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# A smart scanner system for ingredient categorization and identification of nutritional composition in packaged food items

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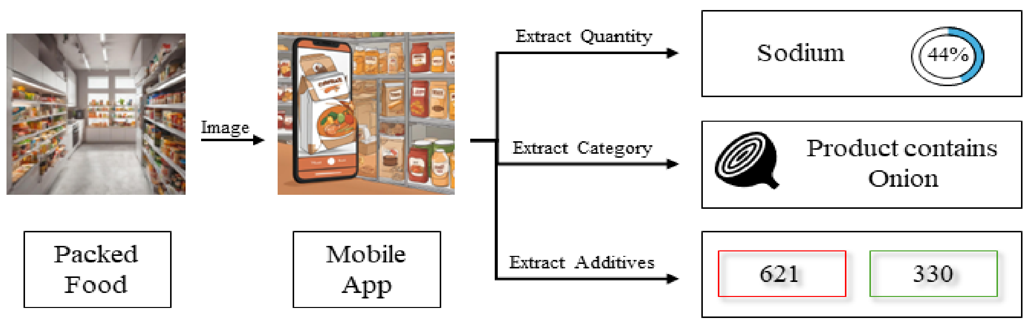
## ABSTRACT




Food constitutes a vital part of the human lifestyle. Packaged food is not avoidable, especially for working professionals. These are highly processed and are sometimes high in artificial colors, preservatives, saturated fats, sodium, and other unhealthy ingredients. It is necessary to identify and avoid the intake of allergic and unhealthy ingredients in packaged food. This research introduces a pioneering AI-based application that seamlessly integrates Optical Character Recognition (OCR) technology with an extensive database of ingredient information, offering users detailed insights into the nutritional composition, categorization, and potential allergens of diverse food products. Going beyond conventional models, this application employs OCR for text extraction, empowering users to scan a wide array of food items beyond those with barcodes. The study evaluates the accuracy of text extraction and the performance of an innovative ingredient categorization model. Google's Vision API emerges as the optimal choice for text extraction, demonstrating exceptional results. The categorization model achieves an accuracy of 84% and a precision of 87%, providing users with a reliable tool to make informed decisions about their dietary choices, ultimately contributing to enhanced health and well-being.


*Keywords: OCR, Text recognition, Food Additives, Nutrition, Food allergies, Digital health*

## INTRODUCTION

Modern lifestyle and improved standard of living originate from new innovations made for society, which demands a more workaholic and stressful environment. This global scenario of heavy workload has changed the constraints on food that is being consumed, from healthy and nutritious to fast and easily accessible with the taste of the food being the most prioritized demand even after the change. A recent survey,[1] conducted among 13,274 school children revealed alarming trends in dietary habits, indicating a widespread deficiency in balanced nutrition. Findings showed that 66% of children had low intake of cereals and millets, 45% consumed vegetables infrequently, 54% lacked adequate milk and milk-based products, 65% had insufficient fruit consumption, 73% consumed pulses sparingly, and 49% of non-vegetarians had low protein intake. Additionally, 53% of children consumed packaged foods or beverages daily, with 53% indulging in salted snacks like chips and instant noodles more than twice a week, 56% consuming sweet treats like chocolates and ice creams at a similar frequency, and 49% drinking sugar-sweetened beverages regularly. Gender and age disparities were evident, with boys and older children showing higher consumption rates of packaged foods and beverages. This study indicates that excessive consumption of food high in fat, salt, or sugar (HFSS) is associated with obesity and non-communicable diseases (NCDs). Thus, proper monitoring of the food being consumed is very essential. Controlling the quantities of various constituents of food such as carbohydrates, fats, proteins, vitamins and minerals is very important as they provide nourishment and are essential for the maintenance of life and for growth.

Understanding the consequences of the situation described, multiple research studies and proposed models[2,3] were analyzed

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that resulted in the designing of a software platform to interact with users on the basis of inputs given as images or interactive questionnaires presented using formerly stored data. All the models analyzed, focused on finding the nutritional value of cooked food and resulted in suggesting a properly balanced diet using the data given. Whereas an ideology of scanning barcodes using Optical Character Recognition (OCR) to identify the packaged product is implemented in a model.[4] The information linked with the product is then used to quantify the nutritional data and thus result in suggesting a balanced diet.

Inspired by the OCR-based image processing model presented earlier, the solution proposed in this paper recognizes the list of ingredients and nutritional values printed on packets of food (including beverages) instead of barcode scanning which limits the scope of solution only to packaged food with a barcode printed. Using this data, the proposed framework will categorize the food ingredients as good or bad for health and thus provide insights to the user about consumption.[5] Food Safety and Standards Authority of India (FSSAI), has also implemented this ideology in framing a new set of rules to rate any packaged food on a scale of 0 to 5 based on various factors which include saturated fat, energy, total sugar, sodium, natural ingredients, and protein and thereby classifying the product using the colored tag which will indicate the effect of contents on the health of the consumer.

## Literature Review

With modern technology, a wide variety of food products have been processed, which has increased the shelf life of products and it is now possible to deliver them in ready to eat packages, instant mix packages or ready to cook & eat packages. The ability to store certain food items for longer duration certainly raises a question about the quality of food being consumed. In order to find a justifying answer to the questions raised, analysis of previously presented works has been mentioned in this section.

The methodology for data acquisition used in software implementation can be of multiple types, one such mechanism implemented to collect information about food contents in any package is Nuclear Quadrupole Resonance.[6] The author has discussed an experimental setup in which Nuclear Quadrupole Resonance Spectroscopy is implemented. Various samples of food and medicine such as L- Proline, L- Histidine and Tylenol have been experimented for their spectral signature extraction. The main purpose of these signatures is to authenticate. The parameters considered for classification here are Amplitude, Frequency Domain and decay time constants. Considered parameters also have manufacturer-centric classification of signatures for nominally identical samples. All data collected is provided to Support Vector Machine and later to which classification is done to result the output. Regarding portability, the devices developed by the authors[6] are designed to be portable and easy to use, which is one of their strengths. They are small, do not require external power, and can be used in the field. However, the authors do note that the devices require some level of technical expertise to operate, which could limit their accessibility to certain users or settings.

Another mechanism that has been implemented to identify nutritional values of cooked food uses thermal imaging and charged coupled cameras to capture images of soups and Thai curries.[7] These images are then classified under various parameters by decision-making using fuzzy logic. Further it proposes a real-time prototype model, in which a thermal camera and charge-coupled camera are attached. The images captured undergo multiple software processes such as Database Preparation, food type classification, and Ingredient boundary detection to provide an accurate result. This method has 14.49% of errors in software and 11.59% of errors in hardware when compared with the conventional destructive method as described by the author. The most basic method to acquire data regarding the food consumed can be manual inputs made by the user in the form of an image of bills,[8] or in text format.[9] Both applications utilize databases for data storage and use it when required to classify the new input made by the user.

Apart from all these, one important and the most commonly used method for image processing to acquire details of packaged food is Optical Character Recognition.[10] Another study presented a survey[11] on post OCR processing techniques developed over the decades. Multiple studies analysed in this paper have their unique way of implementing OCR with different artificial intelligence or machine learning techniques.[12] Wei et al.[13] have implemented a system to recognize printed English text characters from poor quality images using two deep neural networks. First is a pretrained Inception V3 model to obtain suitable information and other neural networks for real classification of the image. The author has performed a comparison of the proposed model to existing OCR space and claims to have achieved an accuracy of over 78% more than it for inferior quality pictures. And proves to work fairly on noisy character images. Similar work to recognize roman scripts is implemented using OCR, Nearest Neighbour (NN) and Artificial Neural Network (ANN).[14] CRNN, a different neural network architecture that combines the benefits of two different NN to perform image text recognition efficiently in both lexicon-based and lexicon-free is implemented by Shi et al.[15] This limited comparison with a few existing models on a limited number of datasets makes it difficult to assess the effectiveness of the system proposed.

Consumption of packaged food items is done on a regular basis so to keep a track of the nutritional value and calorie intake various android applications have been designed such as FoodScan.[16] It offers food recommendations for weekly or monthly plans based on the purchased items recommended by the nutritionist. Through graphical representations it tracks the amount of the type of food may be consumed and tells the user that they have met the recommended amount of healthy diet or not by traffic light color system indication. Authors have also conducted a survey on the ease usage of their application and benefits from using it. Another software-based model[17] is proposed to analyze the nutrition of the food that the user consumes that can be described in steps like Food Image segmentation, which classifies food images on parameters like texture and color. This segmentation further leads to Food portion Recognition that is implemented using SVM and parallelly

the volume detection of food is done, where a static reference object is considered for scaling the image to actual dimensions thus calculating volume. This algorithm may not always accurately identify the types and amounts of ingredients in a dish, especially if the dish is complex or has many components. Additionally, the study only evaluated the accuracy of the algorithm on a limited set of foods, so its generalizability to other foods and dishes is not clear.

The proposed application for ingredient categorization and identification of nutritional composition in packaged food items distinguishes itself from previous studies through its ease of access and user friendliness. The Application can keep track of the quantity of various nutrients consumed unlike other applications which focus primarily on the calorie intake. Also, the values of quantity are more accurate than the estimated values of other models as they are extracted from the nutritional table. By employing distinct ingredient categories, the application can efficiently segregate food items and assist users in determining their suitability for consumption. One notable feature of the application lies in its capacity to detect and notify users about the presence of specific ingredients to which they may be intolerant in packaged fo

od items. This feature marks a significant advancement compared to prior studies, which predominantly focused on analyzing cooked food, grocery receipts, or simply estimating calorie content based on food types. Another notable function of the application is its capability to identify additives in food products and classify them as either beneficial or harmful. This classification is informed by data sourced from the Codex *General Standard for Food Additives* by the Food and Agriculture Organization of the United Nations[18] and other relevant sources.[19] Moreover, the application offers users their Body Mass Index (BMI) based on their height and weight, enabling them to set personalized health goals and strive towards a healthier lifestyle. To summarize, the proposed application addresses a gap in research by providing a user-friendly tool that can be conveniently utilized, such as during grocery shopping, to analyze and categorize packaged food items. Its use of ingredient categories and ability to scan ingredients rather than solely relying on food names or types present an innovative solution to this challenge.

## METHODOLOGY

The food analysis application employs a multifaceted approach that integrates advanced image processing technologies. This approach aims to provide users with a seamless and insightful experience by analysing images of packaged food items.

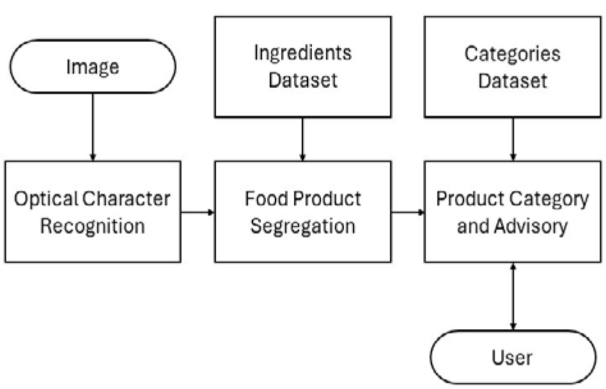


**Figure 1**. Subsections and interconnection of designed model.

The subsequent extraction of meaningful insights from these images is pivotal for the success of the methodology. Figure 1 shows the various subsections and the connections of the designed model.

**Optical Character Recognition**

The implementation of OCR involves the extraction of essential information, such as ingredients and nutritional details, from images of packaged food items. The acceptable daily intake is one important criterion to monitor[20]. To enhance this process, our methodology integrates the Maximally Stable Extremal Regions (MSER) algorithm, which swiftly identifies text regions with high accuracy[21]. After a rigorous evaluation process, Google's Vision API was identified as the optimal choice. This API leverages advanced deep learning techniques, including the Inception network, data augmentation, batch normalization, and dropout regularization. The reliability of Google's Vision API in tandem with MSER is central to this process, providing accurate data and enhancing the overall ef ficacy of the system. This integration not only accelerates processing time by focusing solely on relevant text regions but also effectively mitigates noise generated from OCR by filtering out non-textual components prior to recognition. This ensures a more efficient and accurate extraction of information from images. This kit is found to be better when compared with other open-source OCR models such as easyOCR and Tesseract OCR in recognizing text word by word.

**Food Product Segregation**

*Ingredient Information*

The methodology prioritizes the extraction of ingredient information from images of packaged food items. This process, facilitated by Google's Vision API, ensures precise identification of ingredients from the extracted text. The extracted text is split into individual ingredients, which are then cross-referenced with the Ingredient Dataset. This dataset contains comprehensive information on 240 food additives, uniquely identified under the International Numbering System for Food Additives (INS number). Each entry in the dataset includes the common name of the food additive, its INS number, description, side effects, and health advisories. By matching ingredients extracted from the image with entries in the dataset, the system can determine the health advisories associated with each ingredient.

The dataset was custom made for the application using the data from various sources as no existing dataset was found which contained the data for various food additives. All the existing datasets were regarding the nutritional values or information about the various ingredients found in such foods.

Algorithm 1 is implemented for Ingredient Detection and Product Categorization. To efficiently process the extracted text and identify ingredients.

Algorithm 1 is implemented. This algorithm iterates through the list of extracted ingredients and cross-references them with the entries in the Ingredient Dataset. Additionally, it checks for the presence of user-defined categories by iterating through the Category Dataset.

Algorithm 1: **Ingredient detection and product categorization**

**Input:** Text extracted from input image.

**Output:** Category and health advisory for product.

*Initialization*

$ingrdts \longleftarrow Split\ extracted\ text\ \ to\ form\ list$

$chkCat[\,] \leftarrow boolean\ array\ of\ categories$

$catIdt[][] \leftarrow 2D\ array\ of\ category\ identifiers$

$hasCat[\,] \leftarrow boolean\ array\ if\ category\ found$

$fdAdtv\ \leftarrow dictionary\ of\ ingredients$

$result[\,] \leftarrow Stores\ description\ and\ side\ effects$

**for** $i\ in\ ingrdts$:

  **for** $j\ in\ fdAdtv$:

    **if** $ingrdts[i] == fdAdtv.key()[j]$ **then**:

      $result \leftarrow fdAdtv.values(\,)[j]$

    **end if**

  **end for**

  **for** $k\ in\ chkCat$:

    **if** $chkCat[k] == true$ **then**:

      **for** $p\ in\ catIdt[k]$:

        **if** $ingrdts[i] == catIdt[k][p]$ **then**:

          $hasCategory[k] \longleftarrow true$

        **end if**

      **end for**

    **end if**

  **end for**

**end for**

**return** $result, hasCategory$

The worst-case time complexity of detecting an ingredient and extracting its description and side effects is given through equation (1).

$$T(n) = O(n^2) \tag{1}$$

where, n is the number of ingredients detected from the image of a packaged food.

Time complexity given in e.q. 1, for searching one of the ingredients through entire dataset is $O\ (n)$. Therefore, overall time complexity of finding data related to m distinct ingredients from dataset of n entities is $O\ (m.n)$. For worst case, this time complexity is re-written as $O(n^2)$. Using similar searching approach, the identifiers for various food categories are iterated over categorical dataset and thus deciding whether the food belongs to the category selected by the user.

## Product Category and Advisory

*Categories Information*

Tailored for users with specific health conditions or preferences, this segment focuses on monitoring particular components of food. The application efficiently determines whether the food product contains these specific ingredients or not. The Category Dataset facilitates this process by storing food item categories. It stores a list of keywords used as identifiers to detect the presence of certain ingredients, allowing products to be categorized into groups like nuts-based products, products containing onion-garlic, lactose-based products, and products with allergenic contents. While default categories are provided, users have the flexibility to edit these defaults and add new categories as needed. Figure 2 illustrates the default categories in which the product can be classified.

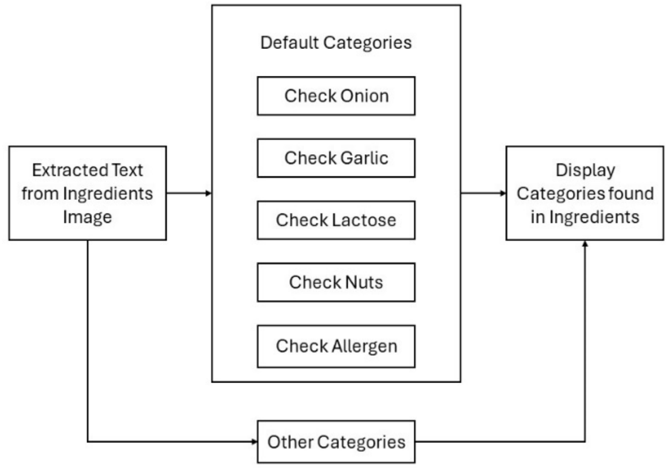


**Figure 2**. Classification of Food into different categories

The results from both comparative blocks play a crucial role in identifying the food product as fit or unfit for the respective user. Local storage of the ingredients dataset and the categories dataset enhances the speed and performance of the application, eliminating the need for continuous internet connectivity and enhancing accessibility.

*Quantity Assessment*

This subsection addresses users with ailments such as diabetes and hypertension, focusing on monitoring specific components of food. It primarily detects the quantities of sugar, carbohydrates, salt (sodium), and energy present in the product by scanning its nutritional table. The nutritional table provides a tabular representation of nutrients present in the product, along with their quantities. The objective is to alert the user regarding the consumed nutrient amounts against the total recommended intake for a healthy individual over a 24-hour period, expressed as a percentage. Mathematically, the nutrient content values can be calculated using equations (2), (3), and (4).

$$\%(sodium) = \left(\frac{amount\ traced}{2300}\right) \times 100 \tag{2}$$

$$\%(sugar) = \left(\frac{amount\ traced}{30}\right) \times 100 \tag{3}$$

$$\%(carb) = \left(\frac{amount\ traced}{325}\right) \times 100 \tag{4}$$

Here, the daily intake limit of sodium for a healthy person is considered 2300 milligrams, that of sugar is considered as 30 grams, that of carbohydrate as 325 grams and of saturated fats as 22 grams for a 2000 calorie-a-day diet.

The values of calories required per person may vary according to the gender, age, and the activity levels of the individual. In order to incorporate these details into the application, the users are asked to fill in their details at the time of User Registration. Based on the inputs provided, the application will select the appropriate value of daily calorie intake as target.

*Calorie Intake Chart*

A chart illustrating calorie intake for various users is depicted in Table 1. The values are based on Estimated Energy Requirements (EER) as outlined in the Institute of Medicine Dietary Reference Intakes macronutrients report from 2002.

**Table 1**. Calories intake for various users[22]

| Gender | Age[a] | Sedentary[b] | Moderately Active[c] | Active[d] |
|---|---|---|---|---|
| Child | 2-3 | 1000 | 1000-1400 | 1400-1800 |
| Female | 4-8 | 1200-1400 | 1400-1600 | 1400-1800 |
| | 9-13 | 1400-1600 | 1600-2000 | 1800-2200 |
| | 14-18 | 1800 | 2000 | 2400 |
| | 19-30 | 1800-2000 | 2000-2200 | 2400 |
| | 31-50 | 1800 | 2000 | 2200 |
| | 51+ | 1600 | 1800 | 2200 |
| Male | 4-8 | 1200-1400 | 1400-1600 | 1600-2000 |
| | 9-13 | 1600-2000 | 1800-2200 | 2000-2600 |
| | 14-18 | 2000-2400 | 2400-2800 | 2800-3200 |
| | 19-30 | 2400-2600 | 2600-2800 | 3000 |
| | 31-50 | 2200-2400 | 2400-2600 | 2800-3000 |
| | 51+ | 2000-2200 | 2200-2400 | 2400-2800 |

*Note:* In Table 1, the superscripts represent the following:

[a] The calculations take into account gender, age, and activity level for individuals of a reference size. The concept of "reference size," defined by the IOM, relies on the median height and weight for individuals up to the age of 18 and the median height and weight corresponding to a BMI of 21.5 for adult females and 22.5 for adult males.

[b] Sedentary denotes a lifestyle characterized by minimal physical activity, limited to the light exertion associated with typical day-to-day activities.

[c] Moderately active characterizes a lifestyle involving physical activity comparable to walking approximately 1.5 to 3 miles per day at a pace of 3 to 4 miles per hour, in addition to the light physical activity associated with everyday life.

[d] Active describes a lifestyle incorporating physical activity equivalent to walking more than 3 miles per day at a pace of 3 to 4 miles per hour, in addition to the light physical activity associated with typical day-to-day life.

**Text Extraction and User Interface**

One of the distinguishable features of the proposed system is its user friendliness. The model accepts input of ingredients in the form of image thus enabling users of all age groups with a smart phone to interact with the application. The extraction of text is an Optical Character Recognition process which involves processing of image and detecting characters using tools of computer vision.

An integral aspect of the methodology is the design and implementation of a user-friendly interface using the Flutter framework. Android Studio, which is built on JetBrains' IntelliJ IDEA, is used as the integrated development environment (IDE) for the development of the application. It offers for seamless integration of Flutter SDK and Dart and Flutter plugins.

Flutter, an open-source framework by Google, allows for the creation of natively compiled, multi-platform applications from a single codebase. The interface is designed with usability and simplicity in mind, enabling users of all age groups to interact seamlessly with the application. It helps to easily identify the product suitability according to the user inputs by following certain steps. These steps are depicted in Figure 3.

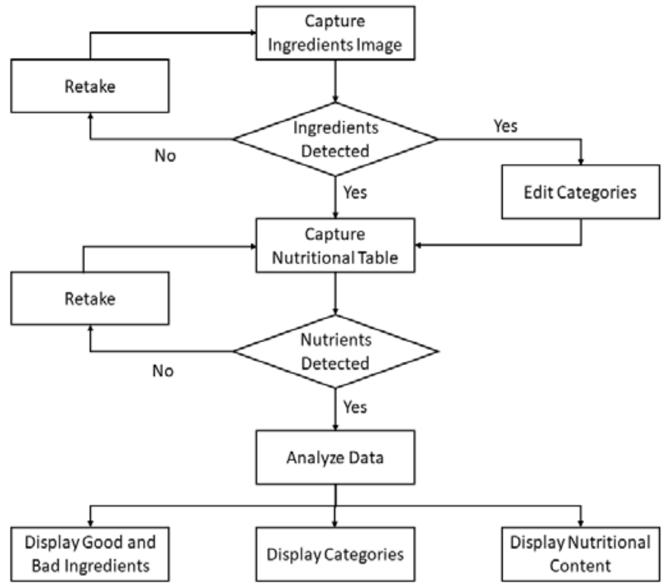


**Figure 3**. Schematic of the user interface layout for the proposed framework.

Users are guided through a series of steps, from capturing images to analyzing results, fostering a straightforward and engaging experience. The Homepage of the application is where the user can view the daily consumption of different nutrients as a ratio between consumed to the daily limit of that nutrient through a progress bar. Additionally, the users can view their calorie consumption and check their BMI with the help of cards which not only make readability easier but also makes the User Interface (UI) more attractive. The BMI of a user is the weight divided by the square of the height. It is calculated as shown in equation (5).

$$BMI=(W/H^2) \quad (5)$$

Where, W is the weight of the user in kilograms (kgs) and H is the height of the user in metres (m).

The analysis of the considered product is done after user captures both the images (ingredients image and nutritional table image). The result is displayed on the Graphical User Interface (GUI) in an expander format integrated with the colour scheme. The ingredients are displayed in red and green for representing bad and good ingredients, respectively. The categorical ingredients are displayed if the user has checked the checkbox for that category of ingredients. The values of Sodium, Sugar, Carbohydrates and Energy are displayed using progress bars indicating the consumption to the daily limit of that nutrient.

## Results and Discussion

The paper meticulously details the precision and recall metrics as pivotal aspects of the application's effectiveness. Utilizing advanced Optical Character Recognition (OCR) techniques, the system achieves commendable precision scores, ensuring accurate alignment of identified outcomes with their designated categories. This precision not only enhances user confidence but also solidifies the application's reputation as a reliable tool for text recognition.

In parallel, the recall metrics shed light on the system's ability to comprehensively capture relevant outcomes within specified categories. The comprehensive nature of the OCR model contributes to high recall, indicating the system's effectiveness in identifying and incorporating all pertinent outcomes. This robust performance translates into real-world applicability, ensuring the system encompasses a broad spectrum of text elements.

The technological synergy with lifestyle choices becomes evident as users seamlessly integrate this OCR application into their daily routines. The convergence of technology with everyday life underscores the societal impact of the application, positioning it as more than just a technological artifact.

The proposed system underwent evaluation using a set of performance parameters, including accuracy, precision, sensitivity, specificity, recall, and F1 score. Three open-source OCR models were integrated into the proposed system, with input from 50 packaged food product images. The output of these models was then compared with the actual list of ingredients printed on food products. Based on this comparative analysis, the Google Vision API model emerged as the most suitable for the proposed system.

The evaluation of the ingredient categorization model followed a similar approach, with input images of ingredients listed on packaged food provided through the GUI. The health effects of the product were compared with the actual health effects, with a set of 100 test images used as input. The performance parameters evaluated showed an accuracy of 84%, with a precision of 87%, sensitivity at 85%, specificity at 82%, recall at 85%, and F1 score at 86%.

Table 2 presents the summary of comparative analysis done for the text extraction models.

**Table 2**. Results of Text Extraction Models

| Sr. No. | Parameter | EasyOCR | Tesseract OCR[23] | ML Vision[24,25] |
|---|---|---|---|---|
| 1 | Character Ratio | 0.19 | 0.17 | 0.15 |
| 2 | Words Ratio | 0.31 | 0.35 | 0.30 |
| 3 | Punctuation Ratio | 0.36 | 0.36 | 0.32 |
| 4 | Overall Accuracy | 83.11% | 79.05% | 87.88% |

Here, the results of different models for various parameters indicate the ratio of incorrect to correct entities. The overall accuracy of the models across all parameters is also provided.

The application adeptly classifies packaged food items, providing users with valuable insights into the safety of consumption. It further enhances user experience by sending notifications, allowing for better monitoring and management of daily routines. The inclusion of a calorie tracker is particularly noteworthy, addressing the high calorie content in many packaged foods and the prevalent issue of weight gain. Progress bars serve as practical tools for users to gauge their daily intake limits effectively. Additionally, incorporating Body Mass Index (BMI) calculations offers users insights into their overall health.

The Camera input page for capturing the Ingredients Image is as shown in Figure 4.

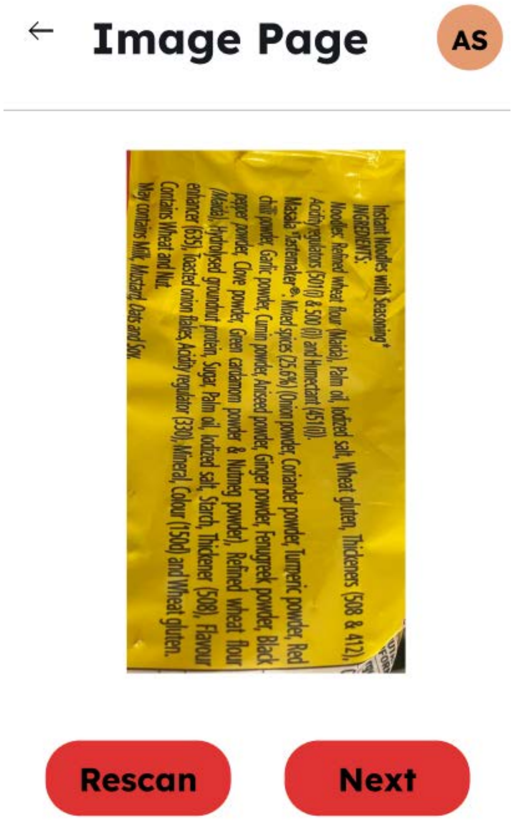


**Figure 4**. Ingredients Image Page with the captured image using the proposed application.

In the food sector, precision is crucial as it directly impacts individuals' health and well-being. With an impressive precision rate of 87%, the proposed system is well-suited for real-time deployment, providing users with a reliable resource to navigate their daily dietary choices. Beyond mere categorization, the system furnishes information on a food product's healthiness or potential drawbacks based on identified ingredients and their associated side effects. This comprehensive approach positions the proposed system as a valuable tool for individuals seeking to make well-informed decisions about their dietary preferences.

Here, the user can either capture an image or select an image from the device storage. The extracted text from the image displayed in Figure 4 is shown here:

*INGREDIENTS:*

*Noodles: Refined wheat flour (Maida), Palm oil, iodized salt, Wheat gluten, Thickeners (508 Acidity regulators (501(i) & 500 (i)) and Humectant (451(1). & 412),* *Masala "Tastemaker: Mixed spices (25.6%) (Onion powder, Coriander powder, Turmeric powder, Red chili powder, Garlic powder, Cumin powder, Aniseed powder, Ginger powder, Fenugreek powder, Black pepper powder, Clove powder, Green cardamom powder & Nutmeg powder), Refined wheat flour (Maida), Hydrolysed groundnut protein, Sugar, Palm oil, lodized salt, Starch, Thickener (508), Flavour enhancer (635), Toasted onion flakes, Acidity regulator (30), Mineral, Colour (150d) and Wheat gluten. Contains Wheat and Nut.*

For the sake of simplicity, the extracted text has been formatted to fit the complete lines of the paragraph. However, the actual representation may vary.

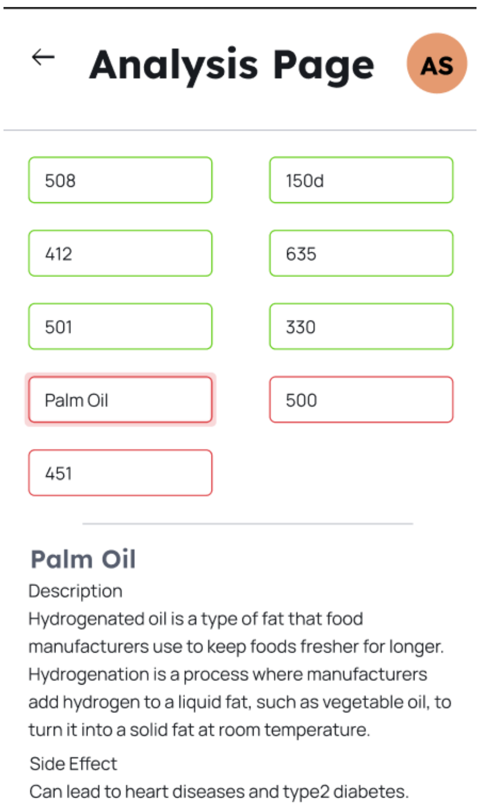


**Figure 5**. Analysis Page with the list of Food Additives and their details

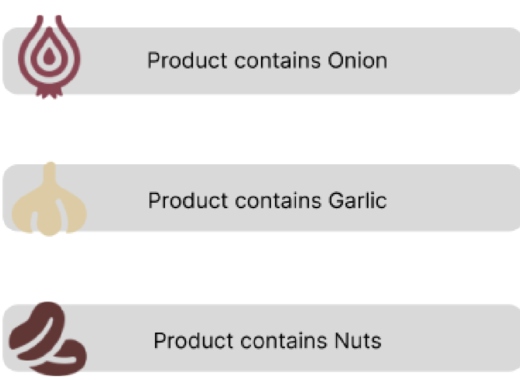


**Figure 6**. Output of categories identification of the product.

The output of the common elements between the Extracted ingredients and the food additives in the dataset are given as output to the users through the Analysis Page and is shown in Figure 5. It also shows the Description and Side Effects of one selected ingredient.

The categories identified in the packed food are identified and displayed to the user and it is shown in Figure 6. All the categories selected by the user and if they are present in the packet, will be displayed. The food item under study has ingredients which fall under three predefined categories and hence the output.

Figure 7 demonstrates the use of progress bars to effectively represent the quantities of Sodium, Sugar, Carbohydrates and Energy in terms of percentage of their daily limit. Here, the value of Daily limit of Calorie intake is taken as 2000 Kcal.

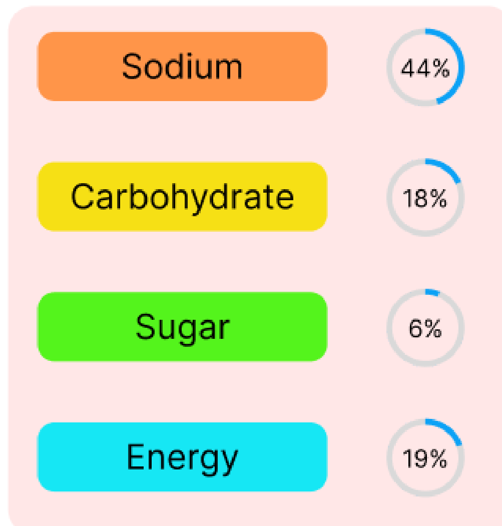


**Figure 7**. Demonstration of the quantity percentages of various nutrients.

## Conclusion

The proposed system acts as recommendation system and effectively addresses the issue of identifying potentially harmful or unhealthy components in packaged food by providing users with accurate information about ingredients and their side effects. The paper delves into a comparative analysis of various OCR techniques, shedding light on their respective strengths and limitations. By evaluating the performance of different OCR models, the paper offers a nuanced perspective on the landscape of text recognition technologies.

The developed mobile application incorporates a unique ingredient categorization feature that sorts food items with an accuracy of 84%, assisting users in determining their suitability for consumption. Moreover, the application alerts users if any of the ingredients they are intolerant to are present in packaged foods with a precision of 87%. However, the issue of data loss resulting from unlisted ingredients highlights the need for further development. Future research should focus on incorporating the scientific and generic names of ingredients into the model to improve its accuracy and enhance its ability to categorize food products more effectively. Overall, the proposed system can help consumers make informed decisions about what they eat and align their dietary needs and preferences with the food they consume, ultimately promoting a healthier lifestyle.

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