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FoodX: An AI-Powered System for Packaged Food Ingredient Analysis and Personalized Health Recommendations

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Abstract: This research presents a technology-driven solution aimed at simplifying the understanding of nutritional information in packaged food products. With the increasing consumption of processed food and rising health concerns, there is a growing need for tools that enable informed dietary decisions. The proposed system integrates optical character recognition (OCR), machine learning (ML), and natural language processing (NLP) to extract, analyze, and personalize nutritional data from product labels. By incorporating user-specific health profiles and real-time image processing, the system offers personalized health insights, alternative recommendations, and educational content to encourage healthier eating habits. Designed with a focus on accessibility, this solution aims to bridge the gap between food packaging and public understanding, promoting proactive health management and consumer empowerment through intelligent food analysis.
Keywords: Packaged Food Analysis, Ingredient Detection, Optical Character Recognition (OCR), Machine Learning for Food Safety, Nutritional Labels, Health Recommendations, Consumer Safety, Food Standards, Dietary Advice, NLP Blogs.

I. INTRODUCTION

Food is crucial for our health and well-being, with unhealthy eating habits leading to chronic conditions. In today's fast-paced world, packaged foods are often filled with preservatives, additives, and unhealthy fats. Artificial Intelligence (AI) can help analyze the nutritional content of packaged foods, providing accurate information on calories, sugar, fats, and other nutrients. The rapid rise in consumption of packaged foods has raised significant concerns regarding health and nutrition, especially among individuals with specific medical conditions such as diabetes, hypertension, or allergies. This research presents an AI-powered system designed to bridge this gap through intelligent analysis and personalized food recommendations. Targeted toward users of all age groups, FoodX aims to simplify the understanding of nutritional content in packaged food and promote healthier food choices through intelligent, comparative, and personalized analysis. This innovative system has the potential to empower consumers with personalized, data-driven insights for healthier food choices. The primary goal of FoodX is to empower individuals of all ages to make informed dietary choices by providing accessible and straightforward nutritional analysis. This research aims to enhance public health awareness, promote safe dietary habits, and provide a technological tool that empowers consumers to make smarter food choices through the combined power of OCR, ML, and NLP. This research aims to enhance public health awareness, promote safe dietary habits, and provide a technological tool that empowers consumers to make smarter food choices.

A. Problem Statement:

FoodX is an AI-powered system designed to simplify the nutritional analysis of packaged food products It uses Google Vision API for Optical Character Recognition (OCR) to analyze packaged food products using scanned images or searchable product data. The system extracts nutritional information directly from product images, such as biscuit packs, and processes it through a trained Artificial Neural Network (ANN) model to classify and assess the nutritional value of the food. The app's architecture comprises a React Native frontend, a Node.js backend, and leverages OCR technology, an ANN model, and a MongoDB Atlas database.

B. Motivation:

Since the effect of appealing advertising methods that frequently mislead consumers especially children into believing that these products are healthy, the increased consumption of ultra-processed and harmful packaged foods remains a serious public health concern. Despite the fact that this problem has been extensively studied, there are currently no practical solutions that enable consumers to make knowledgeable dietary decisions.

Our motive changed from recognizing the issue to actively participating in a technology solution after realizing this gap.The goal of our solution is to change the public's perspective from reactive to proactive health management by combining real-time data processing, user-friendly dashboards, and educational visualizations. Our application demonstrates how technology-driven food analysis may raise nutritional knowledge, lower long-term health risks, and contribute to a society that is more health-conscious.

C. Objectives:

1) To apply automated data extraction and validation methods to examine pre-packaged nutritional products and confirm that they adhere to health claims, and labeling standards.
2) To use OCR and AI-based classification models to precisely identify and indicate harmful compounds found in packaged food goods.
3) To estimate long-term health risks such as obesity, diabetes, and cardiovascular diseases associated with the repeated intake of unhealthy food components in order to increase the model's prediction power.
4) To offer a user-friendly interface that, using each user's medical history and consumption habits, produces customized food safety reports, suggestions for alternatives, and educational insights.

D. Scope:

This project aims to bridge the gap between the availability of packaged food products and the lack of accessible, personalized health information for consumers. It focuses on food safety, consumer health, and technological innovation, aiming to empower individuals to make healthier, more informed dietary choices. The project develops an intelligent system that analyzes ingredients and nutritional content on food packaging using Optical Character Recognition (OCR) and AI/ML models. The system also includes a personalized health risk prediction capability, integrating user-specific medical history to assess the impact of certain ingredients on an individual's health.

In addition to risk detection, the system includes a recommendation engine that suggests safer, healthier alternatives to flagged food items. Natural Language Processing (NLP) techniques are employed to generate user-friendly educational content, including weekly blog posts explaining the risks of certain ingredients, the importance of reading labels, and tips for building healthier eating habits. The project presents check alternative suggestions, and assess their progress toward healthier eating. The project's scope extends beyond technological implementation to public health, consumer empowerment, and digital food literacy.

II. LITERATURE REVIEW

Recent years have seen a rise in interest to the safety of packaged foods, especially in developing countries like India where consumer use of processed and packaged foods has increased significantly due to rapid urbanization and changing lifestyles. Significant knowledge about food safety hazards still exists, despite the Indian government's efforts to raise public awareness through the "JagoGrahakJago" campaign. According to Lt. Col. Puja Dudeja et al. [2], many consumers, especially those from economically disadvantaged groups, are unaware of or undervalue the adverse impacts of food product adulteration and the importance of reading food labels. There is still a pressing demand for better instructional methods and resources to empower customers. Many of those packaged meals are discovered to contain higher-risk elements than the prescribed limits, according to Medical Cadet Shailesh Ishwar [2] Non-communicable diseases (NCDs) like diabetes, high blood pressure, and obesity will become more prevalent as a result of this.

The involvement of unsustainable or hidden components, such as palm oil, in food products which are frequently hidden by complicated labelling or a lack of transparency – is one of those worries. A machine learning-based method created by Jack Foster and Alexandra Brintrup[3] can identify these invisible elements and suggest sustainable alternatives. These algorithms are also frequently used to forecast the long-term consequences of dietary patterns and discover dangerous components.[1][2][3]

The article [4] provides interesting guidelines for the practical design of OCR systems that analyse printed text in the real world. From pre-processing and segmentation to choosing a suitable OCR engine and post-processing methods it can all be extended to your project. By applying comparable practices, you we achieve superior accuracy and robustness in our system, specifically, if you need to analyze noisy, multilingual or stylized text. As per the study experiments in [5] to demonstrate a possible implementation of automated digitization system using Google Cloud Vision API that can be developed as a Web Service API so that other applications can call the service to digitize information.

These results suggest that although Google Cloud Vision API provides a pretty solid base, it can be interesting to combine it with careful pre-processing and some kind of robust (perhaps domain specific) post-processing step (using techniques like string matching) for better accuracy (particularly in languages with really complex rules or image qualities). However as you may expect it will be up to you to manage the dictionary's limitations. [4][5]

As per stated in [7] Artificial Neural Networks (ANNs) are computational systems that analyze and process data in a similar fashion as the biological nervous system, specifically, the human brain. They consist of a large number of highly interconnected processing elements, referred to in the literature as neurons. The structure of an ANN would be based on that of the human brain, with neuron nodes connected in a web-like manner.Usually an ANN involves three or more interconnected layers: an input layer, one or more hidden layers, and an output layer. The input layer takes in data, the hidden layers perform computations and adaptively change information (through transformations), and finally, the output layer outputs the finalresult. Connections between neurons are called synapses (or electromagnetic connections), in which different levels of strength (or "weights") are assigned to inputs. Processing within a neuron typically involves calculating a weighted sum of inputs and passing it through an activation function (which uses a threshold value to determine whether the neuron "fires". As mentioned above, the study used a "perceptron" type structure, with one layer of hidden neurons, also called a "multilayer perceptron" (MLP). They also tested activation functions such as hyperbolic tangent (Tanh), logarithmic (Log), and sigmoid (Sig). ANNs learn by example. training is the process by which the network adjusts its internal parameters (such as weights) to perform a specific task. [6][7][16]

Personalized Health Recommendation Systems (PHRS) have emerged as a critical component in health-focused applications, offering tailored guidance based on an individual's medical history, allergies, dietary preferences, and health goals. In the context of food consumption [10], PHRS enables the analysis of nutritional content and ingredient safety by comparing extracted product information against a user's unique health profile. This approach not only enhances the relevance of the recommendations but also empowers users to make informed food choices aligned with their personal well-being. Integrating PHRS into an OCR-based packaged food analysis system further amplifies its utility. By extracting ingredients and nutritional data from product labels through OCR, the system can dynamically evaluate food safety for each user. For example, if a user with hypertension scans a food item high in sodium, the system can issue a real-time warning or suggest healthier alternatives. This personalized feedback mechanism transforms static label information into actionable insights, thereby promoting preventive healthcare and improving dietary habits. [10][14][15]

Natural Language Processing (NLP) is used to optimize the functionality and user engagement of packaged food analysis systems. By using text summarization techniques [9], entity recognition, and keyword extraction the system would be able to categorize the relevant information and present it in a reader-friendly way thereby being able to continually spread knowledge. Secondarily, an OCR extracted text of an ingredient could be classified and linked against user-specific medical conditions. By doing so, the system can help with recommendation of healthier products, as well as enhancing its personalization of health advice. Therefore, NLP functions as a bridge between raw textual data and relevant health insights. It serves also as a part of the overall aim to proactive consumer health management through AI based systems. [9]

III. METHODOLOGY

A. Image-Based Nutrition Analysis Workflow:

This section details the end-to-end pipeline employed for the automated analysis of nutritional content from packaged food items using a combination of Optical Character Recognition (OCR) and Artificial Neural Network (ANN)-based classification. The methodology is designed to ensure accurate extraction, interpretation, and assessment of nutrition label data, thereby facilitating informed health decisions for consumers.

1) Image Acquisition and Encoding:The process begins when users capture or upload an image of the nutritional information printed on a packaged food product. To maintain compatibility with modern web and mobile interfaces and ensure secure and efficient data transmission, the captured image is first encoded into a Base64 string format. This encoding standard transforms binary image data into ASCII text, allowing it to be easily transmitted across diverse platforms such as RESTful APIs and cloud-based services without corruption or format loss. The encoded data ensures that the image remains intact during transmission and can be decoded back into its original form at the processing server.
2) OCR Processing via Cloud-Based API:Once the image is received in its Base64-encoded form, it is processed using a cloud-based Optical Character Recognition (OCR) API (e.g., Google Cloud Vision API or Microsoft Azure OCR). The purpose of this stage is to extract human-readable text from the image, particularly the structured nutritional table. The internal steps involved in the OCR pipeline are as follows:

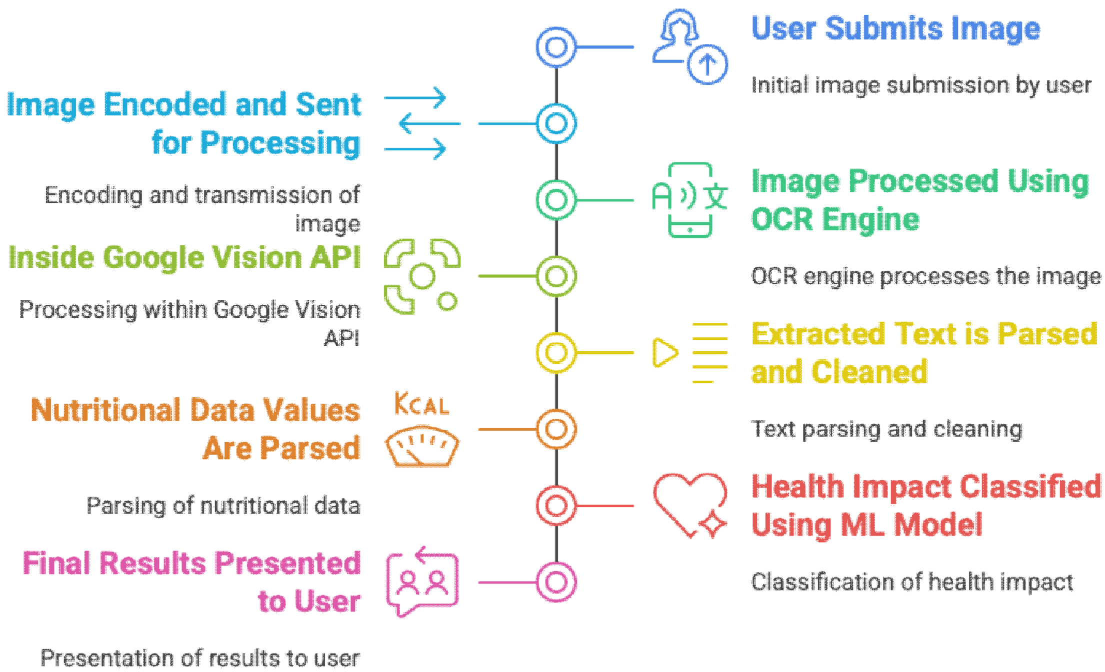

Fig. 1: Methodology

3) Image Decoding: The Base64 string is decoded to reconstruct the original image format (typically JPEG or PNG), which is then passed into the OCR engine for analysis.
4) Preprocessing: To enhance the quality and readability of the image, preprocessing techniques such as grayscale conversion, noise removal, contrast normalization, and geometric correction (e.g., skew correction) are applied. These enhancements significantly improve character recognition accuracy, especially in images with poor lighting or uneven backgrounds.
5) Text Detection: Deep learning-based object detection models (such as EAST or CTPN) are employed to detect and localize textual regions within the image. This step identifies the bounding boxes that potentially contain printed text.Layout Analysis and Bounding Box Detection: The OCR engine further analyzes the spatial arrangement of detected text blocks to understand the structure of the nutritional table. Each text segment is associated with its bounding box coordinates and hierarchical placement (e.g., row, column).
6) Text Extraction and Aggregation: The text from each detected bounding box is extracted using sequence modelling techniques like Long Short-Term Memory (LSTM) networks. The text is then grouped into coherent strings, maintaining the layout of rows and columns found in nutritional labels.
7) Structured Response Generation: The final output is a structured JSON or XML response containing:

- Recognized text strings
- Confidence scores indicating the accuracy of the detection
- Bounding box coordinates
- Text orientation and reading order

This structured output serves as the raw input for the subsequent data extraction phase.

a) Text Cleaning and Nutritional Key Extraction:The OCR response is often noisy and contains redundant symbols, inconsistent spacing, or formatting artifacts. To obtain clean and machine-readable data, text preprocessing and key-value extraction are performed. The key steps include:

- Whitespace and Symbol Removal: Unnecessary line breaks, non-nutritive symbols (e.g., "*", "-", "•"), and irregular spacing are removed to produce a normalized text stream.
- Pattern Matching using Regular Expressions: Custom-defined regular expressions are used to identify and extract relevant nutritional parameters (e.g., “Total Sugars”, “Saturated Fat”, “Sodium”, “Calories”). Each matched key is associated with its respective value, which is parsed from the nearby text context.

- Unit Normalization and Conversion: Values with different unit formats (e.g., “mg”, “g”, “%DV”) are converted into a standard floating-point representation (e.g., grams). Special handling is provided for mixed units or percent-based values by applying known nutritional reference values.The output of this stage is a clean, structured set of numerical nutritional attributes ready for input into the classification model.

b) Classification of Nutritional Data:The extracted and normalized nutritional values are passed into a pre-trained Artificial Neural Network (ANN) model, which has been designed and optimized for nutritional safety classification. The ANN model consists of multiple fully connected layers and is trained on a labelled dataset containing thousands of nutritional profiles along with annotated health categories:

- Input Layer: Each nutritional attribute (e.g., total fat, saturated fat, sugar, sodium, fiber, protein) is treated as a distinct input feature.
- Hidden Layers: The model includes one or more hidden layers with activation functions such as ReLU (Rectified Linear Unit), allowing it to capture non-linear relationships between nutrients and health impacts.
- Output Layer: The model outputs a classification into one of the predefined categories:

➢ Safe: Indicates that the nutritional content is well-balanced and poses no known health risks:
➢ OK: Indicates moderate consumption is advisable; some attributes may be borderline.
➢ Harmful: Indicates the product may contain one or more nutrients at harmful levels for regular consumption.
➢ Very Harmful: Indicates significant risk due to high concentrations of unhealthy components.The ANN model learns classification boundaries based on trends and correlations observed during training, such as high sodium being linked to hypertension or high added sugars contributing to obesity and diabetes.

c) Result Interpretation and Output Generation:Following the classification step, the system generates a comprehensive response for the end user, combining both quantitative data and qualitative insights:

- Safety Classification: The product is labelled under one of the four predefined health categories, enabling users to quickly understand the health implications.
- Cleaned Nutritional Summary: A structured summary of the parsed nutritional information (e.g., Total Sugars: 15g, Sodium: 400mg) is displayed.
- Interpretation Message: A personalized message is generated that explains the rationale behind the classification. For example, “The product is marked as Harmful due to excessive sodium and added sugars exceeding daily recommended limits.”
- Scientific and Dietary References: Where applicable, the system may cite dietary guidelines (e.g., WHO or FDA recommendations) to provide scientific justification for the classification.

This final output empowers users to make informed dietary choices, particularly individuals managing health conditions such as diabetes, hypertension, or cardiovascular diseases.

B. NLP-Driven Food Nutrition Awareness Generation:

This section presents the methodology employed for generating automated, informative articles on food nutrition awareness using a Natural Language Processing (NLP) engine. The objective of this pipeline is to enhance user engagement and promote nutritional literacy by delivering personalized, data-driven content based on historical food scan trends and health considerations. The methodology integrates structured data extraction with generative language models to produce context-aware, human-readable articles on a recurring basis.

1) User Interaction Data Aggregation: The process begins with the systematic aggregation of structured data generated from user interactions with the nutritional analysis system. This includes nutritional profiles of scanned food products, frequency and types of ingredients identified, and historical classification outcomes (e.g., Safe, Harmful). The collected data is anonymized and formatted into a structured tabular representation, capturing trends such as:

- Frequently consumed food categories (e.g., snacks, beverages)
- Repeated detection of harmful or borderline ingredients (e.g., added sugars, saturated fats)
- Health risk patterns correlated with nutritional components

This aggregated dataset serves as the factual grounding for personalized content generation.

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2) Topic Selection and Prompt Engineering:

Based on observed trends in user data, the system selects contextually relevant topics to inform the generation of awareness articles. A predefined topic ontology (e.g., sugar-related health impacts, benefits of fiber, risks of trans fats) is used in conjunction with dynamic user-specific patterns to guide article themes.

To generate meaningful text, a carefully constructed prompt is formulated. This prompt includes:

- A structured summary of key trends (e.g., "frequent consumption of snacks with high sodium")
- A suggested topic or theme (e.g., “Health Risks of High Sodium Intake”)
- Instructions for tone, length, and factual depth (e.g., “Write a 200-word informative article suitable for general readers, citing scientific studies where appropriate”)

The prompt acts as the input to the NLP engine, ensuring that outputs are both relevant and coherent.

3) Article Generation Using NLP Engine:

The NLP engine, powered by a pre-trained transformer-based language model (e.g., GPT or BERT derivatives fine-tuned for healthcare communication), processes the prompt and generates a fluent, semantically accurate article. The generation pipeline ensures:

- Factual Alignment: Generated content remains consistent with input data and health guidelines.
- Readability: Text is optimized for clarity, conciseness, and audience-appropriate language.
- Diversity: Articles vary in structure and tone over time to maintain user interest.

Optional post-processing may include grammar correction, summary extraction, or keyword highlighting to improve usercomprehension and engagement.

4) Article Delivery and User Feedback Integration:

The validated articles are systematically published for end-user consumption on a recurring schedule. The delivery format includes:

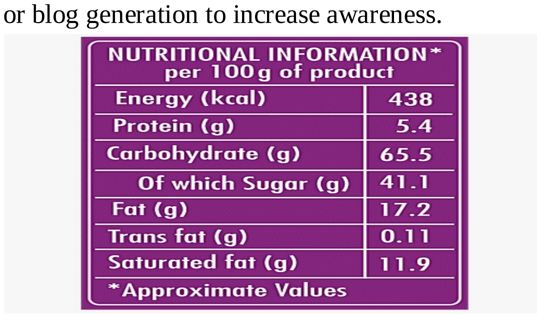
- Headline and summary preview
- Expandable full-length article view
- Associated references or sources

Users may optionally rate or react to articles, and this feedback is logged and integrated into future topic selection and content personalization logic. Over time, this feedback loop helps in tailoring content to user preferences and improving engagement outcomes.

IV. EXPERIMENTATION AND RESULTS

A prototype system that combines a classification model, text extraction module, and image capture interface was created. The Google Vision API was chosen for optical character recognition because of its simplicity of integration and resilience. To categorize nutritional profiles, a neural network model was trained using a lightweight server architecture on the backend.

1) Input Interface: Mobile or web-based platform for image capture
2) Backend Technologies: Server-side framework with ML integration
3) Text Extraction: Google Cloud Vision API
4) Dataset: Collected nutritional label information. Annotated nutritional profiles mapped to health safety categories and used for training and testing.
5) Blog Generation: NLP based article or blog generation to increase awareness.



NUTRITIONAL INFORMATION* per 100g of product	
Energy (kcal)	438
Protein (g)	5.4
Carbohydrate (g)	65.5
Of which Sugar (g)	41.1
Fat (g)	17.2
Trans fat (g)	0.11
Saturated fat (g)	11.9
*Approximate Values	

Fig. 2: Product Label Image Sample

A. Dataset Collection and Annotation

Images were collected from common food categories like biscuits. Nutritional details were annotated manually, focusing on:

- Energy (kcal)
- Fats (total and saturated)
- Sugars (total and added)
- Sodium
- Protein
- Carbohydrates

Each sample was categorized into one of the predefined health categories: Safe, Moderate, Risky, or High Risk, based on standard dietary guidelines and thresholds.

B. Evaluation Metrics

Two main performance areas were evaluated:

1) Text Extraction (Vision API)

- Character Recognition Rate (CRR): Measures accuracy of individual characters extracted.
- Word-Level Accuracy (WLA): Measures correct identification of full nutritional terms and values.

2) Classification Performance

- Precision, Recall, and F1-Score: Assessed per category.
- Overall Accuracy: Percentage of correctly predicted health categories.

User feedback was also gathered for evaluating usability and usefulness.

C. Results:

Vision API Performance

Google Vision API provided high text recognition accuracy even under varied conditions such as lighting and image angle.

TABLE I

Vision API Performance

Metric	Approximate Value
Character Recognition Rate	~97%
Word-Level Accuracy	~94%
Average Extraction Time	~1–2 seconds

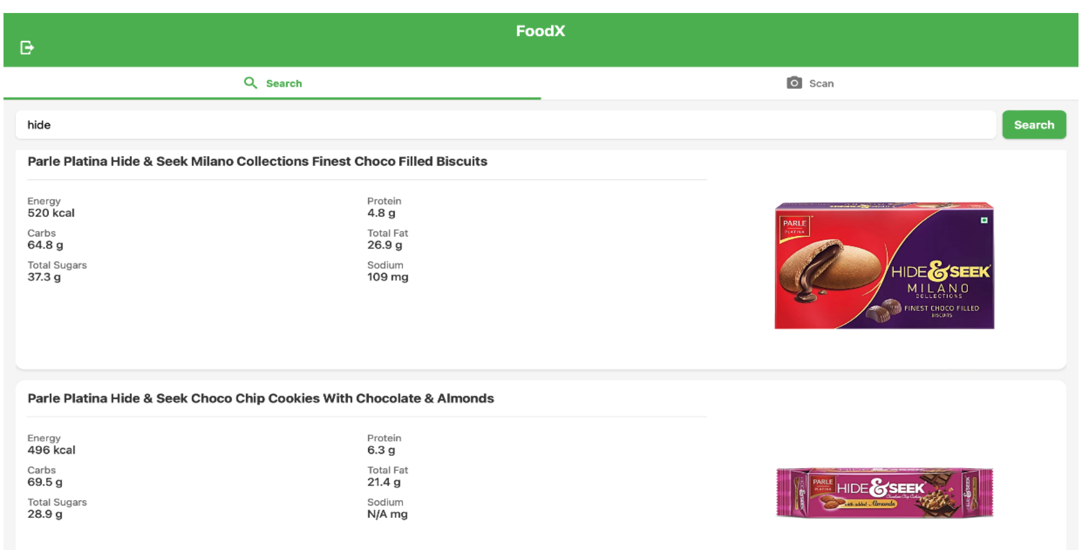


Fig. 3: Search/Scan Function Screenshot

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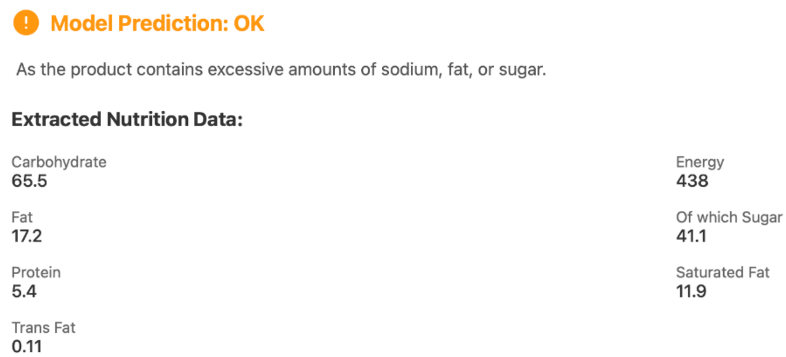

Fig. 4: Classification Output

D. Classification Results

TABLE II
Classification Results

Category	Precision	Recall	F1-Score
Safe	High	High	High
Moderate	Moderate	High	Moderate
Risky	High	High	High
High Risk	Very High	High	Very High
Overall Accuracy	—	—	~90%

E. User Feedback

User feedback was gathered through informal interactions with the chatbot-based nutrition analysis system. Overall, users responded positively to the system’s ability to provide clear and understandable health categorizations. The conversational interface made the experience more engaging and user-friendly, while the explanatory messages accompanying each classification helped users better interpret the results. Many users expressed that the system could influence their food choices and found the information useful for making more informed decisions.

V. DISCUSSION

A. Key Findings:

1) *High OCR Accuracy Using Google Vision API:* Effective and incredibly precise text extraction from nutritional label photos was made possible by the integration of Google Cloud Vision API. The API continuously produced good character and word recognition rates despite differences in font styles, layouts, and languages, which added to the system's overall dependability.
2) *Effective Classification of Nutritional Profiles:* The neural network model demonstrated strong capability in classifying food products into predefined health categories such as Safe, Moderate, Risky, and High Risk. The model's accuracy exceeded 90%, indicating its effectiveness in interpreting nutritional content and aligning it with dietary standards.
3) *Importance of Nutritional Attributes:* A review of classification results showed that some nutritional elements, in particular sodium, saturated fats, and added sugars, were highly predictive of detrimental categories. These characteristics can be regarded as important indicators in health risk assessment and had a considerable impact on the classification outcome.
4) *Alignment with Dietary Guidelines:* The system's classifications corresponded closely with established dietary standards from organizations such as WHO, FDA, and ICMR. This consistency with expert guidelines validated the practical applicability of the system in real-world health monitoring and consumer awareness.

Although OCR technologies such as Tesseract and Google Cloud Vision have demonstrated reasonable performance in extracting text from images, their application in food packaging remains limited by environmental factors like poor lighting, distortions, and the use of multilingual or decorative fonts. Existing OCR systems often lack the domain-specific adaptability needed to accurately extract ingredient names and nutritional data from real-world food labels.

Furthermore, traditional artificial neural network (ANN) models used for product classification are typically designed for generic datasets and do not incorporate personalized health parameters such as allergies or chronic conditions, which limits their effectiveness in delivering individualized food safety assessments.

In addition, while Natural Language Processing (NLP) techniques have seen widespread use in chatbots and text classification, there is a clear gap in their application for generating health-oriented content and real-time user guidance in the food domain. Most existing systems do not leverage NLP to create personalized health blogs or contextual explanations about harmful ingredients. Similarly, product classification models like NOVA provide a broad understanding of food processing levels but fall short in linking specific ingredients to user-centric health risks.

VI. CONCLUSION

This paper presents a comprehensive approach to packaged food analysis and personalized health recommendation by integrating OCR, machine learning, and natural language processing techniques. By addressing key limitations in existing systems—such as lack of personalization, poor label recognition accuracy, and limited user awareness tools—our proposed model aims to empower consumers with real-time, health-conscious food choices. The inclusion of features like ingredient classification, medical history-based filtering, and NLP-generated educational content ensures that the system is not only technically robust but also user-centric and impactful for public health awareness.

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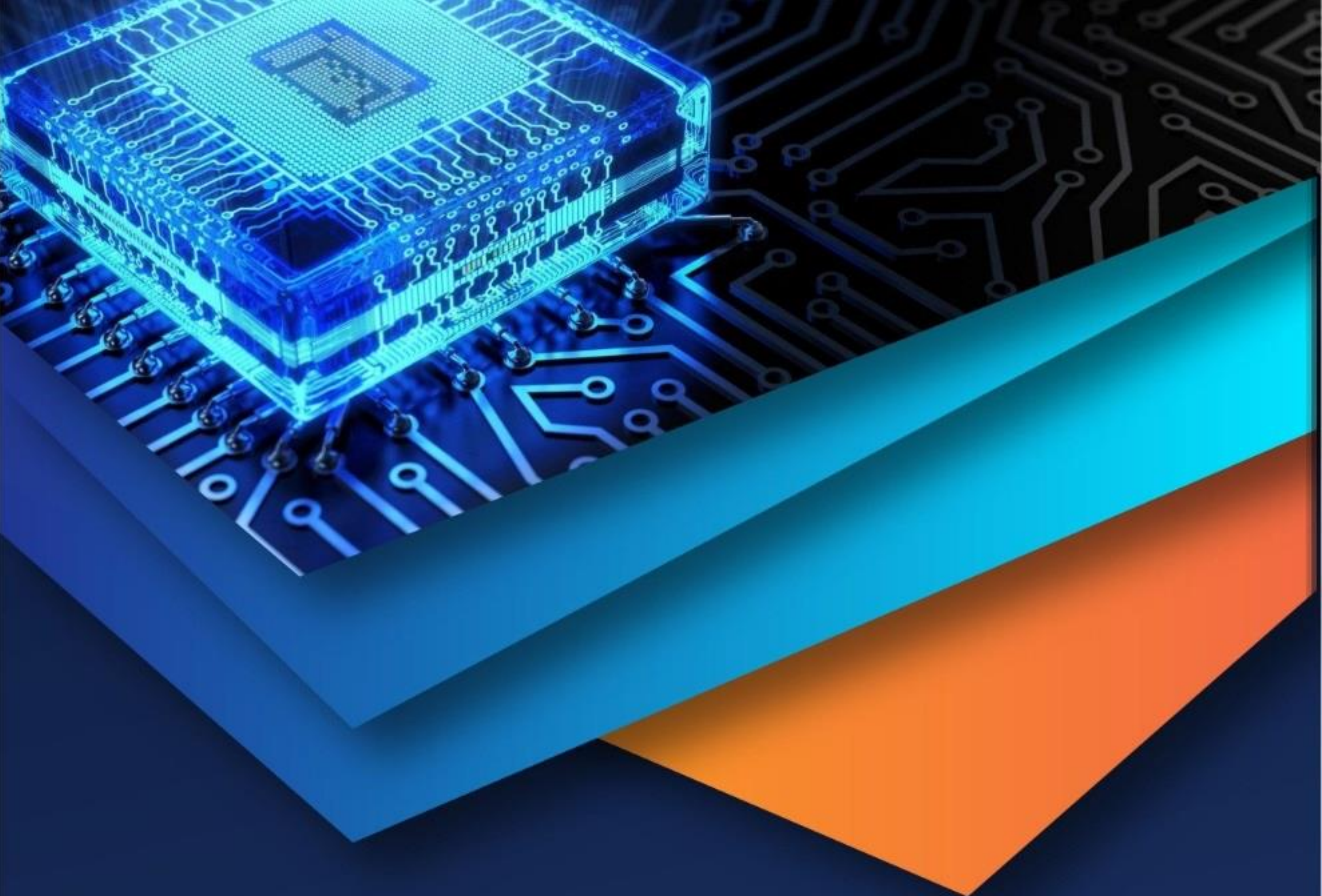

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