Analyzing the Nutritional Content of Packed Foods using Smart phone Camera/Computer vision and Machine Learning - A Comprehensive review

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Abstract

The increasing demand for healthy and convenient food options has led to a rise in the use of technology for analyzing the nutritional content of packed foods. In this comprehensive review, we explore the application of smart phone camera/computer vision and machine learning in this domain. We delve into the challenges faced in analyzing nutritional content and the limitations of traditional methods. The potential benefits of using smart phone cameras/computer vision and machine learning are discussed, including the ease of use and accessibility to a wide range of consumers. We examine various studies that have implemented these technologies for nutritional analysis and evaluate their effectiveness. The potential for future developments and improvements in the field is also considered. By leveraging the power of technology, we can gain deeper insights into the nutritional content of packed foods, leading to more informed consumer choices and improved public health outcomes. This review aims to provide a comprehensive overview of the current state of the art and stimulate further research in this exciting and rapidly evolving field.

Keywords: Nutrition Analysis, Packed Foods, Smartphone Cameras, Convolutional Neural Networks, Nutrition Labels, and Machine Learning

1 Introduction

Recently, smart phone cameras have been employed with machine learning and computer vision techniques to examine the nutritional value of packaged foods. This approach offers a practical solution for people to track their dietary intake and make informed decisions about their nutrition. The fact that there are 285 million individuals globally who suffer from visual impairment, including 19 million children under the age of 14 [1], underscores the need for accessible nutritional information. Visual impairments in children may result from nutritional deficiencies, birth defects, and infections, which can impede their growth and development. To accomplish daily tasks such as object recognition and navigation, visually impaired individuals rely on assistive systems [2].Therefore, utilizing machine learning and computer vision techniques to analyze the nutritional content of packed foods can have a significant impact on the accessibility of nutrition information for visually impaired individuals.

The reviewed studies demonstrate the potential of these approaches in accurately recognizing and segmenting nutrition labels from images captured by smart phone cameras and predicting the nutritional content of packed foods. However, challenges such as improving prediction accuracy, dealing with varying lighting conditions, and expanding the number of recognized food categories need to be addressed. The use of machine learning and computer vision in analyzing the nutritional content of packed foods has the potential to revolutionize the field of nutrition and healthcare by providing personalized and accessible dietary guidance. This comprehensive review article aims to provide an overview of the current state-of-the-art in this field, identify challenges, and suggest future research directions to improve accuracy and reliability. By improving the accessibility of nutritional information, machine learning and computer vision techniques have the potential to improve the health and well-being of individuals globally, particularly those with visual impairments.

2 Methodology

This review article critically examines the application of machine learning, computer vision, and smart phone cameras for analyzing the nutritional content of packaged foods. It includes an extensive literature review of existing methodologies and techniques from academic databases such as Scopus, Web of Science, IEEE Xplore, and PubMed, including relevant studies from publishers such as Elsevier, Wiley, Springer, and Hindawi. The review focuses on food recognition, volume estimation, and ingredient detection and draws from 31 relevant reviewed studies out of more than 124 studies referred to. The article highlights the potential of these technologies for providing personalized dietary guidance but also identifies significant challenges, such as improving accuracy and addressing varying lighting conditions.
The Literature review of the nutritional content of packed foods using smart phone camera/computer vision and machine learning study is given below.

2.1 Literature review

Shen et al. [3] introduced an industrial food application designed to assist individuals in achieving a balanced diet by measuring the food attributes. The application employs Convolutional Neural Networks (CNN) for food recognition, enabling it to detect and identify food items in an image. By transferring data from the internet, the system can evaluate food properties accurately. The Inception-v3 and Inception-v4 models were used in the study as they are based on CNN and are considered more reliable in addressing the problem.

Onu et al. [4] employed AI models to forecast low moisture content in drying potatoes. Three models were used in the study, namely the Response Surface Methodology (RSM), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and Artificial Neural Network (ANN). Although all three models gave good predictions with the experimental data, RSM and ANFIS demonstrated better results than ANN.

In another study, [5], researchers developed a system that utilized image processing techniques in combination with a Support Vector Machine (SVM) classifier to classify healthy and diseased rice plants. The system achieved a resolution rate of over 90%. Similarly, in [6], researchers proposed a network structure for classifying potato leaf diseases based on Convolutional Neural Networks (CNN). The architecture comprised 14 layers and demonstrated an average overall test accuracy of 98%.

In reference [7], a Convolutional Neural Network (CNN) built on the pre-existing AlexNet network was utilized to recognize apple leaf diseases, resulting in an accuracy rate of 97.62%. Similarly, in reference [8], a framework for fruit harvesting robots was introduced, which included three classification models based on CNN with fine-tuning and transfer learning on pre-trained models. These models displayed high accuracy rates of 99.01%, 97.25%, and 98.59% for instant classification of fruit images depending on their type, ripeness, and harvest decision.

Researchers in [9] utilized deep Convolutional Neural Networks (CNN) to differentiate between healthy and damaged date fruits, achieving an overall classification accuracy of 96.98%. Meanwhile, [10] employed a modified AlexNet model to detect food defects and compared the performance of three algorithms. The study achieved a recognition rate of 92.50% for apple detection, which outperformed the commonly used Back-propagation Neural Network (BPNN), Support Vector Machine (SVM), and Particle Swarm Optimization (PSO) algorithms.

A mobile application for automatic food detection was proposed by Silva et al. in [11], utilizing a quadratic Support Vector Machine (SVM) on an expanded database comprising 60 food classes. Their SVM classifier, which used color, histogram of oriented gradients (HOG), modified local binary patterns (LBP), Gabor, and speeded-up robust features (SURF), performed better than the standard model on a validation Food-101 dataset. Furthermore, by utilizing Deep Learning (DL)-based features, an overall performance of 87.2% was attained.

Tiankaew et al. [12] and Park et al. [13] created deep CNN models for detecting food images, achieving test accuracies of 82% and 91.3%, respectively. However, these models have limited detection capabilities to a specific number of food categories. On the other hand, Tomescu et al. [14] estimated food volume by utilizing 3D modeling from smart phone images, which produced reliable and accurate results, with only a slight overestimation of 0-10%.

Mezgec and Seljak [15] proposed a model called "NutriNet," which was fine-tuned on a dataset of 225,953 images consisting of 520 categories of food and drinks. The model achieved a top-5 accuracy of 55% on real images taken with a mobile phone. However, the authors did not perform segmentation, which makes image recognition challenging in the presence of irrelevant items in the image. In contrast, Freitas, Cordeiro, and Macario [16] developed a segmentation approach using a region-based convolutional neural network (RCNN) to classify Brazilian food types. Their CNN-based segmentation model was integrated into a mobile application, achieving an intersection over the union (IoU) accuracy of 0.70 in their segmentation analysis.

According to the systematic review conducted by Amugongo et al. [17], most mobile computer vision-based solutions for food recognition, volume estimation, and calorific estimation do not differentiate between food and non-food, and only one application provided explanations for classification. While these applications have potential in healthcare, it is important to improve trust by providing clear explanations for their estimations.

Sanaeifar et al. [18] utilized dielectric spectroscopy and a computer vision system to assess the quality of virgin olive oil in a non-destructive manner. They employed the correlation-based feature selection (CFS) method to extract dielectric and color features and reduce input data dimension. The researchers selected the classifier model using ANN, SVM, and Bayesian networks (BN) and predicted six parameters, including peroxide value, p-Anisidine value, total oxidation value, modeling free acidity, UV absorbance at 232 nm and 268 nm, chlorophyll, and carotenoid, as quality indices of virgin olive oil. The BN model showed superior performance with 100% accuracy, outperforming the ANN and SVM models.

By utilizing the inception V3 pre-trained model and the food-11 dataset containing 11 categories of food, the authors of [19] were able to achieve an accuracy rate of 92.86%. The proposed approach was further tested on 20 and 25 food categories, achieving accuracy rates of 97.00% and 96.52%, respectively. Additionally, the method incorporates web scraping to provide relevant information about the recognized food item.

The authors conducted a classification task on Bengali food images, employing transfer learning with the VGG16 model. Their approach achieved high levels of accuracy and F1 score, both reaching 98%. Additionally, they proposed a new approach utilizing the inception V3 model for transfer learning, which achieved an accuracy of 97% and an F1 score of 0.99867. This approach was tested on nearly three times the number of classes, demonstrating its scalability and ability to produce precise results. Overall, the proposed model is more practical for real-world implementation, particularly in the analysis of diverse data.

The authors of study [21] chose a more sophisticated approach by incorporating Natural Language Processing (NLP) into their analysis. This was necessary because the data they gathered from multiple online sources was generic in nature. To address this issue, they developed a methodology where only the most trustworthy websites were used for data extraction, ensuring high-quality data. By doing so, they were able to obtain very specific data while maintaining data integrity.

The study by Davies et al. [22] involved the development of a machine-learning approach for predicting fiber content in packaged food products using nutrient information. They trained and tested their model on an Australian dataset of packaged foods, utilizing the k-nearest neighbor algorithm. Their machine learning model outperformed a manual fiber prediction approach, achieving a higher R2 value of 0.84 compared to 0.68. This suggests the potential for machine learning to efficiently and accurately predict fiber content in packaged products on a large scale.

In their study, Ismail and Yuan [23] employed a deep multi-label learning approach to visually recognize different food ingredients. They evaluated various state-of-the-art neural networks and determined that the Xception encoder combined with a global average-pooling-based decoding scheme performed the best. This approach achieved a mean average precision score of 78.4% on the Nutrition5K dataset.

In their work [24], PRENetis utilized as a self-attention mechanism and a progressive training strategy to learn multi-scale features for visual food recognition. While attention-based networks have shown promising results for this task by contextualizing and dynamically prioritizing information, their full potential has not yet been fully explored for recognizing food ingredients and multiple food items.

The Dietary Intake and Exposure Task Force of the International Life Sciences Institute (ILSI) Europe evaluated 43 technology-based dietary assessment tools between 2011 and 2017 and proposed quality standards for future applications. Their analysis revealed that the majority of tools relied on self-reported dietary intakes (79%) and text entry (91%). Only 65% of the tools had integrated databases for estimating energy or nutrients, and less than 50% contained customization features. Most tools reported usability and validity, with a percentage of 77%.

The researchers Fakhrou et al. [26] created a food recognition app for visually impaired children that runs on smart phones. They utilized an ensemble of deep CNN models with soft voting to enhance food recognition accuracy. Their customized food dataset included 29 different types of food and fruits. The ensemble model outperformed current state-of-the-art CNN models, achieving an accuracy of 95.55%. The app delivers real-time predictions on devices with capable hardware. The researchers plan to expand the app to multiple platforms and develop a model capable of detecting multiple food items simultaneously.

In their research, Pandey et al. [27] presented EnsembleNet, which combines three distinct CNN models for food image classification. They first fine-tuned three separate CNN models (pre-trained GoogleNet, pre-trained AlexNet, and pre-trained Residual neural Network) on the food dataset. The output of the three models was then fused together to improve food classification performance.Meanwhile, Foresti et al. [28] proposed a wide slice residual network (WISeR) for food recognition. This deep CNN architecture includes two distinct branches: a residual network and a slice network.

Kayikei et al. [29] introduced a mobile application that uses a pre-trained Inception V3 model, fine-tuned on the Food 24 dataset, for recognizing Turkish food dishes. They also evaluated the performance of various pre-trained CNN models, including InceptionV3, InceptionResNetV2, ResNet50, and Xception, for the food classification task. Results showed that Inception V3 outperformed all the other pre-trained CNN models on the Food 24 dataset.

Kong et al. [30] utilized a perspective distance algorithm with three captured views of food objects and segmented them by clustering the features of each one. The segmentation accuracy was tested on images containing 1–5 objects and achieved a 100% success rate for one type of food in the image and a 76% success rate when five food items were included. In another study [31], users were asked to draw a bounding box and select a proper food tag from an available list, and the food was automatically segmented using the GrabCut technique. The semi-automatic segmentation tool has been found effective when used on a large image dataset; however, it still requires user intervention. In table 1, the summary table of a few literature reviews is given,

Table 1. Summary table of the literature review

Reference	Approach	Result/Advantages	Limitations
[6]	CNN-based network structure to classify potato leaf diseases	High overall test accuracy of 98% in classifying potato leaf diseases using CNN network structure.	Limited to potato leaf disease classification
[9]	Deep CNN to distinguish healthy and damaged date fruits	The successful distinction between healthy and damaged date fruits using deep CNN with an overall rating accuracy of 96.98%.	Limited to-date fruit classification
[10]	Modified AlexNet model to detect food defects	Successful detection of food defects using a modified AlexNet model with a recognition rate of 92.50%.	Limited to food defect detection
[11]	Interactive mobile application for automatic food detection	Successful automatic food detection using an interactive mobile application with an overall performance of 87.2%.	Limited to mobile platform
[12] and [13]	Deep CNN models for food image detection	Successful food image detection using deep CNN models with test accuracies of 82% and 91.3%, respectively.	Limited to food image detection
[14]	3D modeling from smartphone images to estimate food volume	Successful estimation of food volume using 3D modeling from smart phone images with accurate and reliable results.	Limited to food volume estimation
[15]	NutriNet model fine-tuned on a dataset of food and drink images	Successful classification of food and drink images with 520 categories using the NutriNet model fine-tuned on a dataset of 225,953 images achieving a top-5 accuracy of	Did not perform segmentation

		55% on mobile phone images.	
[16]	Segmentation approach using RCNN for Brazilian food types	Successful segmentation of Brazilian food types using RCNN with an IoU accuracy of 0.70.	Limited to Brazilian food types
[18]	Non-destructive method to the assess quality of virgin olive oil using dielectric spectroscopy and computer vision	Successful assessment of the quality of virgin olive oil using a non-destructive method with Bayesian networks achieving 100% accuracy.	Limited to virgin olive oil quality assessment
[19]	The approach achieved high accuracy on food datasets using a pre-trained Inception V3 model	Successful classification of food items with high accuracy rates using the Inception V3 pre-trained model with web scraping used to provide food details.	Dependent on web scraping for food details
[20]	Transfer learning with VGG16 and Inception V3 models for Bengali food images	Transfer learning with VGG16 and Inception V3 achieved high accuracy on Bengali food images, making it practical for real-world implementation.	Limited to Bengali food images
[21]	NLP-based approach to extract specific data from trusted websites	NLP was used to extract specific data from trusted websites while maintaining their integrity.	Limited to specific data extraction
[22]	Machine learning to predict fiber content in packaged products	Machine learning was utilized to predict fiber content in packaged products with higher accuracy than manual prediction.	Limited to fiber content prediction
[26]	Smartphone-based food recognition app for visually impaired children	Smartphone-based food recognition app for visually impaired children achieved high accuracy.	Limited to a specific user group

3 Result and Discussion

In Table 2. Some of the existing methods of Nutritional Analysis Applications using Computer Vision and Machine Learning with its accuracy are shown,

Table 2. Nutritional Analysis Applications using Computer Vision and Machine Learning

Application	Method	Key Findings	Accuracy
[6]	CNN network structure	Classification of potato leaf diseases	98%
[9]	Deep CNN	Distinguishing between healthy and damaged date fruits	96.98%
[10]	Modified AlexNet model	Detection of food defects	92.50%
[11]	Interactive mobile application	Automatic food detection	87.2%
[12]	Deep CNN models	Food image detection	82%
[13]	Deep CNN models	Food image detection	91.3%
[16]	Segmentation approach using RCNN	Recognition of Brazilian food types	IoU accuracy of 0.70
[18]	Non-destructive method using dielectric spectroscopy and computer vision	Assessment of the quality of virgin olive oil	Bayesian networks achieving 100% accuracy
[19]	Inception V3 pre-trained model	Accurate classification of food images	92.86% accuracy for the food-11 dataset and 97.00% accuracy for 20 and 25 categories
[20]	Transfer learning with VGG16 and Inception V3 models	High accuracy rates on Bengali food images	98% and 97%, respectively

This study provide insight into the different methods used for recognizing and classifying food items, estimating food attributes, and assessing the quality of food products. Researchers have utilized various deep learning models, such as convolutional neural networks, pre-trained models, Bayesian networks, and self-attention mechanisms, for food recognition and assessment. Numerous studies have reported high accuracy rates, with some utilizing pre-trained models, such as Inception V3 and VGG16, for transfer learning. Smartphone-based apps have also been developed for visually impaired children and Turkish food recognition, showcasing the potential for accessibility and widespread use. Despite the reported success, limitations in distinguishing between food and non-food items and providing explanations for estimations have been identified. Hence, the article emphasizes the need for further research and improvement to enhance the accuracy and efficiency of these models and address their limitations. NLP techniques have been employed to extract specific data from trusted websites, maintaining their integrity, and showing promising results in predicting food attributes accurately. Moreover, non-destructive methods, such as dielectric spectroscopy and computer vision, have been proposed for assessing food quality, achieving high accuracy rates. Integrating these techniques with mobile-based applications can provide a more user-friendly interface for food recognition and measurement. Overall, the review article provides a comprehensive overview of the recent advancements in the field of food recognition using machine learning and computer vision techniques and highlights areas for future research and improvement.

4 Conclusion

In conclusion, the utilization of machine learning and computer vision techniques in analyzing the nutritional content of packed foods using smart phone cameras has shown great potential in various studies. The reviewed studies demonstrate the effectiveness of these approaches in food recognition, volume estimation, ingredient detection, and even fiber content prediction. However, there are still challenges that need to be addressed, such as improving accuracy, dealing with varying lighting conditions, and increasing the number of food categories that can be recognized.

5 Future Scope

Future research should focus on addressing these challenges and expanding the scope of the technology to incorporate more advanced features such as real-time feedback on dietary intake, personalized nutrition recommendations, and monitoring of nutrient deficiencies. Moreover, more work should be done to incorporate additional data sources, such as user-generated content and external databases, to improve the accuracy and reliability of the predictions. Additionally, further research should be conducted to develop user-friendly applications that can be used by a wider range of users, including visually impaired individuals and those with limited access to healthcare services. Overall, the use of machine learning and computer vision in analyzing the nutritional content of packed foods has the potential to revolutionize the field of nutrition and healthcare by providing personalized and accessible dietary guidance to individuals.

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