Food Aayush: Identification of Food and Oils Quality

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1 Introduction

The quality of food consumed by a person plays a significant role in determining a person's health and quality of life. The food consumed must be edible and fresh to avoid the risk of food-borne diseases. The nutritional value of the food is an equally important parameter in determining the quality of the food. Food rich in nutrients is essential to develop a person's immunity. Lack of nutritious food may harm immunity and the person's health in general. The quality of oils used in cooking the food also needs to be taken into consideration. If a particular oil sample is used repeatedly, it may become rancid due to the exposure to high temperatures. Rancid oils not only spoil the taste of food but may also be harmful to human health. Since it is not always possible to know the quality of food and cooking oils, a system must be designed to accurately determine the freshness of food and the rancidity levels of oils. This will allow a person to be sure of the food or oil quality and make an informed decision as to whether the food is suitable for consumption or the oil is ideal for cooking. The system must also predict the nutritional value of food items and determine the required consumption of various nutrients for a particular person based on their daily calorie consumption. This will facilitate the consumption of a healthy, balanced diet by the person and thus be conducive to the right immunity level, thereby preventing susceptibility to diseases.

2 Existing Methodology

Food quality verification is usually done manually or with automated systems that use extensive hardware and complex methods. Manual verification is tedious, time-consuming, and may also be inaccurate. The current automated systems, on the other hand, are tremendously expensive and complicated. Therefore, they are suitable only for industrial or laboratory use and not for everyday use. Also, they are not easily portable. For checking the rancidity of oils, the pH value of oils is not considered as a factor. Usually, the rancidity of oils is checked manually by observing the visual properties and odor. This method may lead to inaccuracy in the determination of rancidity. Currently, calculating the nutritional value of dishes consumed is a cumbersome manual task. Hence, it is challenging to keep track of one's daily nutrient intake.

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3 Literature Survey

Many methods have been proposed to classify the quality of food and oils, using machine learning, deep learning, computer vision, and image processing. A classification model using Support Vector Machine (SVM) was developed for the classification of food images. This model made use of the pre-trained AlexNet and VGG16 models for feature extraction. The model was experimentally tested on three different datasets, and the average accuracy was found to be higher than that of CNN models [1]. Among the methods proposed for food quality check, there is one that involves microcontrollers for detecting gases released from food to detect food spoilage. This method also uses machine learning models for predicting the probability and the time required for the spoilage of foods [2]. Other methods use the visual properties of foods, such as color. A plan has been proposed, which first classifies various food items from the images and then, for a particular food item, extracts information about the color using machine learning algorithms and uses the HSV values to detect spoilage in the food item [3]. Classification methods specific to particular food items have been proposed as well. A two-layer method for banana grading has been devised, which classifies bananas based on color and texture using a Support Vector Machine. The second layer uses the YOLOv3 model to check the banana peel's affected areas to prevent the banana's ripening [4].

Similarly, a method for mangoes has been proposed which uses computer vision to determine properties such as mass, volume, density, and defects, enabling the classification into different categories of quality, even considering sweetness as a parameter [5]. For the rancidity check of cooking oils, a system was developed that used color and photodiode sensors to extract visual information about the oils and accordingly detect the oils' frequency of use. The oils are classified into five usability categories with the k-nearest neighbor's algorithm implemented on an embedded system platform. This will help to determine if a particular oil sample is suitable for further use in cooking. The use of pH sensors, temperature sensors, and gas sensors has been made to classify food items [6–8].

4 Proposed Methodology

The model proposed in this paper uses artificial intelligence and image processing to classify food items into various levels of freshness based on the food images captured using a mobile phone camera. In the case of oils, the classification into different rancidity levels is done based on oil sample images captured through the mobile phone camera and the pH value of oils captured through a pH sensor and given as an input to the application. For finding the nutritional value of food items, either the ingredients of the dish or an image of the dish are taken as input. Additionally, the daily dietary requirements for a particular person are calculated from daily calorie consumption. The application thus has the following main features:

- Identification of the freshness of food items
- Identification of repeated frying on cooking oils from the rancidity levels of oils
- Nutritional evaluation of dishes
- Calculation of nutritional requirements for a particular individual

The system is a simple mobile application developed using the Flutter Toolkit, which uses the DART programming language. For the rancidity level check feature, there is an option to integrate the application with a pH sensor using a microcontroller to evaluate the rancidity levels using pH values and the oil sample images.

The nutritional analysis feature and dietary requirements calculation require data analysis and are developed using Streamlit, a Python framework.

In addition to these functionalities, the application also has some customer care features that help guide customers and answer common customer questions. These include a grievance portal, a frequently asked questions page, and an about us page.

The following figure shows a block diagram representation of the application (Fig. 1).

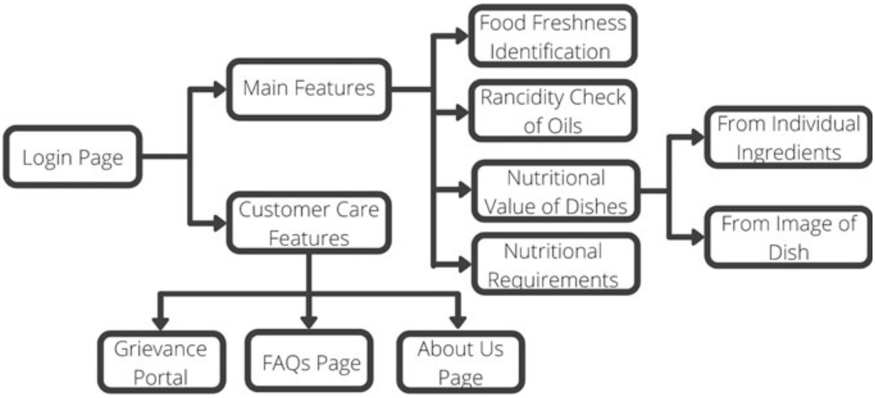

Fig. 1. Block diagram

The figure shows the features of the application. The two categories of features are the main features and customer care features. The main features are the freshness identification of food items, rancidity check of oils, analysis of the nutritional value of dishes from ingredients present, and the calculation of daily dietary requirements for a particular user based on daily calorie intake. Customer care features include a grievance portal where customer-specific issues or questions can be addressed, a frequently asked questions page, and an about us page for contact information.

Each of the main features of the application shall now be described in detail.

A. *Identification of the freshness of food items*

For the development of this feature, firstly, a training dataset of food images is created. Pictures of different food items are captured daily. The images are captured using a simple mobile phone camera. With the progression of days, the food items would become stale. Depending on the day when the food images were captured, each image is labeled into one of three categories:

- Fresh
- Medium
- Stale

This creates the training dataset. The classification model is trained on this dataset. The model is trained first to identify the food item from the image. After identifying the food item, the model must identify the food item's visual properties from the image and accordingly classify it into the appropriate freshness level. Subsequently, when the image of a new food item is captured, the model will identify the food item and its freshness level from the image (Fig. 2).

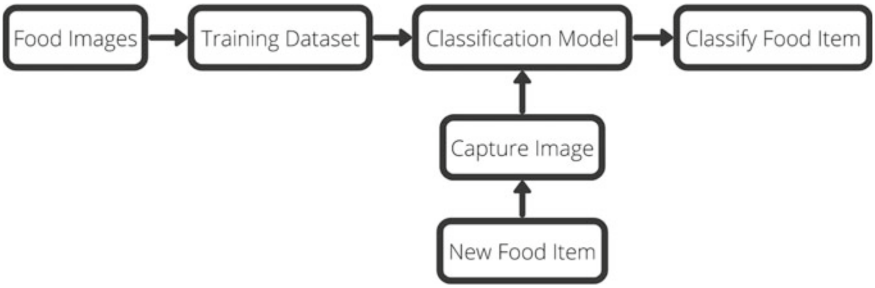

Fig. 2. Diagrammatic representation of food freshness detection feature

The figure shows the working of the food freshness detection feature. Initially, food images are captured, which form the training dataset. The classification model is trained on this dataset. Subsequently, when new food items are to be classified, the new food item's image is captured. The trained model then classifies the new food item into a particular freshness level.

B. Identification of repeated frying on cooking oils from the rancidity levels of oils

Here, first, the training dataset of oil sample images is created. The oil sample images are labeled into different categories of rancidity based on their visual properties. The model is trained using this training dataset. For this feature, the mobile application is also integrated with a pH sensor that will record the oil samples' pH values. An IoT microcontroller will act as an interface between and integrate the mobile application and the pH sensor.

pH value shows the level of acidity or basicity of any solution. It ranges from 0 to 14. pH values below 7.0 indicate that the solution is acidic, while pH values above 7.0 indicate basic solutions. pH 7.0 indicates a neutral solution. As oils become rancid, their acidity levels increase. Oils with lower pH will thus be more rancid.

The pH sensor records the pH value of the oil samples. pH sensor outputs analog value in range of 0.5V to 3V. ESP32 microcontroller processes these values and decides the rancidity of oil.

The model thus considers the visual properties of the oil and the pH values to classify a new oil sample into a particular rancidity level (Fig. 3).

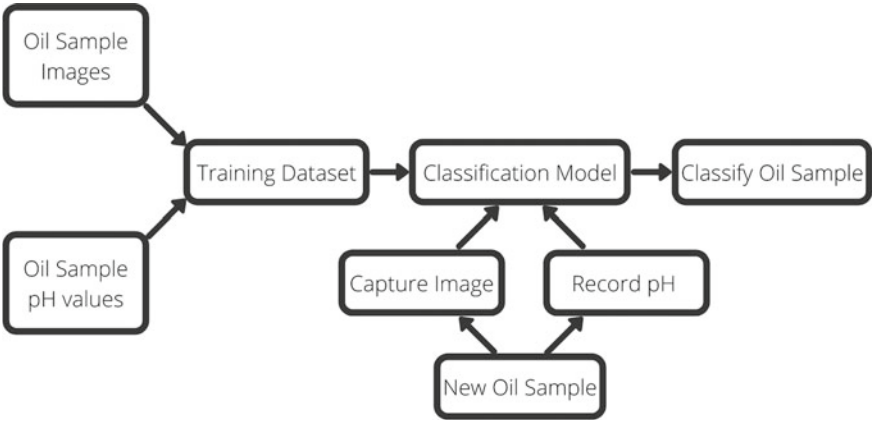

Fig. 3. Diagrammatic Representation of Oil Rancidity Check Feature

The figure shows the working of the oil rancidity check feature. Oil sample images and pH values of oils are recorded to create the training dataset. The classification model is trained. For any new oil sample, the image is captured, the pH value is recorded, and then classification is done using the trained model.

C. Nutritional evaluation of dishes

This feature uses a dataset of dishes and their ingredients. An analysis of the data is performed. When a particular dish is given as input, its nutritional value is calculated from the ingredients present in the dish. Additionally, a matrix is designed, which contains various combinations of food ingredient types. There are certain combinations of ingredients that, when used together, lower each other's nutritional value. In some cases, certain combinations may even be harmful to health. The matrix contains information about each combination of ingredients, regarding whether it is suitable or harmful. Thus, the nutritional analysis feature also helps a user identify if a particular dish contains an unhealthy combination of ingredients (Fig. 4).

The figure shows the working of the nutritional analysis of dishes. The ingredients of the dish are given as an input to the application, either individually or by capturing the image of the dish. Based on the dataset of dishes and their ingredients, the nutritional analysis of the dish is performed. Additionally, a matrix is used that identifies suitable and harmful combinations of ingredients.

D. Calculation of Nutritional Requirements for a Particular Individual

The daily nutritional requirements, i.e., the required daily consumption of various nutrients such as proteins, carbohydrates, and fats for a particular person, depends on the

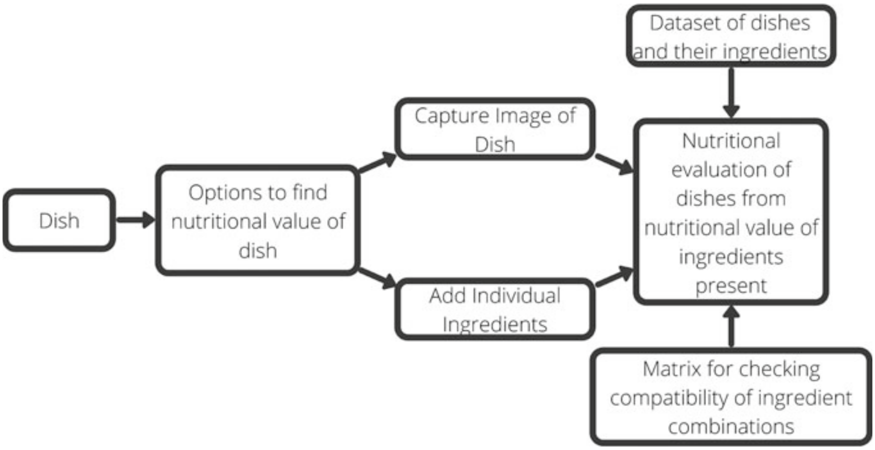

Fig. 4. Diagrammatic representation of nutritional evaluation feature

person's daily calorie consumption. Additionally, the ideal daily calorie consumption also varies from person to person. One of the factors that determine suitable daily calorie consumption is gender. This feature takes as input the number of calories consumed by the user daily. Accordingly, the output is the quantity of proteins, carbohydrates, and fats required daily for the specific user. The feature also asks the user to enter their gender, and according to the gender tells the user the ideal daily calorie consumption for the user. The user can now use the feature again to calculate the daily nutritional requirements as per this ideal calorie consumption (Fig. 5).

Fig. 5. Diagrammatic representation of dietary requirements feature

The figure shows how the nutritional requirements for a particular individual are determined. Based on the daily calorie intake, the required amounts of various nutrients are calculated. The ideal daily calorie intake is also informed to the user based on their gender.

Classification Model:

The models for the classification of food images and oil sample images use convolutional neural networks (CNNs) for image classification. Convolutional neural networks are suitable since the process of feature extraction is performed conveniently. The CNN consists of four layers: the convolution layer, the nonlinear layer, the pooling layer, and the fully connected layer. The features and visual properties of the images (color and texture for both food and oil images, and the presence of surface defects in case of food images) are identified using the CNN layers, and the images can be classified accordingly.

The following figure shows the modular diagram of the application, i.e., a brief overview of the application's entire functioning and its various features (Fig. 6).

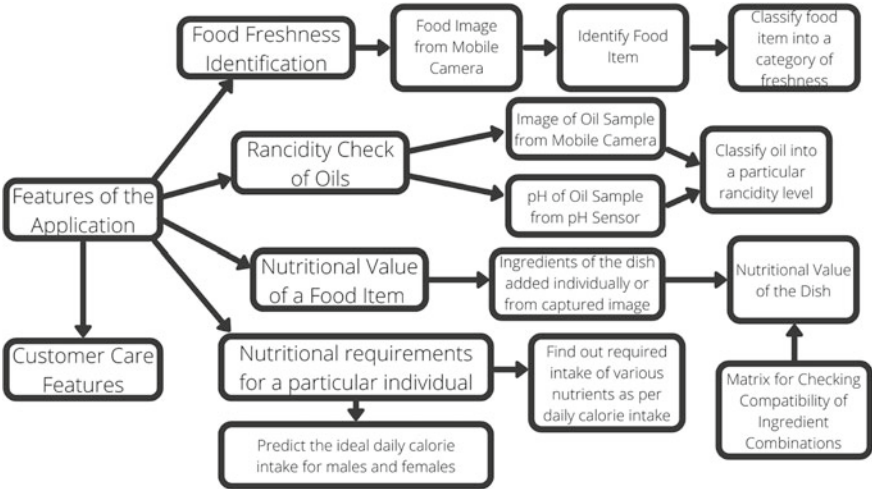

Fig. 6. Modular diagram of the application

The figure shows a summary of the features of the application. Food freshness detection uses images for training the dataset and performs classification for new food items. For rancidity check of oils, images, as well as pH values, are used. The nutritional evaluation of food items considers the ingredients of the food item and performs the analysis based on the food ingredients dataset. The matrix for checking compatibility of ingredient combinations is also used. Nutritional requirements for an individual are calculated from the daily calorie consumption.

5 Results and Discussions

The accuracy of the classification model depends on the size of the training dataset. As the size of the training dataset is increased, the accuracy of the classification model increases. This is because the separation between the different classes becomes more visible. Therefore, sufficient images of each food item are required in each category (fresh, medium, and stale). The same holds for the oil samples, i.e., sufficient images, as well as pH values of oil samples, are required in each rancidity level.

6 Conclusion

The proposed system will prove useful in ensuring a good quality of food and oils before consumption. It would help prevent health-related problems due to the consumption of stale or low-quality food and the consumption of food cooked in rancid oils. The nutritional analysis feature would allow the system users to enter the dishes that they are consuming daily and inform them about these dishes' nutritional value. The users would thus be able to keep track of their daily nutritional intake. Users would also find out their ideal daily calorie consumption and ideal daily nutritional intake according to the calories consumed. Thus, the application would also act as a means of ensuring a healthy and balanced diet, which would ensure adequate immunity levels and resistance to diseases, thereby incorporating a healthy lifestyle.

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