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FOOD RECOGNITION AND NUTRITION FACTS DETERMINATION WITH DEEP CONVOLUTION NEURAL NETWORK MODELS

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ABSTRACT
Food recognition plays a crucial role in various domains including healthcare, nutrition, and the food industry. In healthcare, food recognition is valuable for individuals to monitor their daily food intake and manage their diet effectively. It also aids dietitians and nutritionists in creating personalized meal plans for patients based on their nutritional requirements and preferences. The objective of this research was to develop software capable of recognizing and predicting the nutritional information of commonly consumed fruits and vegetables in Turkey. Basic nutrition data for each food item was collected and organized. A dataset comprising 9,000 food images was gathered, encompassing 200 images for each food item. To train the images, deep learning (DL) algorithms such as GoogleNet, ResNet-50, and Inception-v3 were utilized on platforms like Matlab and .NET Core. Additionally, 900 food images were reserved for external validation purposes. The DL algorithms achieved excellent accuracy, with all models surpassing 98.3% accuracy in predicting food categories. Notably, the Inception-v3 algorithm outperformed the others, achieving an accuracy of 99.1% during the testing phase. Consequently, the Inception-v3 algorithm was chosen to develop software for food recognition and nutrition analysis, intended for both computers and smartphones. The software can be relied upon for food recognition and nutrition analysis, making it highly valuable in healthcare, particularly in tracking the dietary intake of patients with chronic conditions like diabetes, heart disease, or obesity. The system can effectively track the types and quantities of foods consumed, providing personalized feedback to both patients and healthcare providers.

1.Introduction

Maintaining a healthy diet is crucial for good health and can help prevent various chronic noncommunicable diseases such as heart disease, diabetes, and cancer (Ruthsatz and Candeias, 2020). Across the world, there has been an increased awareness of healthy eating, which includes the tracking of calories and nutrition information, by consumers (Miller and Cassady, 2015; Shao et al., 2023). The accurate prediction and tracking of dietary calorie and nutrient consumption are important for assessing the effectiveness of weight loss interventions and for maintaining a healthy lifestyle (Sawamoto et al., 2017). In order to make informed decisions about what we eat, it is necessary to know the attributes, nutritional facts, and calorie content of food products. This knowledge is also essential for checking the quality and safety of food products for consumers worldwide (Miller and Cassady, 2015; Khan et al., 2021; Khan, 2022; Khan et al., 2022).Detecting food quality and attributes is commonly done using modern techniques such as electronic noses (Seesaard et al., 2022), computer vision (Tarlak et al., 2016a; Tarlak et al., 2016b), and spectroscopy (Habibi and Khosravi-Darani, 2017). However, there is a practical demand for a fast, easy, accurate, and automatic way to detect food quality and attributes in daily life. To address this, pattern recognition and image processing methods have been applied to automatically classify and distinguish food items, resulting in the development of more accurate and effective food intake reporting systems (Allegra et al., 2020; Jiang et al., 2020). These systems use databases showing nutrition facts and calories of the food products to produce daily food consumption reports, but first, it is necessary to identify and classify the consumed food product. Classifying food product images is considered challenging due to numerous parameters such as the identification of multiple food classes within a single plate or the variance of food texture for the same type (Yang et al., 2010; Boushey et al., 2017).

Image analysis of food products can be broken down into four main phases: food detection, classification, weight determination, and nutrition analysis. Advances in image processing, object detection, and machine learning, particularly in the use of convolutional neural networks (CNNs), have significantly improved the accuracy of image identification and recognition. As a result, there has been growing interest in using image analysis for food products.

In recent years, CNNs have been increasingly used for food recognition purposes, outperforming traditional machine learning approaches. For example, in one study, the authors modified the structure of the AlexNet model (Bossard et al., 2014) and created a deep CNN that greatly improved the prediction performance on the Food-101 dataset (Krizhevsky et al., 2012). In another study conducted by Kawano and Yanai (2014), the authors used a CNN on a dataset of 10 food classes and achieved a detection accuracy of 73.7%. Kawano and Yanai (2014) have also used convolutional neural net for food recognition and identification, the dataset which was in their work was comprised of 10 food classes. The results showed the great performance of convolutional neural net in contrast with other traditional techniques by giving a detection accuracy of 73.7%. Kawano and Yanai (2015) have retrained the AlexNet model with two different datasets, namely UEC-FOOD-100 and UEC-FOOD-256. In their work, they got maximum accuracy 78.8% for UEC-FOOD-100 dataset and 67.6% for UEC-FOOD-256. These findings suggest that convolutional neural networks offer superior predictive abilities compared to conventional machine learning methods (Subhi and Ali, 2018; Shirmard et al., 2022).

The main objective of this research was to create software utilizing deep learning (DL) algorithms, specifically GoogleNet, ResNet-50, and Inception-v3, in in Matlab and .NET Core platforms. The software is intended to be used for the identification of fruits and vegetables commonly found in Turkey, as well as predicting their nutritional information.

2. Materials and methods

This work comprises of five key steps (as shown in Fig. 1): i) acquisition of food images and image augmentation, ii) collection of nutrition facts, iii) implementation of deep learning algorithms for training the food images, iv) development of Matlab and .NET Core software and v) validation and assessment of software outcomes. The following subsections provide comprehensive details regarding each of these steps.

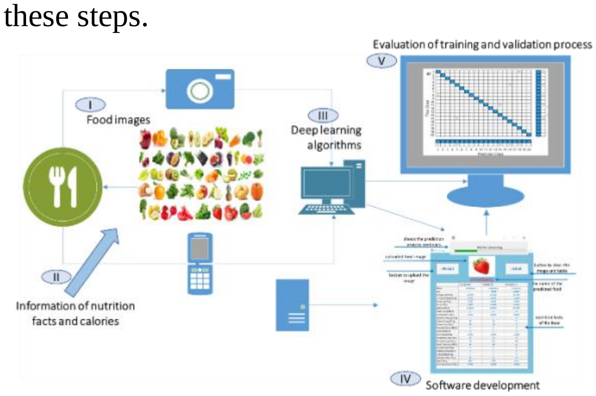

Figure 1. Steps followed to develop prediction software.

2.1. Food images

In Turkey, a variety of fruits and vegetables are commonly consumed such as apple, apricot, artichoke, avocado, banana, beet, broccoli, carrot, celery, cherry, cucumber, damson, dill, eggplant, fig, grape, grapefruit, green beans, green pepper, green plum, kiwi, leek, lettuce, mandarin, melon, mint, okra, onion, orange, parsley, pea, peach, pear, pineapple, potatoes, pumpkin, purslane, quince, radish, red pepper, spinach, strawberry, tomatoes, watermelon, and zucchini. These images were randomly obtained from internet sources using the food names as keywords in the Google search engine. The class number of these forty-five food products were shown in Table S1, supplementary information.
Image augmentation is a technique used in computer vision and deep learning to artificially increase the size of a training dataset by applying transformations to existing images. These transformations can include rotations, translations, flips, zooms, shears, and colour adjustments. By applying these transformations, new variations of the existing images can be created, which can help to improve the robustness and generalization ability of a machine learning model. This is especially useful when the size of the training dataset is small or when the model is prone to overfitting. By applying random transformations to the images during training, the model is exposed to a wider range of variations and is forced to learn more robust features. This can help to prevent overfitting and improve the model's performance on unseen data. In this work, image augmentation technique was randomly applied using rotations, translations, flips, zooms and colour adjustments, which the number of original images was to be four-fold.

To develop the software, original 50 food images were collected for each of the 45 food products and applied to be four-fold image augmentation, resulting in a total of 9,000 images. A sample of the food images used can be seen in Fig. 2.

Figure 2. Sample images used to develop prediction software for foods and nutrition facts.

2.2. Nutrition facts and calories

The nutritional values and calorie content of the food products were obtained from the Fatsecret food nutrition database (https://www.fatsecret.com/calories-nutrition/). By writing the food name, searching was done. Energy (kcal/100 g), carbohydrate (g/100 g), protein (g/100 g), fat (g/100 g), water (g/100 g), total fiber (g/100 g), soluble fiber (/100 g), insoluble fiber (g/100 g), vitamin c (mg/100 g), calcium (mg/100 g), phytosterols (mg/100 g), starch (g/100 g), fructose (g/100 g), phosphorus (mg/100 g), potassium (mg/100 g), total folate (mcg/100 g), carotene (mg/100 g), vitamin a (mcg/100 g), sodium (mg/100 g), glycemic index (-), orac (-), antioxidant (mmol/100 g) were gathered. For each of the forty-five food categories, the fundamental nutrition values were collected.

2.3. Deep learning algorithms

Deep learning is a type of machine learning algorithms that enables computers to learn and perform tasks by using artificial neural networks to extract meaningful features from data (Alzubi et al., 2018). These networks are composed of interconnected processing layers, which use simple elements to perform complex computations in parallel, much like the biological nervous system (Prieto et al., 2016). By training on large amounts of data, deep learning models can achieve high levels of accuracy in tasks such as object recognition, often surpassing human performance. In this study, three deep learning algorithms, GoogleNet, ResNet-50 and Inception-v3, were utilized in the Matlab software's deep learning toolbox to train food images. These algorithms have 22, 50, and 48 layers, respectively. Main components of these learning structures were shown in Fig. 3.

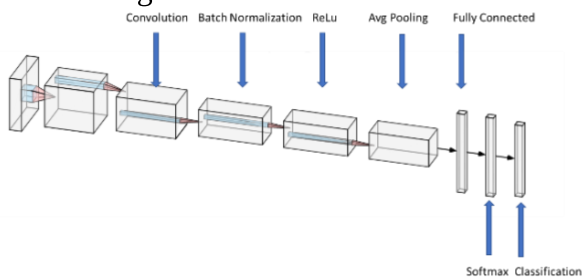

Figure 3. Main components of used deep learning structures.

2.4. Software development

The aim of developing the software was to recognize the commonly consumed vegetables and fruits in Turkey and predict their nutritional information and calorie content. The Matlab software interface for the computers is illustrated in Figure 4 and is available for download at https://static.gedik.edu.tr/article/Tarlak_et_al_2023.rar. A tutorial video demonstrating how to use the software is also provided at the same location. Additionally, NET Core software for the smart phones is available for download at https://food.gedik.edu.tr/.

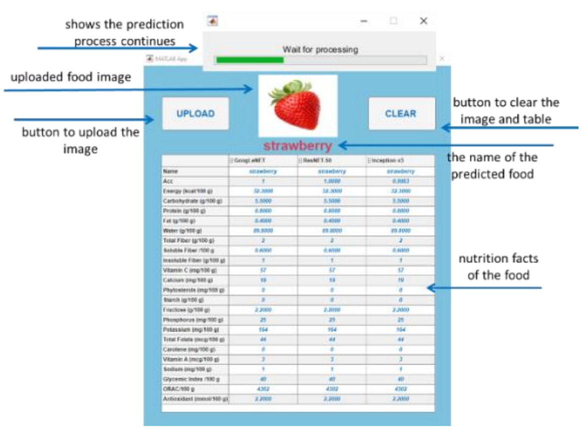

Figure 4. Main components of used deep learning structures.

2.5. Evaluation of training and validation process

To train the recognition software, a total of nine-thousand food images were collected, comprising two-hundred images for each of the forty-five food categories. To validate the performance of the software, twenty additional food product images were gathered, which is different from the ones that are used for training purpose and resulting in a total of nine-hundred images used for validation purposes.

When it comes to classification problems, the performance of a classifier is often assessed based on the confusion matrix that corresponds to the classifier. Furthermore, it is possible to calculate several metrics, such as Average accuracy, Error rate, Precision, Recall, and Fscore using equations (1), (2), (3), (4), and (5) respectively (Sokolova and Lapalme, 2009), based on the values in the matrix.

$$Average\ accuracy = \frac{\left(\sum_{i=1}^{l} \frac{tp_i + tn_i}{tp_i + fn_i + fp_i + tn_i}\right)}{l} \quad (1)$$

$$Error\ rate = \left(\sum_{i=1}^{l} \frac{fp_i + fn_i}{tp_i + fn_i + fp_i + tn_i}\right)/l \quad (2)$$

$$Precision = \left(\sum_{i=1}^{l} \frac{tp_i}{tp_i + fp_i}\right)/l \quad (3)$$

$$Recall = \left(\sum_{i=1}^{l} \frac{tp_i}{tp_i + fn_i}\right)/l \quad (4)$$

$$Fscore = \sum_{i=1}^{l} \frac{(\beta^2 + 1) \times Precision \times Recall}{\beta^2 \times Precision + Recall} \quad (5)$$

where tp_i is the number true positive class, tn_i is the number true negative class, fp_i is the number false positive class, fn_i is the number false negative class, l is the number of evaluated class.

3.Results and discussions

The deep learning algorithms, GoogleNet, ResNet-50, and Inception-v3, which have 22, 50, and 48 layers respectively, were used to train the food images in the Matlab software. The training process involved a variety of commonly consumed fruits and vegetables such as apple, apricot, artichoke, avocado, banana, beet, broccoli, carrot, celery, cherry, cucumber, damson, dill, eggplant, fig, grape, grapefruit, green beans, green pepper, green plum, kiwi, leek, lettuce, mandarin, melon, mint, okra, onion, orange, parsley, pea, peach, pear, pineapple, potatoes, pumpkin, purslane, quince, radish, red pepper, spinach, strawberry, tomatoes, watermelon, and zucchini. A total of nine-thousand food images were used for training, with two-hundred different food products for the whole food category.

In the field of machine learning, particularly in the area of statistical classification, a confusion matrix, also referred to as an error matrix, is a visual representation that shows the performance of an algorithm, usually a supervised learning algorithm. The matrix has two dimensions, "actual" and "predicted", with each row representing the instances in an actual class and each column representing the instances in a predicted class. In this study, the confusion matrix was utilized to evaluate the training process of the GoogleNet, ResNet-50, and Inception-v3. The matrix was presented in Figures S1-S3, supplementary information, where blue markers represent true predictions and other colours indicate the number of errors for each specific class.

The class codes were assigned to the food products alphabetically, where apple, bagel, carrot, cucumber, egg, eggplant, fermented sausage, grape, green pepper, honey, mint, olive, omelette, parsley, peach, potato, tea, tomato, white cheese, and zucchini were assigned codes 1 to 45, respectively. The GoogleNet produced 221 error predictions during the training process, while ResNet-50 and Inception-v3 produced 15 and 8 false predictions out of 9000 samples, respectively. These results showed that ResNet-50 and Inception-v3 gave better performance than GoogleNet for training process (Figures S1-S3).

Table 1 presents the statistical evaluation metrics used in this study, including average accuracy, error rate, precision, recall, and Fscore. The results indicate that the average accuracy of GoogleNet, ResNet-50, and Inception-v3 were 99.891%, 99.992%, and 99.996%, respectively. These findings suggested that the Inception-v3 performed better than GoogleNet and ResNet-50 in the training process. Other statistical metrics, such as error rate, precision, recall, and Fscore, further support the conclusion that the Inception-v3 outperformed GoogleNet and ResNet-50 in terms of accuracy and training capability.

Table 1. Statistical evaluation for the training process.

Network	Average accuracy	Error rate	Precision	Recall	Fscore
N-1	99.89124	0.108763	97.64822	97.61038	97.6293
N-2	99.9923	0.007695	99.83078	99.82955	99.83016
N-3	99.9959	0.004104	99.91009	99.90909	99.90959

*N1: GoogleNet, N-2: ResNet-50, N-3: Inception-v3

To evaluate the validation process of the GoogleNet, ResNet-50, and Inception-v3, a confusion matrix was generated and is presented in Figures 5-7. The blue markers in Figures represent true predictions, whereas the other colours indicate the number of errors for each specific class. The false prediction numbers were 338, 213 and 204 out of 900 samples (when considered all food products in testing process) for GoogleNet, ResNet-50, and Inception-v3, respectively, indicating that Inception-v3 was the most accurate network in order to recognise food products and their nutritional values.

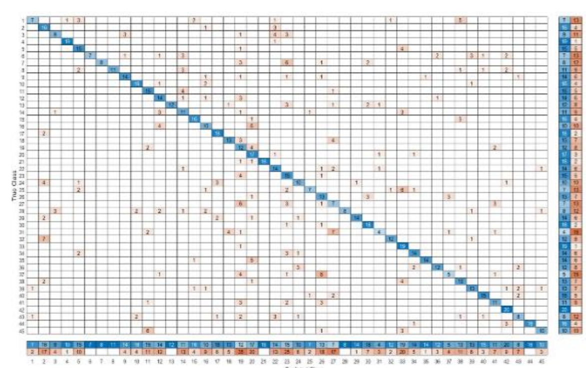

Figure 5. Confusion matrix for testing process of GoogleNet.

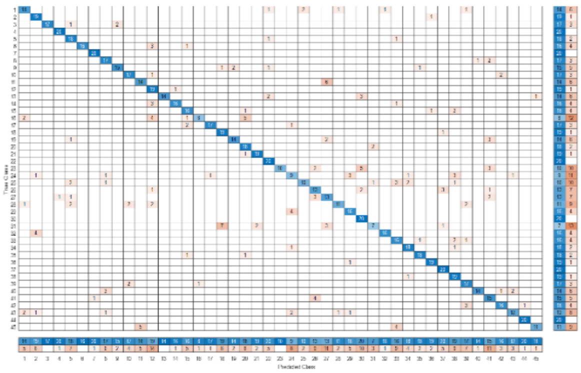

Figure 6. Confusion matrix for testing process of ResNet-50.

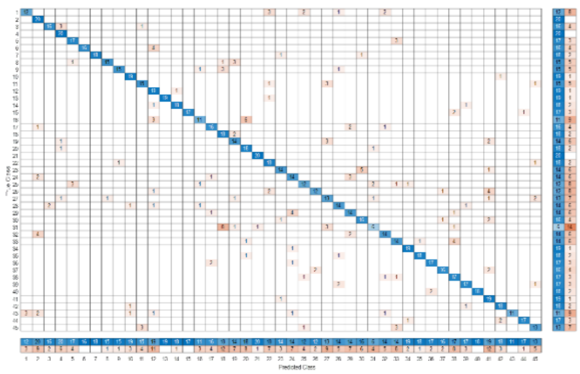

Figure 7. Confusion matrix for testing process of Inception-v3.

Table 2 summarizes the statistical evaluation metrics, such as average accuracy, error rate, precision, recall, and Fscore. The GoogleNet and ResNet-50 respectively achieved an average accuracy of 98.36% and 99.03% and an error rate of 1.64%, and 0.97%, whereas the Inception-v3 had average accuracy of 99.07% with error rate of 0.93%. These findings indicate that in the validation process, the Inception-v3 provided superior prediction performance compared to the GoogleNet and ResNet-50. Although there were slight variations in precision, recall, and Fscore between the ResNet-50 and Inception-v3, the Inception-v3 achieved the highest values of 80.40%, 79.09%, and 79.74%, respectively, suggesting that it was the most efficient network for the validation process.

Table 2. Statistical evaluation for the training process.

Network*	Average accuracy	Error rate	Precision	Recall	Fscore
N-1	99.89124	0.108763	97.64822	97.61038	97.6293
N-2	99.9923	0.007695	99.83078	99.82955	99.83016
N-3	99.9959	0.004104	99.91009	99.90909	99.90959

*N1: GoogleNet, N-2: ResNet-50, N-3: Inception-v3

A comparison between the current research and previously published works is summarized in Table 3. The results indicate that the number of food product categories utilized in the published works is fewer when compared to the number of food categories included in this study. Nevertheless, the deep learning (DL) algorithms implemented in this research demonstrated exceptional accuracy, as all models surpassed a 98.3% accuracy rate in accurately predicting food categories.

Table 3. Comparison of food recognition works published.

Source	Dataset	#Category	Accuracy
Ege et al. (2017)	Web image mining	15	80.60%
Subhi and Ali (2018)	Malaysian foods	11	74.70%
Jeny et al. (2019)	Bangladeshi foods	6	98.16%
Razali et al. (2021)	Sabahan foods	11	94.01%
Nadeem et al. (2023)	Junk food and fizzy drinks	14	80.10%

The outcomes of the training and validation process, including the confusion matrices and statistical evaluation metrics, consistently showed that Inception-v3 was the most effective deep convolutional neural network. When considering elapsed time of training process of the deep learning algorithms, the elapsed time may vary depending on the computer used. On a computer with an Intel(R) core(TM) i5-1035G1 CPU @ 1.00 GHz 1.19, GoogleNet, ResNet-50, and Inception-v3 took 113 minutes, 683 minutes and 666 minutes, respectively for the first 400 iterations, showing that GoogleNet was the fastest algorithm for training process (Fig. 8). The deep learning toolbox in the Matlab software indicates that the size of GoogleNet, ResNet-50, and Inception-v3 are 27.0 MB, 96 MB, and 89 MB, respectively. This difference may be attributed to their complexity and network size, which means that GoogleNet is more advantageous in terms of training time if the classification process is not too complex. However, regarding learning durations for the whole training images in this work, GoogleNet, ResNet-50, and Inception-v3 require 990 minutes, 275 minutes and 241 minutes, respectively. These results indicated that Inception-v3 were the best deep learning algorithm from accurate and fast processing perspective.

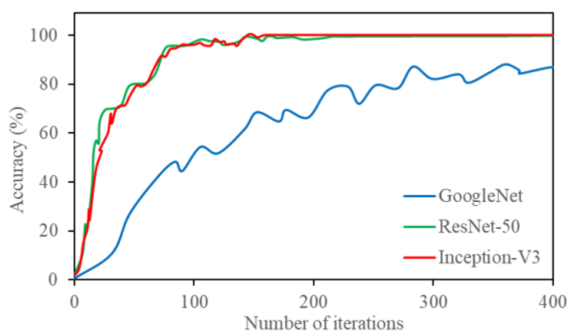

Figure 8. Accuracy of the deep learning algorithms for training process by iteration.

4. Conclusions

The automatic recognition of food in images has numerous practical applications, particularly in the field of nutrition and dietetics where it can be used for nutritional tracking. The main objective of this project was to develop software capable of recognizing food products and predicting their nutritional information. To achieve this goal, a selection of commonly consumed fruits and vegetables in Turkey were used, and their nutritional data was collected. The images were then trained and validated using three deep learning algorithms - GoogleNet, ResNet-50, and Inception-v3 - in Matlab and .NET Core platforms. The Inception-v3 algorithm was found to be the most effective for food recognition. The developed software can be reliable for fast and accurate food recognition and nutritional analysis and has significant potential for use in the nutrition and dietetics field.

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