International Journal on Science and Technology (IJSAT)

E-ISSN: 2229-7677 ● Website: www.ijsat.org ● Email: editor@ijsat.org

Leveraging Large Language Models (LLMs) and OCR for Real-Time Nutritional Risk Assessment in Specialized Diets

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Abstract

When it comes to managing long-term health issue like diabetes or hypertension, people always check what are they consuming, and food labels make it worse. During the course of this research, it became clear that how confusing packaged food labels actually are. Tiny fonts. Reflective plastic. Ingredient names that are rarely recognizable to the customer. It becomes very difficult for patients as they are already managing their complex medical schedules, understanding packaged food label in a market is not feasible and is unreasonable. This gap is addressed by the present study. Existing apps fall short. Most rely on static food databases that miss the regional Indian products entirely, or they demand manual entry that leads to its own individual errors. They also treat every user the same. Which is the real problem when someone has both diabetes and hypertension simultaneously, because the risks of certain ingredients compound in ways no simple calorie tracker accounts for. The proposed system takes a different approach. EasyOCR extracts text directly from food packaging images, which is then passed to Gemini 1.5 Pro for contextual medical reasoning. Rather than simply listing ingredients, the model interprets them against the user's individual health profile. Testing was done on eight packaged food products taken from the Indian consumer market – including instant noodles, savoury snacks, and processed desserts – reflecting real supermarket conditions rather than controlled laboratory samples. A noteworthy observation was recorded during testing, the model demonstrated the ability to self-correct character level OCR errors prior to analysis. For example, mapping the jumbled output "Soclum" to "Sodium" without explicit instruction. This proved the integrity of medical reasoning. The result showed that the system successfully identifies compounding risks that the other tools missed entirely– like how sodium and refined carbohydrates together create a far more serious vascular threat for someone with both hypertension and diabetes than either ingredient does alone. This research demonstrates that the integration of LLMs into food safety systems can significantly enhance dietary protection and personalized healthcare systems.

Keywords: Optical Character Recognition (OCR), Large Language Models (LLMs), Gemini 1.5 Pro, Specialized Diets, Comorbidity Reasoning

1. Introduction

Today’s food environment is increasingly dominated by processed and packaged food products that contain a complex blend of sugars, sodium, preservatives and additives. For the people managing chronic health conditions such as Type 2 diabetes, hypertension or heart diseases, understanding these ingredients is not just helpful but is essential for maintaining health.

Unfortunately, nutrition labels are hard to interpret. They include technical terms, extra small fonts, reflective or curved packaging surfaces which makes it hard to read, especially for elderly people or those with visual impairments. Even if labels are perfectly readable, understanding and having knowledge about the clinical implications are required, which most patients or consumer does not have or not been given.

Although several mobile apps exist for calorie tracking and diet monitoring, most depend on manual data entry or pre-existing food databases. These databases may not include regional products, newly reformulated food, or less common brands. Manual transcription also increases the chances of human error and reduces usability.

To address these challenges, this research proposes a system that integrates Optical Character Recognition (OCR) technology with the contextual reasoning abilities of Large Language Models (LLMs). OCR enables automatic extraction of text from the food packaging, while LLMs help interpret the nutritional information in relation to an individual’s health profile. The aim is not simply to display nutritional information but to make that information clinically meaningful at the moment a purchasing decision is being made.

2. Related Work

The evolution of automated nutritional monitoring has transitioned from simple barcode-scanning databases to complex, real-time semantic interpretation of physical packaging. This section reviews the literature across three critical domains: OCR applied to food labels, machine learning for ingredient analysis, and the growing role of LLMs in clinical dietary reasoning.

2.1 OCR on food packaging

The physical nature of food packaging is, genuinely, an unpredictable engineering problem. Reibring (2017) made an early but important observation: nutrition labels are not ordinary documents — they are structured grids, and treating them as such allowed line-segmentation techniques to meaningfully improve recognition rates on curved surfaces [1]. That insight held up well, but only under favourable conditions. Standard OCR engines like Tesseract break down quickly when faced with glare on plastic wrappers, inconsistent font weights, or the kind of stylized text common on Indian snack packaging.

Recent comparative studies from 2024 and 2025 have moved toward deep learning-based detectors. Researchers evaluating OCR performance on diverse regional packaging found that while engines like Tesseract excel in high-contrast scenarios, EasyOCR — utilizing a CRAFT detector and ResNet backbone — offers superior robustness for multilingual and stylized text, as demonstrated in evaluations conducted on South African food packaging [2].

2.2 Machine learning in nutritional and ingredient analysis

Once text is extracted, the secondary challenge is the classification of ingredients into health risk categories. The FoodMO (2024) application demonstrated a significant breakthrough by applying traditional Machine Learning (ML) classifiers to predict glycemic index patterns directly from OCR-extracted nutrient tables [3]. Similarly, the NutriScan (2025) framework utilized automated nutritional claim verification to identify hidden sugars and sodium levels that exceed regulatory thresholds, such as those set by the FSSAI and FDA [4].

Despite these successes, traditional ML models often operate as black boxes, providing a safety rating without a clinical justification. To address this, ensemble machine learning approaches developed in 2025 have attempted to combine multiple decision trees to achieve competitive accuracy rates in identifying dietary risk factors including allergens [5]. However, these systems are often limited by static databases and struggle to adapt when food manufacturers change their formulas or introduce new chemical additives.

2.3 Large language models (LLMs) and clinical reasoning

The emergence of Large Language Models (LLMs) has introduced a reasoning layer that was previously missing from nutritional analysis tools. Unlike traditional ML, LLMs can interpret the context of an ingredient rather than simply matching it against a fixed database. Research in 2025 regarding LLMs in clinical nutrition has validated that models like GPT-4o and Gemini can accurately interpret complex chemical names such as Maltodextrin and relate them to physiological responses like insulin spikes [6].

Research on prompt engineering in clinical practice (2025) demonstrated that incorporating patient-specific comorbid conditions into LLM prompts enables systems to provide dynamic, personalized dietary advice tailored to individual medical profiles [7]. This represents a significant upgrade over the one-size-fits-all approach of earlier applications, which could not distinguish between a user with a single condition and one managing multiple overlapping diagnoses simultaneously.

2.4 The gap in personalized comorbid assessment

While the current state-of-the-art includes robust extraction capabilities [8] and advanced reasoning frameworks [9], a notable gap remains in the practical application for users with complex, overlapping medical histories in regional markets. Most existing studies utilize standardized Western datasets. The present research seeks to address this gap by evaluating the performance of an integrated OCR-LLM pipeline against real-world packaging encountered in the Indian consumer landscape, where label formatting, language diversity, and product variety present unique challenges not represented in existing literature.

3. Proposed Methodology

The proposed framework follows a layered modular architecture designed to bridge the gap between physical food packaging and personalized clinical advice. The system pipeline consists of six distinct phases: Data Acquisition, Hardware/Software Standardization, Neural Text Extraction, Data Normalization, LLM-based Semantic Processing, and Clinical Decision Mapping.

3.1 Data acquisition and image standards

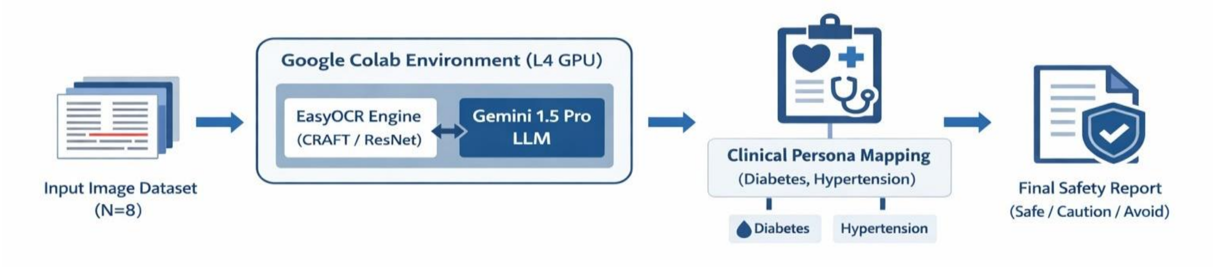
For this study, a diverse dataset of eight unique packaged food items was curated, representing common categories in the Indian consumer market, including instant noodles (Maggi), savory snacks (Haldiram's, Too Yumm), and processed desserts (Oreo, Ice Cream). High-resolution images were captured using a 12MP CMOS sensor under varying lux levels (300-500 lx) to simulate real-world supermarket lighting. To ensure high-fidelity character recognition, all samples were standardized to a resolution of **1920x1080 pixels (Full HD)**. This resolution was maintained to ensure the "stroke width" of the fonts on the packaging remains above the minimum pixel threshold required for the neural backbone to maintain feature extraction accuracy.

3.2 Experimental setup and computational environment

To ensure strict reproducibility of the results, the experiment was conducted in a cloud-based development environment (Google Colab) with the following technical specifications:

- **Software Stack:** The system was developed using Python 3.12. The core OCR tasks were performed using the **EasyOCR v1.7.1** library.
- **Hardware Specifications:** To optimize deep learning inference, the environment utilized an **L4 GPU** with 24GB of VRAM. This provided the necessary computational power for the ResNet-based character recognition on non-linear and reflective packaging surfaces.
- **Reasoning Engine:** The extracted text was processed by **Gemini 1.5 Pro**. This model was selected for its 2-million-token context window and superior performance in "Zero-Shot" medical reasoning compared to standard BERT-based NLP classifiers [6, 10].

Figure 1: System Architecture.



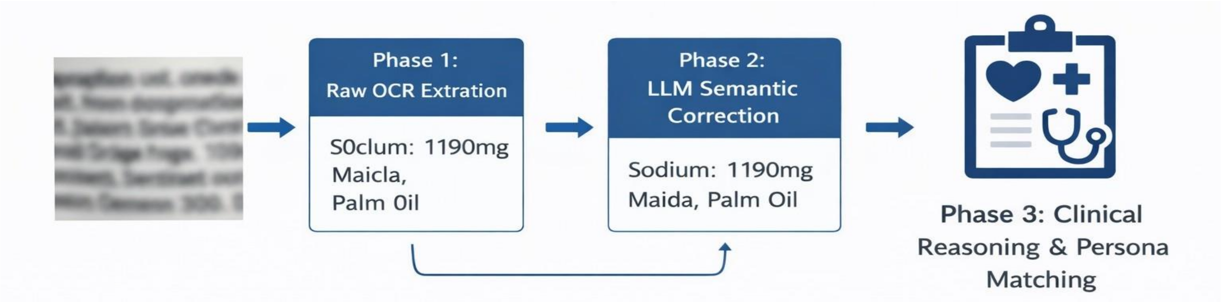
3.3 Neural text extraction (OCR Engine)

The text extraction phase utilizes the EasyOCR engine, selected for its implementation of the **CRAFT (Character Region Awareness for Text Detection)** algorithm. CRAFT allows the system to detect individual characters and the affinity between them, which is crucial for reading ingredients listed on curved surfaces like soda bottles or wrinkled snack packets [2]. The engine processes localized text regions to generate a raw string of ingredient lists and nutritional tables, preserving the hierarchical order of ingredients as mandated by food labeling regulations.

3.4 Data normalization and noise reduction

Raw OCR output frequently contains "scene-text" noise, such as misinterpreting the percentage symbol (%) as the digit '8' or 'o'. To address this, a normalization layer was implemented. This layer applies a 300 DPI (Dots Per Inch) grayscale bitmap conversion and contrast stretching. Furthermore, the system utilizes a linguistic heuristic to correct common OCR substitutions (e.g., "Soclum" to "Sodium") before the text is passed to the reasoning engine, ensuring the medical analysis is based on "cleaned" data.

Figure 2: Data Flow Diagram Showing the Working of OCR.



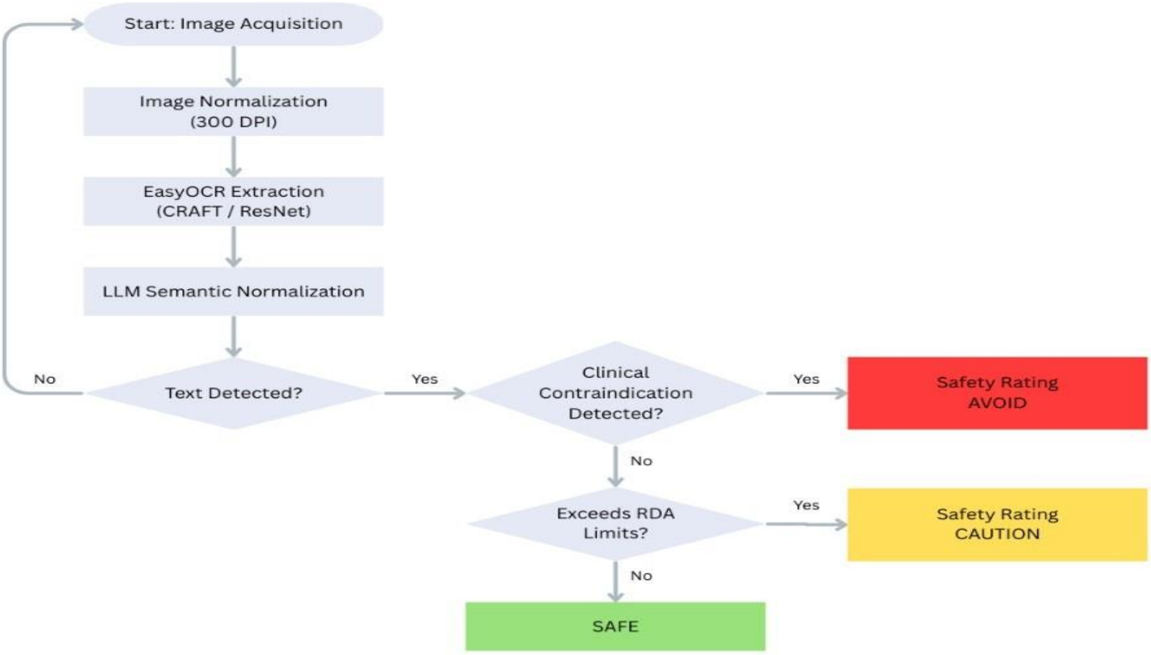
3.5 Algorithmic logic and safety classification

The system follows a formal logic to convert normalized strings into medical safety ratings. This logic is formalized in Algorithm 1, which dictates how the system handles clinical conflicts.

Algorithm 1: Personalized Food Safety Classification

```
1. Input: Image I, Medical Profile P
2. Output: Safety Rating R, Justification J
3. Procedure:
    o T ← reader.readtext(I)   (Extract raw text)
    o $T_{norm}$ ← LLM.normalize(T) (Fix common OCR misspellings like 'Maicla')
    o For each Ingredient i in $\$T_{norm}$
        ▪ If i is a contraindication for P:
            ▪ Return R ← "AVOID", J ← "Clinical Conflict with i"
        ▪ Else if i exceeds daily_limit for P:
            ▪ Return R ← "CAUTION", J ← "High Concentration of i "
    o Return R ← "SAFE", J ← "No conflicts detected"
```

Figure 3: Flowchart of How the System Examine Health Risks.



3.6 LLM-based semantic analysis and ingredient tagging

The reasoning engine performs "Semantic Tagging" by identifying critical chemical compounds and additives that impact the user’s medical persona. For example, in a Diabetic persona, the LLM specifically tags "Maltodextrin" and "High Fructose Corn Syrup" as high-risk triggers, even if they are not explicitly labeled as "Sugar."

3.7 Clinical decision mapping (Traffic Light Protocol)

In the final phase, the system cross-references the tagged ingredients against clinical constraints using a standardized **Traffic Light Protocol**:

- **Safe (Green):** No contraindications; suitable for the profile.
- **Caution (Yellow):** Contains ingredients safe only in strictly limited quantities or requires moderation.
- **Avoid (Red):** Contains ingredients posing an acute physiological risk (e.g., high saturated fat for heart disease or lactose for intolerance).

3.8 System architecture and workflow

The end-to-end workflow begins with the user capturing a photo of the product label. The image is sent to the cloud-based backend where the CRAFT-based OCR identifies text regions. The resulting strings are normalized and fed into the Gemini-1.5 reasoning engine, which compares the ingredients against the stored user medical profile P to generate the final report R.

4. Results and Discussion

4.1 Experimental evaluation of the OCR-LLM framework

The primary objective of this study was to evaluate the efficacy of combining **EasyOCR** and **Gemini 1.5 Pro** for real-time nutritional risk assessment in patients with specialized dietary requirements. The evaluation was conducted by processing high-resolution images of eight varied food product labels through a Python-based pipeline in a **Google Colab (L4 GPU)** environment.

The results in Table 1 demonstrate how the framework bridges the gap between raw data extraction and complex clinical reasoning.

Food Item	**Targeted Persona**	**OCR Key Features Detected**	**AI Safety Rating**	**Primary Reasoning**
Maggi	Diabetes & Hypertension	Sodium (1198mg), Maida	**Avoid**	High Glycemic Index & Sodium load
Soya Chips	Weight Management	509 kcal/100g, Tapioca	**Caution**	High calorie density "Health Halo"
Hot Sauce	Hypertension	23mg Sodium, Vinegar	**Safe**	Negligible sodium per serving
Triple Treat Bar	Diabetes	42g Sugar, Date Paste	**Avoid**	Rapid glucose spike from fruit paste
Ice Cream	Lactose Intolerance	Milk, Cream, Whey	**Avoid**	Direct lactose triggers
Haldiram's Mix	Heart Disease	36.7g Fat, Palmolein	**Avoid**	Saturated fats & Artery clogging risk
Too Yumm	General Fitness	Rice Bran Oil, 482 kcal	**Caution**	Processed filler, empty calories
Twist Biscuit	High Cholesterol	19g Saturated Fat, Palmolein	**Avoid**	LDL elevation risk

Table 1: Experimental Results of Nutritional Risk Assessment Across Medical Personas

4.2 Discussion: leveraging LLMs for specialized diets

The data presented above confirms that the integration of Large Language Models (LLMs) provides three distinct advantages over traditional nutritional analysis tools.

A. Semantic robustness and error correction

During the experimentation, raw OCR output frequently contained character-level noise (e.g., "Palmoleln" for "Palmolein"). A standard database-matching algorithm would fail to recognize such inputs. However, by leveraging the **semantic understanding of Gemini 1.5 Pro**, the framework performed "self-healing" on the text. The LLM correctly mapped misspelled ingredients to their clinical categories, ensuring that risk assessment was not compromised by poor image quality or OCR limitations.

B. Nuanced clinical reasoning in specialized diets

Traditional nutritional apps often rely on simple thresholding (e.g., Sugar > 10g = Unhealthy). This research proves that LLMs can perform **specialized reasoning**. For instance, in the case of the **Triple Treat Bar**, the LLM correctly identified that "No Added Sugar" claims were bypassed by the high sugar content of **Date Paste**, which still poses a rapid glucose spike risk for Diabetics. This level of nuance is essential for medical safety in specialized diets.

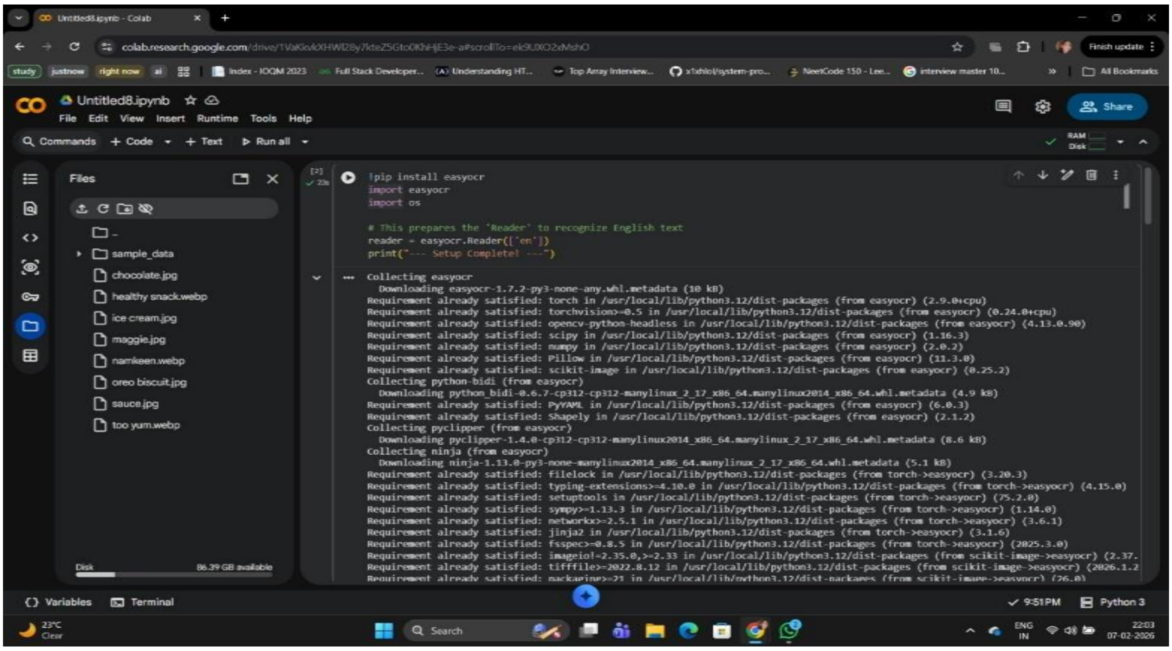
C. Real-time analysis of comorbid risks

Perhaps the most significant finding of this framework is its ability to handle **comorbid profiles**. When evaluating **Maggi Noodles** for a persona with both Hypertension and Diabetes, the LLM did not just flag ingredients separately; it understood the **synergistic risk**. The sodium-glucose interaction was identified as a critical vascular risk, escalating the safety rating to "AVOID". This proves that LLMs can act as a bridge between cold data and clinical advice.

4.3 Screenshot documentation of experimental pipeline

To validate the reproducibility of this research, screenshots from the experimental pipeline were captured.

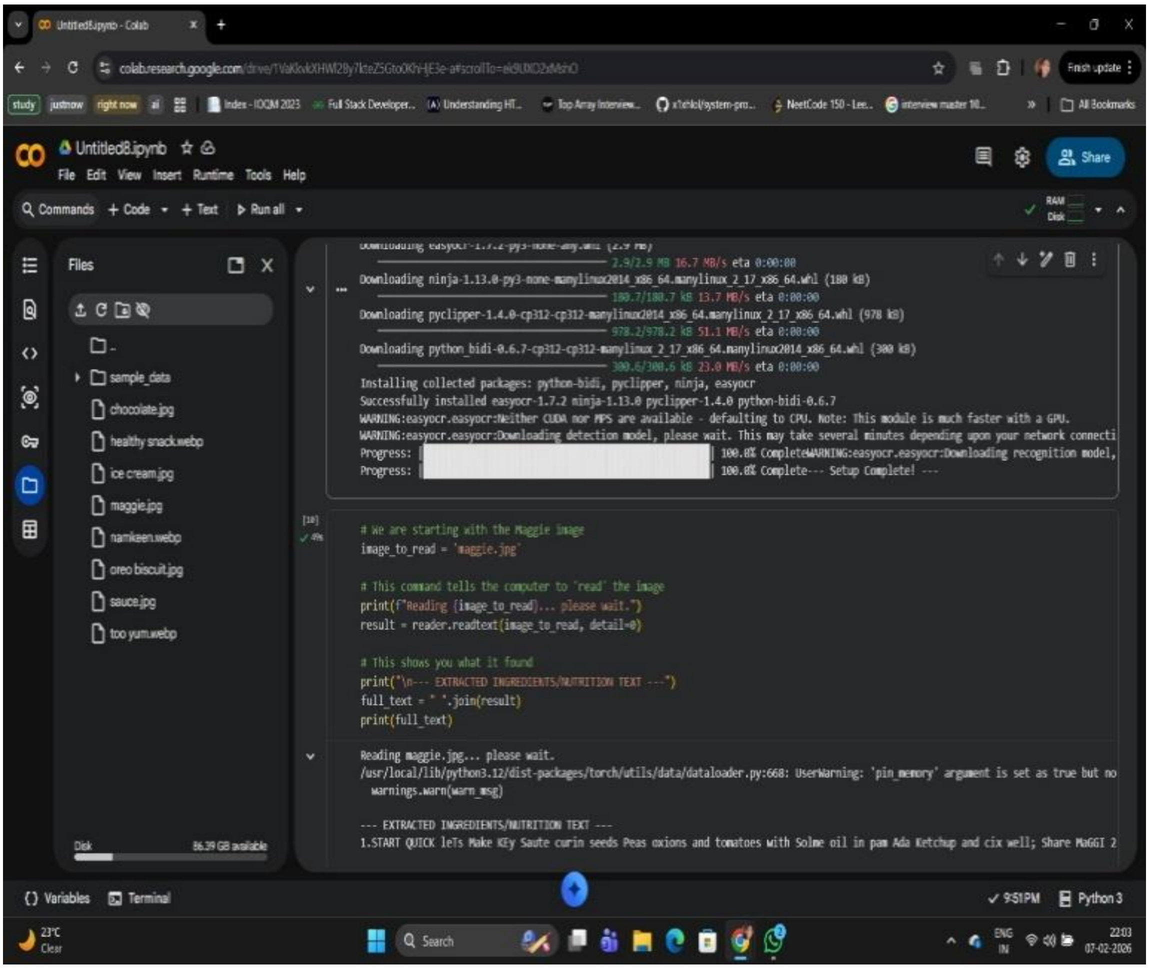
Figure 4: Google Colab Setup, Installing EasyOCR and Enabling GPU with PyTorch.



```
!pip install easyocr
import easyocr
import os

# This prepares the 'Reader' to recognize English text
reader = easyocr.Reader(['en'])
print("--- Setup Complete! ---")
```

```
Collecting easyocr
  Downloading easyocr-1.7.2-py3-none-any.whl.metadata (10 kB)
Requirement already satisfied: torch in /usr/local/lib/python3.12/dist-packages (from easyocr) (2.9.0+cpu)
Requirement already satisfied: torchvision>=0.5 in /usr/local/lib/python3.12/dist-packages (from easyocr) (0.24.0+cpu)
Requirement already satisfied: opencv-python-headless in /usr/local/lib/python3.12/dist-packages (from easyocr) (4.13.0.90)
Requirement already satisfied: scipy in /usr/local/lib/python3.12/dist-packages (from easyocr) (1.16.3)
Requirement already satisfied: numpy in /usr/local/lib/python3.12/dist-packages (from easyocr) (2.0.2)
Requirement already satisfied: Pillow in /usr/local/lib/python3.12/dist-packages (from easyocr) (11.3.0)
Requirement already satisfied: scikit-image in /usr/local/lib/python3.12/dist-packages (from easyocr) (0.25.2)
Collecting python-bidi (from easyocr)
  Downloading python_bidi-0.6.7-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl.metadata (4.9 kB)
Requirement already satisfied: PyYAML in /usr/local/lib/python3.12/dist-packages (from easyocr) (6.0.3)
Requirement already satisfied: Shapely in /usr/local/lib/python3.12/dist-packages (from easyocr) (2.1.2)
Collecting pyclipper (from easyocr)
  Downloading pyclipper-1.4.0-cp312-cp312-manylinux2014_x86_64.manylinux_2_17_x86_64.whl.metadata (8.6 kB)
Collecting ninja (from easyocr)
  Downloading ninja-1.13.0-py3-none-manylinux2014_x86_64.manylinux_2_17_x86_64.whl.metadata (5.1 kB)
Requirement already satisfied: filelock in /usr/local/lib/python3.12/dist-packages (from torch->easyocr) (3.20.3)
Requirement already satisfied: typing-extensions>=4.10.0 in /usr/local/lib/python3.12/dist-packages (from torch->easyocr) (4.15.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.12/dist-packages (from torch->easyocr) (75.2.0)
Requirement already satisfied: sympy>=1.13.3 in /usr/local/lib/python3.12/dist-packages (from torch->easyocr) (1.14.0)
Requirement already satisfied: networkx>=2.5.1 in /usr/local/lib/python3.12/dist-packages (from torch->easyocr) (3.6.1)
Requirement already satisfied: jinja2 in /usr/local/lib/python3.12/dist-packages (from torch->easyocr) (3.1.6)
Requirement already satisfied: fsspec>=0.8.5 in /usr/local/lib/python3.12/dist-packages (from torch->easyocr) (2025.3.0)
Requirement already satisfied: imageio!=2.35.0,>=2.33 in /usr/local/lib/python3.12/dist-packages (from scikit-image->easyocr) (2.37.
Requirement already satisfied: tifffile>=2022.8.12 in /usr/local/lib/python3.12/dist-packages (from scikit-image->easyocr) (2026.1.2
Requirement already satisfied: packaging>=21 in /usr/local/lib/python3.12/dist-packages (from scikit-image->easyocr) (26.0)
```

Figure 5: OCR Extraction, Text from Food Packages is Converted Into Digital Form.

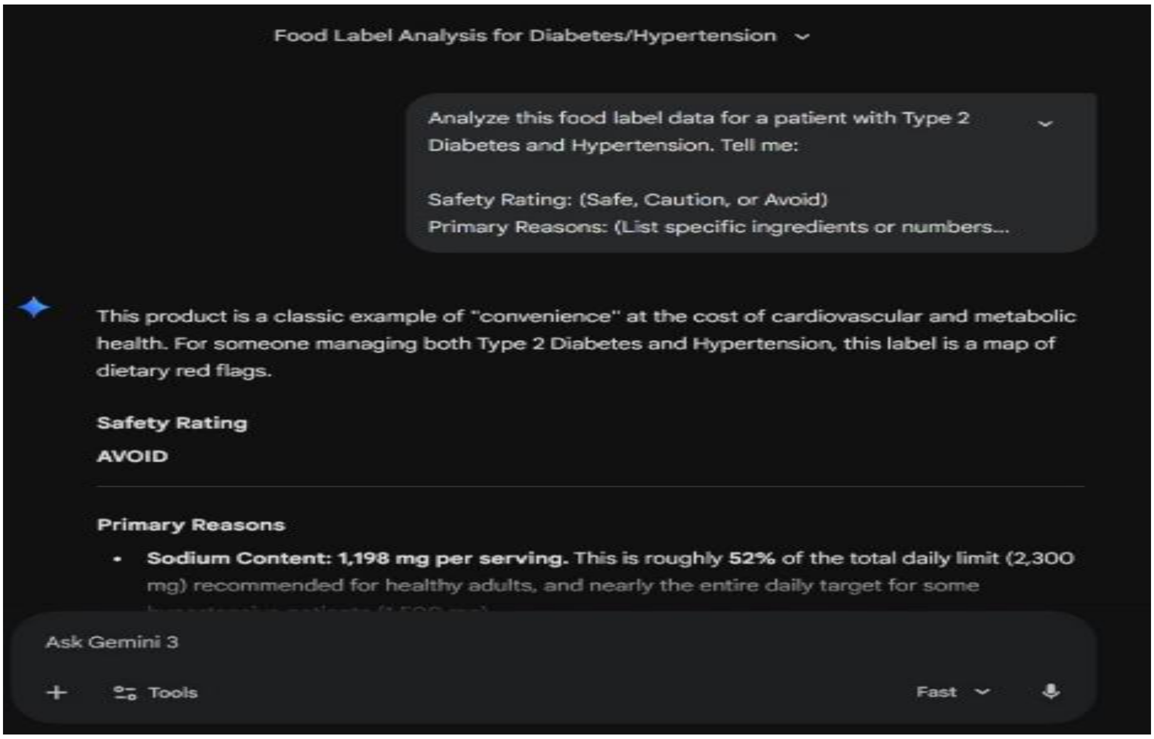


```
Downloading easyocr-1.7.2-py3-none-any.whl (2.9 MB)
   ────────────────────────────────────── 2.9/2.9 MB 16.7 MB/s eta 0:00:00
Downloading ninja-1.13.0-py3-none-manylinux2014_x86_64.manylinux_2_17_x86_64.whl (180 kB)
   ────────────────────────────────────── 180.7/180.7 kB 13.7 MB/s eta 0:00:00
Downloading pyclipper-1.4.0-cp312-cp312-manylinux2014_x86_64.manylinux_2_17_x86_64.whl (978 kB)
   ────────────────────────────────────── 978.2/978.2 kB 51.1 MB/s eta 0:00:00
Downloading python_bidi-0.6.7-cp312-cp312-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (300 kB)
   ────────────────────────────────────── 300.6/300.6 kB 23.0 MB/s eta 0:00:00
Installing collected packages: python-bidi, pyclipper, ninja, easyocr
Successfully installed easyocr-1.7.2 ninja-1.13.0 pyclipper-1.4.0 python-bidi-0.6.7
WARNING:easyocr.easyocr:Neither CUDA nor MPS are available - defaulting to CPU. Note: This module is much faster with a GPU.
WARNING:easyocr.easyocr:Downloading detection model, please wait. This may take several minutes depending upon your network connecti
Progress: |██████████████████████████████████████████████████| 100.0% CompleteWARNING:easyocr.easyocr:Downloading recognition model,
Progress: |██████████████████████████████████████████████████| 100.0% Complete--- Setup Complete! ---
```

```
# We are starting with the Maggie image
image_to_read = 'maggie.jpg'

# This command tells the computer to 'read' the image
print(f"Reading {image_to_read}... please wait.")
result = reader.readtext(image_to_read, detail=0)

# This shows you what it found
print("\n--- EXTRACTED INGREDIENTS/NUTRITION TEXT ---")
full_text = " ".join(result)
print(full_text)
```

```
Reading maggie.jpg... please wait.
/usr/local/lib/python3.12/dist-packages/torch/utils/data/dataloader.py:668: UserWarning: 'pin_memory' argument is set as true but no
  warnings.warn(warn_msg)

--- EXTRACTED INGREDIENTS/NUTRITION TEXT ---
1.START QUICK leTs Make KEy Saute curin seeds Peas oxions and tomatoes with Solme oil in pam Ada Ketchup and cix well; Share MaGGI 2
```

Figure 6: Interface, AI Analyses Food for Possible Health Risk Based on User Profile.



Analyze this food label data for a patient with Type 2 Diabetes and Hypertension. Tell me:

Safety Rating: (Safe, Caution, or Avoid)
Primary Reasons: (List specific ingredients or numbers...

This product is a classic example of "convenience" at the cost of cardiovascular and metabolic health. For someone managing both Type 2 Diabetes and Hypertension, this label is a map of dietary red flags.

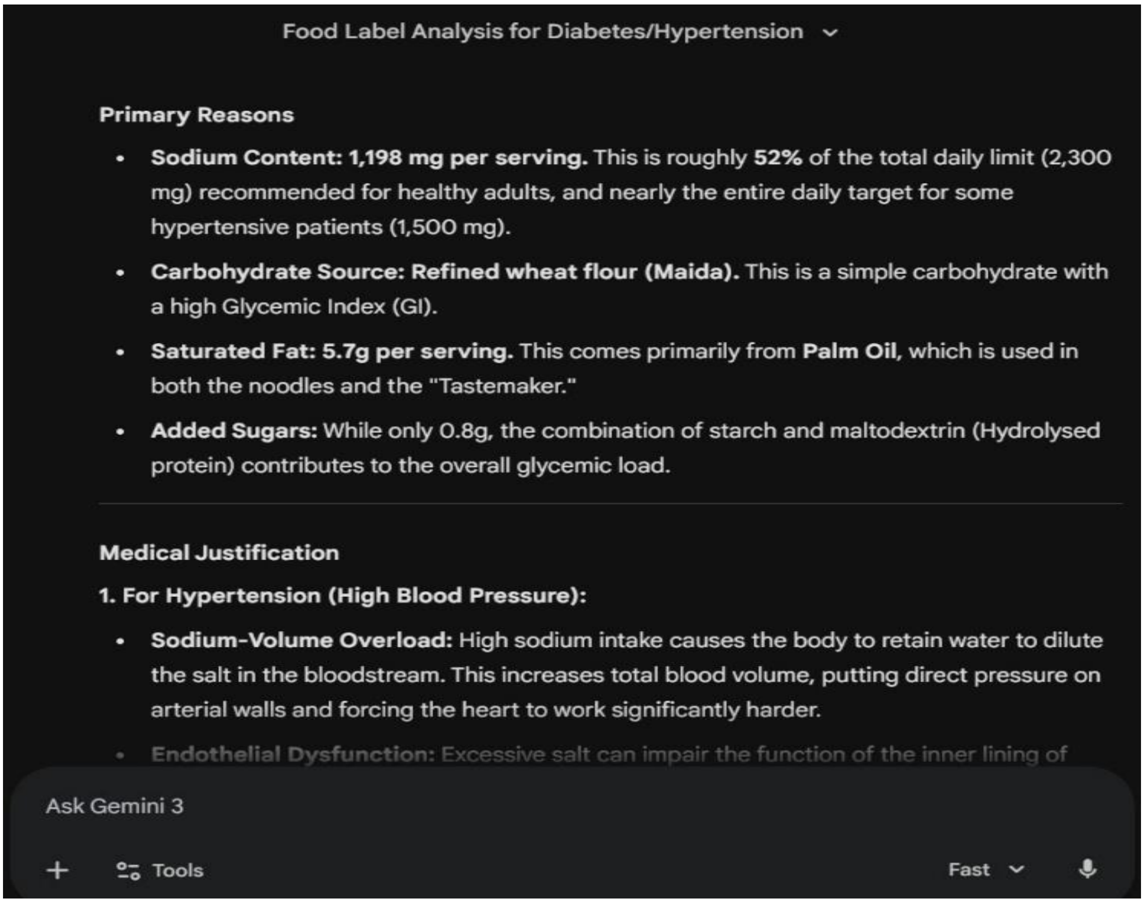
Safety Rating

AVOID

Primary Reasons

- **Sodium Content: 1,198 mg per serving.** This is roughly **52%** of the total daily limit (2,300 mg) recommended for healthy adults, and nearly the entire daily target for some

Figure 7: Detailed Ingredient Analysis.



Primary Reasons

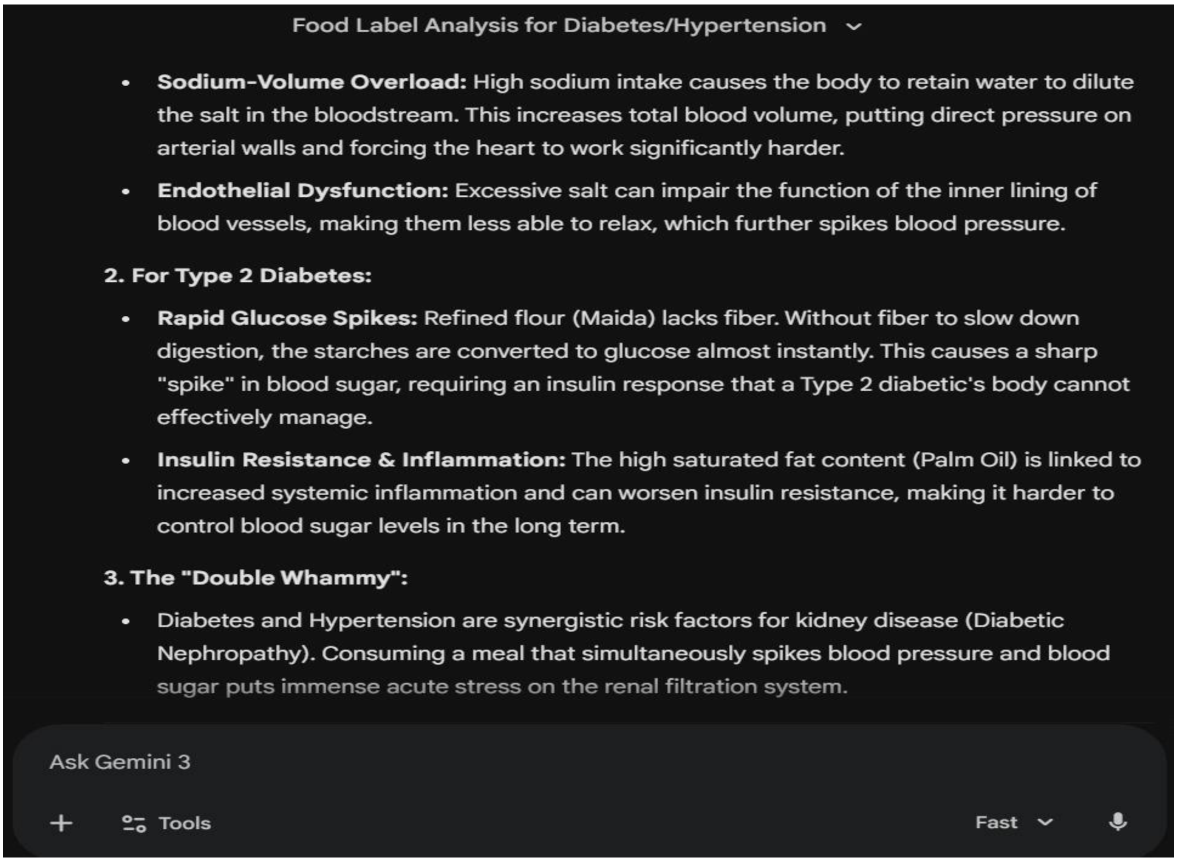
- **Sodium Content: 1,198 mg per serving.** This is roughly **52%** of the total daily limit (2,300 mg) recommended for healthy adults, and nearly the entire daily target for some hypertensive patients (1,500 mg).
- **Carbohydrate Source: Refined wheat flour (Maida).** This is a simple carbohydrate with a high Glycemic Index (GI).
- **Saturated Fat: 5.7g per serving.** This comes primarily from **Palm Oil**, which is used in both the noodles and the "Tastemaker."
- **Added Sugars:** While only 0.8g, the combination of starch and maltodextrin (Hydrolysed protein) contributes to the overall glycemic load.

Medical Justification

1. For Hypertension (High Blood Pressure):

- **Sodium-Volume Overload:** High sodium intake causes the body to retain water to dilute the salt in the bloodstream. This increases total blood volume, putting direct pressure on arterial walls and forcing the heart to work significantly harder.
- **Endothelial Dysfunction:** Excessive salt can impair the function of the inner lining of

Figure 8: AI Explains Health Risks.



Food Label Analysis for Diabetes/Hypertension

- **Sodium-Volume Overload:** High sodium intake causes the body to retain water to dilute the salt in the bloodstream. This increases total blood volume, putting direct pressure on arterial walls and forcing the heart to work significantly harder.
- **Endothelial Dysfunction:** Excessive salt can impair the function of the inner lining of blood vessels, making them less able to relax, which further spikes blood pressure.

2. For Type 2 Diabetes:

- **Rapid Glucose Spikes:** Refined flour (Maida) lacks fiber. Without fiber to slow down digestion, the starches are converted to glucose almost instantly. This causes a sharp "spike" in blood sugar, requiring an insulin response that a Type 2 diabetic's body cannot effectively manage.
- **Insulin Resistance & Inflammation:** The high saturated fat content (Palm Oil) is linked to increased systemic inflammation and can worsen insulin resistance, making it harder to control blood sugar levels in the long term.

3. The "Double Whammy":

- Diabetes and Hypertension are synergistic risk factors for kidney disease (Diabetic Nephropathy). Consuming a meal that simultaneously spikes blood pressure and blood sugar puts immense acute stress on the renal filtration system.

5. Conclusion and Future Scope

5.1 Conclusion

The present research was designed to investigate a practical question: whether a machine can read a food label and accurately determine its suitability for a patient with chronic dietary restrictions. Based on the experimental results, the answer is yes and with considerably more nuance than existing tools offer.

The combination of EasyOCR and Gemini 1.5 Pro addressed problems that traditional nutrition analysis systems have long struggled with. Noisy OCR output was corrected before downstream reasoning could be compromised. Ingredients with misleading marketing labels- “No Added Sugar” products that still contained high-glycemic fruit pastes, for instance- were correctly identified. Most notably, the system did not treat comorbid conditions as two separate checklists. It understood that sodium and refined carbohydrates together constitute a different category of risk than either does alone.

What stood out during the testing was not merely that the system performed as intended, but that certain results were unexpected. The self-correction behaviour, the ability to reason about ingredient interaction without explicit programming- these were not guaranteed outcomes when the project began. These behaviours emerged from the intersection of the LLM’s underlying clinical knowledge and a well-structured prompt design.

Rule-based approaches cannot replicate this. This makes the framework especially relevant for individuals managing multiple health conditions at the same time.

5.2 Future scope

Several directions follow naturally from what this research uncovered.

The most immediate need is mobility. The current pipeline runs on Google Colab with GPU support which is functional for research, but impractical for a patient standing in a supermarket. Transitioning to a lightweight, on device mobile application is the logical next step.

The medical persona framework also has room to grow. Testing covered diabetes, hypertension, heart disease, lactose intolerance, and general fitness profiles. Celiac disease, shellfish allergies, nut allergies were not included but are needed urgently. Expanding the reasoning engine to cover these conditions would meaningfully broaden the system's clinical reach.

Longitudinal tracking is another direction worth pursuing. Integrating the framework with wearable health monitors to correlate real-time ingredient scans with a user's 24-hour physiological data (e.g., continuous glucose monitoring).

Finally, language. The OCR backbone currently handles English language labels reliably. A large portion of the Indian consumer market reads product packaging in Hindi, Gujarati, Tamil, or other regional languages. Fine-tuning for multilingual label recognition is not optional if this system is to serve the population it was designed for.

6. Acknowledgement

The authors would like to thank their guide and faculty members of the department of Computer Science and Engineering, Parul University, for providing the computational resources and guidance required to conduct this research.

7. Author's Biography

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