AI Based Automatic Detection and Classification of Organic and Non-Organic Vegetables Using Image Texture Analysis

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Abstract: The increasing consumption and awareness of consuming organic vegetables has shown the requirement for accurate organic versus conventional produce inspection. The recent increase of information available and powerful techniques related to Artificial intelligence, image-based techniques like computer vision, and image texture analysis for the accurate classification of fruits or vegetables produce by image analysis has increased to reduce manually assisted quality. Hence, this paper aims to analyze recent works where AI approaches and image texture analysis were applied effectively in an image-based system to classify whether it is an organic or an organic fruit or vegetable. We survey several machine and deep learning algorithms that employ transfer learning, a combination of classifier algorithms. Finally, we will analyze the positive and negative points of the methods proposed till now with the potential research gaps and guidelines for future scope of effective, robust, expandable image analysis solutions for smart agriculture.

Keywords: Artificial Intelligence;Organic Vegetables;Non-Organic Vegetables; Image Texture Analysis;Computer Vision; Deep Learning; Smart Agriculture; Food Quality Assessment.

Introduction

Increased awareness of the importance of health for humans and consumers also increased interest in natural food, where the growth of organic food has led to the market growth of demand. Consequently, it is important to have trustworthy criteria to distinguish organic from conventionally grown vegetables. Traditional inspection requires manual process which is tiresome, subjective and cannot accommodate high processing capacity needed for massive produce inspection systems. In such scenario, smart classifying systems built using AI and visual sensing has been attracted researchers. Artificial intelligence, computer vision techniques and machine deep learning method provide more powerful way of analyzing visual patterns such as colour texture shape and surface condition of the image to reveal less obvious cues and distinctions. Amongst the models which commonly applied for food classification is Deep Learning models which have provided satisfactory classification accuracies for quality determination. Further more the recent trend has also discussed approaches such as the thermal imaging method and the hybrid machine learning-based classifier system have provided further increase in classifier performances for food grade classification [7]. Also, chemical and physical properties of foods such as content in water, total soluble solids (Brix), firm- ness, firmness of texture, pH, total organic acid content provide us important visual clues [6].

In the present study, most existing approaches have only taken images as feature alone and has not merged with multiple modal features which help improve overall prediction accuracy. This article will review researches about classification of fruit and vegetable, application of Thermal Imaging, and Deep Learning Based agricultural Inspection. In the review part, common architectural models in computer vision like VGG16, VGG19, ResNet50 and ResNet101 will also be taken into a reference. Our intention is to systematically analyse the up-to-date research, and identify a possibility to develop more effective and robust systems for organic vegetables classifier.

Related work

Automated discrimination of organic fruit from conventionally grown fruit combines three areas of research. These are image-based fruit recognition, non-destructive sensing of internal quality, and the analytical chemistry that reveals what organic cultivation changes in the fruit. This section reviews each area and compares it to the most relevant deep-learning and analytical studies.

Fruit Recognition Using Convolutional Architectures

Convolutional neural networks with transfer learning are the dominant paradigm for fruit grading and defect detection. Ismail and Malik [3] built real-time and offline inspection systems for apples and bananas, with Efficient Net reaching 99.2% accuracy for apples in offline mode. Zhu et al. [4] combined a pre-trained ResNet101 backbone with an SVM classifier for carrot appearance grading, achieving 98.17%. Buyukarikan and Ulker [5] paired CNN feature extraction with classical machine-learning classifiers to categorize physiological disorders in apples, illustrating the recurring benefit of hybrid CNN-plus-classifier pipelines, and broader surveys of deep-learning computer vision in agriculture [11] confirm that transfer learning from large pre-trained CNNs is now standard practice for small agricultural datasets. Most relevant to the present work, Mashayekhpour et al. [1] benchmarked thirteen pre-trained CNNs together with LDA, SVM, RF and MLP classifiers for organic-versus-conventional classification, reaching up to 100% on visible apple images. These studies, however, treat the problem as purely image-driven and rely on convolutional inductive biases; none incorporate transformer attention or the chemical markers that physically distinguish organic produce.

Thermal Imaging in Agriculture

Thermal imaging contains cues to the surface temperature and the internal quality that are hidden from rgb images and independent of the illumination. Vadivambal and Jayas [12] have reviewed thermal imaging applications for agriculture and the food industry and have concluded that it can be used as a non-destructive method for the evaluation of crop health and product quality. Bhole et al. [6] merged both color and texture information from matched visual and thermal images of 11 types of fruits achieving up to 100% accuracy on color images and 93.4% accuracy on thermal images by means of a Random Forest classifier. Extending this line, Mashayekhpour et al. [1] found that thermal imaging is competitive with or even superior to color images for specific products e.g. Mushrooms whereas for others e.g. Apples visual data achieve better performance. This modality specific result justified to use multimodal images and combine them as done in this work.

pH and Organic Acid Markers

The premium paid for organic fruit is, in the end, an assertion about how fruit was raised, and analytics is hard evidence of that reality. Jn and Davide [2] compared eleven organic and conventional cultivars for sugar, acid total-soluble-solids and pH attributes, and reported that in their comprehensive measurement of fruit nutritional composition, only the pH revealed statistically significant differences between systems; fruit weight and diameter were the other discriminators. Their analyses, likewise, found malic to be the acid of choice, composing nearly 100% of their analyzed organics, and fructose to predominate among the organic compounds termed sugars, congruent with the compositional profiling of apple cultivars by Wu and colleagues [13]. Cross-cultivar studies of integrated versus organically cultivated apples post-harvest [14]and of acid-, and sugar, and ph content across cultivar systems [14] conclude that most compositional features show considerable overlap between organic and conventionally farmed orchards, and that the ph of organic apples offers one of the most concrete chemical signals differentiating it from fruit grown the conventionally way

Deep learning methods

VGG16 and VGG19 are one of the most favorite deep learning architectures widely used in classification and computer vision application. They are the Convolutional Neural Network (CNN) architectures developed by the Visual Geometry Group (VGG) in Oxford University. Their CNN architecture is simple and achieved good classification accuracy and consist of 16 and 19 trainable layers, respectively that make it learn more complicated features of image.

These architectures employ small 3 x 3 convolutional filters and max-pooling layers to learn hierarchical image features.

For AI-based automatic detection and classification of organic and non-organic vegetables based on image texture analysis, VGG16 and VGG19 can find differences in texture, color, shape and surface characteristics of organic and non-organic vegetables. Unlike the non-organic vegetables which usually have uniform color and texture due to traditional planting, the texture, color, shape, and surface characteristics of organic vegetables are mostly irregular. These slight changes in visual information can be automatically learnt by VGG models without manual feature engineering. Since transfer learning can be used in VGG16 and VGG19 architectures, pre-trained models have been transferred and fine-tuned by using a dataset of organic and non-organic vegetables to speed up training time and improve classification accuracy.

Besides image pre-processing such as resizing, normalization and data augmentation can further improve the performance of the models. Even though VGG16 and VGG19 architectures requires huge computational resource because they are very parameter-hungry, they still can achieve relatively good classification performance. Thus, these architectures are widely use in benchmark deep learning architecture, quality assessment of food, smart farming and automatic classification of organic vegetables.

ResNet50 & ResNet101 are sophisticated deep models that rely on deep Residual Network and skip (residual) connections to deal with the issue of vanishing gradient in extremely deep network structures. Res Net models with already trained weights by transfer learning on other vegetable data sets can gain effective performance with the very small dataset. The use of depth and hierarchical feature extraction, on account of Res Net models, is appropriate for autonomous vegetable identification, quality appraisal of edible items and so on smart-agriculture-associated techniques Table1 compares the experiments in the previous research study carried out by others as same to this work study.

Table 1. Compares this work with the related work or previous research by other researchers

Author	Year	Architecture	Accuracy	Remarks
[1]	2026	13 pre-trained CNNs + LDA/SVM/RF/MLP (visible + thermal)	100% (apple, visible, LDA)	Closest prior work; image-only, no transformer or chemical marker
[2]	2017	Statistical (ANOVA / LSD)	—	pH the only significant organic marker (chemical, not ML)
[3]	2022	Efficient Net (transfer learning)	99.2% (apples, offline)	Healthy vs. defective grading, not organic status
[4]	2021	ResNet101 + SVM	98.17% (carrot)	Appearance quality grading

[5]	2022	CNN + ML hybrid	High (see ref.)	Apple physiological disorder classification
[6]	2020	Color–texture fusion (digital + thermal)	100% vis / 93.4% thermal	11 fruit species; classical features
[7]	2021	Vision Transformer (ViT)	SOTA on ImageNet	Pure-transformer backbone
[8]	2021	Swin Transformer	87.3% (ImageNet-1K)	Hierarchical shifted-window backbone
[9]	2022	Lightweight ViT	—	Plant disease, RGB only
[10]	2024	ViT + GAN augmentation	99.92% (Plant Village)	GAN-generated training images

Conclusions

The current review indicates the artificial intelligence and texture analysis for image feature are the excellent method to achieve automatically classify organic and non-organic vegetable. Especially for VGG, Res Net, some methods using them extracted well discriminating features, in some application area such as the temperature data and combo methods can obtained classification results from improved. On the other hand, current methods are based on the visual image data only, ignore use multimodal data sources, some of them work well in a fixed condition, some methods cannot well adapt to varied kinds of vegetables and conditions. In future, one should conduct further investigations in the classification system by means of visual image, temperature data as well as chemometric approaches in conjunction for better performance and extensibility so that can better apply to intelligent agriculture, decrease labour cost and upgrade quality control of vegetables.

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