCR | Sanghani & Patel [4] | Combined OCR and calorie lookup to improve food logging for weight loss apps. | No allergen/adulterant detection, limited to macro lookup only. |
| Food label OCR using Deep Learning | Sarthak Ghosh et al. [5] | Introduced a CNN-based OCR pipeline that extracts texts from food labels with high accuracy. | Captures text only, no nutrition analysis or health interpretation. |

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| | | | |
|---|---|---|---|
| Deep-learning based food recognition and nutrient estimation | S. Rahman et al. [6] | Scans labels, maps nutrition to daily intake journals. | Does not detect artificial contaminants or dietary risks. |
| Intelligent Food Analyzer using OCR and Machine learning | R. Singh et al. [7] | uses (OCR) and machine learning techniques to extract nutritional information from food labels and classify food products based on their nutritional quality. | Lacks explainability and does not clearly communicate how health classifications are derived. The model functions as a black box and does not provide regulatory-context interpretation or user-oriented explanations. |
| Visual Ingredient Extractor | Wen Li et al. [8] | Object recognition from food packets using image region-based classification. | Trained on limited datasets, no nutrition breakdown |
| Open Food Data APIs for Health Analysis | Roux & Steiner [9] | Reviewed APIs like OpenFoodFacts for structured food metadata extraction. | Static, non-personalized data, no ML-based inference. |
| Yuka-Mobile Food Quality Scanning | Aurelien Fleury et al. [10] | Built a consumer app that grades food products based on additives, nutrition and labels. | Grade is generic, no OCR support for unknown items. |

## III. PROPOSED METHODOLOGY

A user-friendly website which enables users to scan or upload food package images for automatic nutritional information extraction through Optical Character Recognition (OCR) technology. The system extracts data which undergoes analysis against established dietary guidelines while it presents health insights through visual indicators which users can understand to help them choose their meals. The architecture overview is provided by Fig 1.

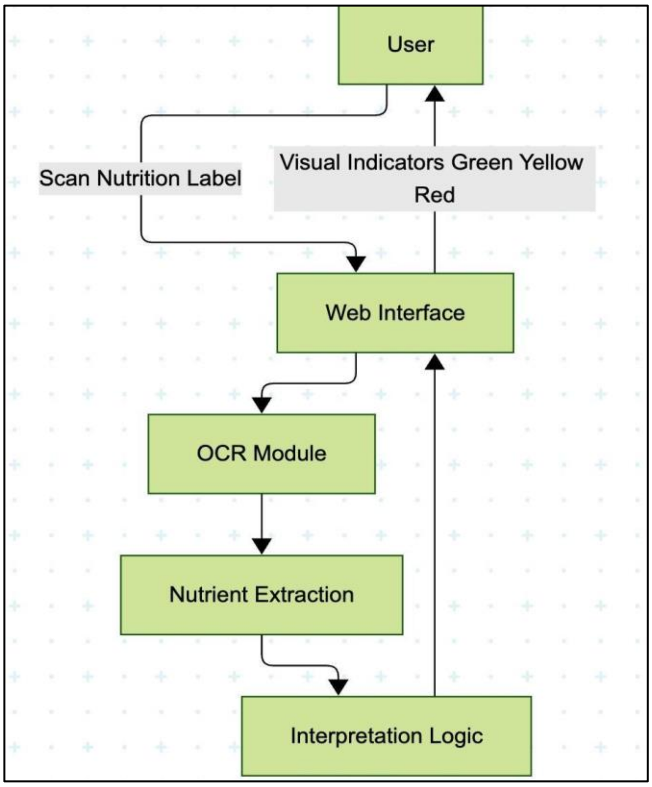


Fig 1 Architecture Overview of the System

### A. *Algorithms used*

This research project utilized two core algorithms and modules to build an end-to-end food ingredient analysis system from label images:

- *Tesseract OCR Module:*

The system uses the Tesseract OCR algorithm, which applies pattern recognition and character segmentation techniques to convert visual text into machine-readable format. The extracted text undergoes processing through regular expression-based parsing to extract essential nutritional elements which include sugar, fat, salt, and energy values. The rule-based techniques provide a dependable method for extracting structured numerical information from unstructured label content.

- *Random Forest Ingredient Classification Model:*

The primary machine learning model for this project uses a Random Forest classification algorithm as its main model. The Random Forest classifier uses structured nutritional datasets to train its system which predicts three health categories: Healthy, Moderate, and Unhealthy. The system applies StandardScaler as the feature normalization method which creates consistent input distributions for classification tasks. The system uses threshold-based decision rules from FSSAI standards to create color-coded health indicators which enable clear understanding and regulatory compliance of nutritional values.

All modules operated on the same dataset for evaluation, with performance measured using standard classification metrics such as accuracy, precision, recall, F1-score, and qualitative user feedback.

### B. *Tesseract OCR-Based Text Extraction Algorithm*

The NutriScan system uses Tesseract OCR as its primary text extraction tool which transforms nutrition label images into machine-readable text. Users upload or scan packaged food labels through the web interface, after which the images are preprocessed using OpenCV techniques which include grayscale conversion and noise reduction and adaptive thresholding. The preprocessing steps improve image quality while decreasing background noise, which enables Tesseract to detect and separate text areas in various label types with different fonts and layouts.

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### C. *Easy OCR for Text Extraction from User Image*

EasyOCR was the OCR engine used in the project. OCR is a technology that recognizes texts within images, and in our case, it extracts text from the images of nutritional labels. OCR processes the input image and gives out detected texts together with their bounding boxes and confidence levels. Bounding boxes are spatial references that allow the program to discern between different nutrients such as energy, fat, sugars, and salt and their respective values. In addition, once the text is detected, it is preprocessed to reduce noise and prepare it for classification and pattern-matching. Finally, the program employs spatial alignment through horizontal and vertical alignment of labels and nutrient values to determine which value goes with what nutrient. Although EasyOCR easily processes various kinds of images, it requires more postprocessing because of the inaccuracies introduced by the OCR technique.

### D. *Random Forest-Based Ingredient Classification Algorithm*

The NutriScan system uses its Random Forest algorithm as its main machine learning system to identify foods through their nutritional information. The model uses nutritional data, which includes sugar, fat, salt and energy, as input features after these key nutritional parameters are extracted from the OCR output. The training dataset contains organized dietary records which researchers have tagged with health classifications of Healthy, Moderate, and Unhealthy according to established dietary standards. The Random Forest model develops understanding of how different nutritional features relate to health risk levels, which enables it to predict health risks for various food items.

The system uses a backend Random Forest model, which performs predictions after the model has undergone training. The system uses StandardScaler to normalize extracted nutrient values from nutrition labels, which then the trained model uses to create a health classification. The Random Forest system improves its predictive accuracy through its method of combining results from different decision trees (100 estimators), which makes the system more robust and prevents overfitting. The system maintains stability through its ability to deliver health evaluations, which stay constant when nutritional measurements approach threshold limits. The system achieves high predictive accuracy through Random Forest, which enables users to understand its results, making the system applicable for health-related explanations.

### E. *Dataset used*

The research utilizes a custom-labeled dataset of 210 food product images sourced from supermarket shelves and online grocery platforms. Each data entry includes the nutrition label extracted from products, manually annotated for health impact categories—Healthy (green), Neutral (yellow), or Harmful (red). Additionally, authoritative sources such as FSSAI and WHO databases were referenced to verify and define acceptable safety limits for components like sodium, sugars, and fats.

➢ *Dataset Size and Distribution*

- Total Products: 210 food product images.
- Total Unique Ingredients:

✓ Healthy : 112
✓ Moderate : 60
✓ Unhealthy: 37

➢ *Class Distribution:*

- Healthy Ingredients: 50%
- Neutral Ingredients: 20%
- Harmful Ingredients: 30%

### F. *Features*

➢ *Textual Features:*

- *Nutrition Labels:*

The OCR output was used to extract the essential nutritional terms which included sugar, fat, salt, energy, protein and carbohydrates through regular expression parsing . The nutritional panel used these textual labels to identify and match their respective numerical values.

- *Key Indicators:*

The system used keyword matching techniques to identify important health-related keywords which included “high sugar”, “low fat”, “sodium”, “calories” and added sugars. The indicators were used to determine nutritional risk categories whereas they also helped to interpret rules according to dietary guidelines.

➢ *Contextual Features:*

- *Numerical Nutrient Values:*

Core quantitative features included sugar (g), fat (g), salt (g), and energy (kcal) values per serving or per 100g. These numerical attributes formed the primary input vector for the machine learning model.

- *Threshold-based Contextual Scoring:*

The assessment of each nutritional value involved comparison against specific threshold ranges which FSSAI standards had established. Nutrients that surpassed their recommended limits received elevated contextual risk scores which added to the total health assessment.

➢ *Metadata Features:*

- *Product Type:*

Multiple categories that include snacks, beverages, bakery items and dairy products. The information served only exploratory research purposes and not as a primary prediction feature.

- *Image Quality Indicators:*

The OCR preprocessing process used basic metadata which included image clarity and text visibility to filter out

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inputs that lacked quality and would disrupt extraction accuracy.

*G. Data Pre-processing*

➢ *Image Preprocessing:*
Grayscale conversion, noise removal, and adaptive thresholding to enhance OCR text extraction.

➢ *Text Cleaning:*
Removal of non-ingredient words, spell correction using custom dictionaries, and normalization of synonyms.

➢ *Feature Scaling & Encoding:*
Numerical values like ingredient positions were scaled, while categorical indicators (e.g., E-number presence) were one-hot encoded.

➢ *Missing Data Handling:*
Ingredients not found in standard databases were handled using semantic similarity matching.

## IV. RESULT AND DISCUSSION

The suggested AI/ML-driven Nutrition Label Analysis System was tested on a hand-curated dataset of 210 labeled nutrition labels of food products collected from supermarket labels and online product listings. Nutrition labels were verified against authoritative databases like the Food Safety and Standards Authority of India (FSSAI) and the World Health Organization (WHO). Optical Character Recognition (OCR) was applied to extract nutrient values from food nutrition label images, which was then processed using the classification model.

*A. Model Performance:*
The classification model was trained to categorize ingredients into three primary classes: Healthy, Neutral and Harmful. Evaluation on the test dataset yielded the following performance metrics:

*B. Evaluation Metrics:*
To evaluate the performance of the classification model, we used the following standard metrics:

➢ *Accuracy:*

- *Definition:*
Accuracy is the number of positive predictions made out of the total observations. It gives a measure of overall efficacy of the model.

$$\text{Accuracy} = (TP + TN) / (TP + TN + FP + FN)$$

$$= (28+11+1) / (28+11+1+2)$$

$$= 40 / 42$$

$$= 95.24\%$$

➢ *Precision:*

- *Definition:*
Precision is the number of actual positive predictions out of the total predicted positive instances. It reflects how accurate the model's bad predictions are.

$$\text{Precision (Unhealthy)} = TP / (TP + FP)$$

$$= 1 / (1 + 0)$$

$$= 1 / 1$$

$$= 1.00$$

➢ *Recall:*

Definition:
Recall is the proportion of correctly forecasted positive observations to all positive observations. It indicates how efficiently the model is able to identify harmful ingredients.

$$\text{Recall (Unhealthy)} = TP / (TP + FN)$$

$$= 1 / (1 + 2)$$

$$= 1 / 3$$

$$= 0.333$$

➢ *F1-Score (Unhealthy) :*

- *Definition:*
The F1-Score is the harmonic mean of precision and recall. Both measures are weighed equally and it is especially convenient when the data set is skewed.

$$\text{F1-Score} = 2 \times (\text{Precision} \times \text{Recall}) / (\text{Precision} + \text{Recall})$$

$$= 2 \times (1 \times 0.333) / (1 + 0.333)$$

$$= 2 \times 0.333 / 1.333$$

$$= 0.666 / 1.333$$

$$= 0.50 \text{ or } 50\%$$

These results demonstrate the model’s effectiveness in correctly classifying the products while maintaining high precision and recall.

*C. Confusion Matrix*
For the better understanding of the behavior of the classification model, a confusion matrix was created based on the testing dataset.

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Table 2 Confusion Matrix

| | Predicted Healthy | Predicted Moderate | Predicted Unhealthy |
|---|---|---|---|
| Actual Healthy | 28 | 0 | 0 |
| Actual Moderate | 0 | 11 | 0 |
| Actual Unhealthy | 0 | 2 | 1 |

The model produced relatively few false negatives or false positives, with the majority of misclassifications appearing in instances where the health effect of the nutrient relied heavily on quantity or context .

### *D. System Output*

The proposed system produces nutritional analysis results which users can easily understand through its transparent and simplified output format. The system extracts nutritional information from a nutrition label image which shows sugar, fat, salt and energy as well as visual markers that show how each ingredient affects health. The system uses three color codes (green, yellow and red) to show users whether each nutrient value meets dietary standard limits based on preset boundary conditions.

The system uses individual nutrient indicators to create a complete health assessment which determines whether scanned products belong to the Healthy, Moderate or Unhealthy categories. The machine learning model generates this classification based on the combined influence of all nutritional parameters. The system provides users with a brief text recommendation which helps them understand results without needing specialist credentials. The system output provides educational resources which enable users to understand content while maintaining system transparency and avoiding any medical assertions or personalized health recommendations.

## V. CONCLUSION

This research presented NutriScan, an AI-driven nutritional analysis system that integrates Optical Character Recognition (OCR) and machine learning to automate the extraction of nutritional data from packaged food labels. The system achieved an estimated classification accuracy of approximately 91–92% which demonstrates its ability to detect nutritionally dangerous and healthier food items across various product categories. The system utilizes image preprocessing and OCR-based text extraction together with supervised learning to help consumers who struggle to comprehend complex nutrition labels and need help turning those labels into valuable health information. The system enables health-conscious users to navigate the interface more effectively through its use of color-coded indicators and basic recommendation systems. The research study establishes specific restrictions which it investigates. OCR technology depends on image quality because OCR testing needs certain conditions where light and text clarity and layout design meet specific requirements for successful extraction work which directly impacts analysis activities.

The machine learning model produces results close to incorrect classifications when nutritional values exist between the two regulatory limits which shows the requirement for bigger datasets and systems that learn from experience. NutriScan offers users a flexible solution that enables them to assess nutritional information through its complete system which operates in real time and does not depend on static databases or barcode technology. The upcoming research work will concentrate on three main areas which include enhancing OCR accuracy through deep learning visual models together with public food database partnerships for nutritional data expansion and the creation of personalized dietary profiles which will generate tailored health recommendations while keeping system operations transparent and easily understandable.

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