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Deep transfer learning CNN based for classification quality of organic vegetables

Suksun Promboonruang, Thummarat Boonrod *

Digital Technology Department, Faculty of Administrative Science, Kalasin University, Nuea, Thailand

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ABSTRACT

This study introduces a system based on a Convolutional Neural Network (CNN) with deep transfer learning for classifying organic vegetables. It aims to evaluate their quality through artificial intelligence. The approach involves three key steps: collecting data, preparing data, and creating data models. Initially, the data collection phase involves gathering images of organic vegetables from packing facilities, organizing these images into training, testing, and validation datasets. In the preparation phase, image processing techniques are applied to adjust the images for training and testing, resizing each to 224 x 224 pixels. The modeling phase involves using these prepared datasets, which include 3,239 images of two types of organic vegetables, to train the model. The study tests the model's effectiveness using three CNN architectures: Inception V3, VGG16, and ResNet50. It finds that the Inception V3 model achieves the highest accuracy at 85%, VGG16 follows with 82% accuracy, and ResNet50 has the lowest accuracy at 50%. The results suggest that Inception V3 is the most effective at accurately classifying organic vegetables, while VGG16 shows some limitations in certain categories, and ResNet50 is the least effective.

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1. Introduction

In recent times, there has been a noticeable increase in individuals prioritizing their health, leading them to opt for foods that offer health benefits. Organic vegetables are becoming particularly popular due to their environmentally friendly cultivation methods and absence of chemical additives. This preference has significantly contributed to the growth of the organic vegetable market. Maintaining the quality of organic vegetables is crucial for sustaining consumer trust in these products. This trust, in turn, supports the broader growth of the organic agriculture sector (Gundala and Singh, 2021). Vegetable quality evaluations have historically depended mainly on labor-intensive and manual examinations carried out by specialists. However, as the market for organic vegetables continues to grow, it becomes clearer that improved quality categorization techniques are required. As a result, creative solutions have been sought, with deep learning Convolutional Neural Networks (CNNs) emerging as an attractive approach to tackle this problem (Mukhiddinov et al., 2022).

Deep learning CNNs, which combine deep learning and transfer learning, are powerful approaches. When working with scant amounts of labeled data, transfer learning makes use of trained models on large datasets. CNN-based transfer learning has tremendous promise for differentiating between different quality levels of organic vegetables using color images (Morshed et al., 2022).

We are using deep transfer learning and image processing to increase the classification of organic vegetable quality. Using color images as input data, we are concentrating on classifying organic veggie quality into three levels consisting of small, medium, and large sizes. This paper proposes to examine the capabilities of three training models that serve as the cornerstones of the transfer learning framework based on CNN consisting of Inception V3, VGG16, and ResNet50. The main research objective is how to accurately categorize organic veggies into six different quality classes using deep transfer learning techniques, using three models consisting of Inception V3, VGG16, and ResNet50. To fulfill the particular problem of classifying the quality of organic vegetables, we adapt and enhance these models that were created for different tasks. This paper also compares the abilities of several deep

* Corresponding Author.
Email Address: thummarat.bo@ksu.ac.th (T. Boonrod)
https://doi.org/10.21833/ijaas.2023.12.022
Corresponding author's ORCID profile:
https://orcid.org/0009-0006-6014-2803
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transfer learning models to distinguish between the three grades of organic vegetable quality based on color images.

In addition, we investigate how much the combination of deep transfer learning and image processing methods may improve the precision and durability of organic vegetable quality classification. Furthermore, we evaluate the effects of regularization of the classification layer on the functionality and generalizability of the chosen deep transfer learning models.

This paper provides a ground-breaking method in the field of deep transfer learning by building on the landmark work of Alsirhani et al. (2023) and Hidayat et al. (2022). Our goal is to deliver a game-changing response to the ongoing problem of organic vegetable quality classification. We work on sustainable and health-conscious agriculture and encourage the use of high-quality, chemical-free organic vegetables.

2. Background

The integration of artificial intelligence (AI) technology in agriculture has revolutionized product classification for enhancing efficiency and sustainability. AI-driven systems, empowered by state-of-the-art machine learning algorithms, computer vision techniques, and sensor technologies, offer substantial benefits by automating and optimizing agriculture. While previous research has applied AI in agriculture, such as crop monitoring, agricultural products prediction, and pest detection, a comprehensive examination of AI-enabled systems for agricultural product quality classification remains lacking (Khan and Afzal, 2022; Lee et al., 2022; Ali et al., 2021; Abisha and Bharathi, 2023; Chen et al., 2022; Reddy et al., 2023; Gulzar, 2023; Ezat et al., 2020). Consequently, there is a research gap in thoroughly examining the implications and benefits of AI technology in the context of agricultural product quality classification and sorting, particularly concerning efficiency, accuracy, resource optimization, and sustainability.

Vegetable quality evaluation has historically placed a significant emphasis on arbitrary manual carried out by human specialists. However, the necessity for more accurate and efficient quality classification systems has grown more obvious because of the ongoing spike in demand for organic goods. The search for novel solutions has been sparked by this urgent requirement, and deep learning, in particular Convolutional Neural Networks (CNNs), has emerged as an appealing approach to solve this problem.

Recent studies have illuminated the potential of deep learning methods, particularly CNNs, to revolutionize the classification of the quality of organic vegetable images. This paper has made significant contributions to our understanding of the capabilities of CNN-based techniques, demonstrating their capacity to classify organic vegetables efficiently and effectively according to quality parameters.

Research gap and contribution: Despite these developments, previous research has mostly concentrated on aspects relating to crops, ignoring the thorough evaluation of product quality in agriculture. Additionally, specialist solutions are required due to the special requirements of the organic agriculture sector to close the perception gap between customer quality expectations and market realities. By improving the classification of organic vegetable quality through the seamless integration of deep transfer learning and image processing techniques, our research closes this crucial gap. In the research using color images as input data, we focus on classifying organic veggies into three separate quality categories consisting of small, medium, and large sizes.

The primary objective of this paper is to develop a robust and precise model capable of predicting and classifying the quality of organic vegetables into six distinct categories. This is achieved through a detailed evaluation of the performance of widely recognized pre-trained models, namely Inception V3, VGG16, and ResNet50.

3. Related works

The classification method has garnered interest from numerous researchers. Their studies on approaches to classification techniques primarily depend on Convolutional Neural Networks (CNN). These studies serve as a reference for applying CNNs to the task of classifying the quality of organic vegetables. The findings are organized by year, as presented in Table 1.

4. Methodology

The creation of a deep transfer learning CNN-based system for classifying agricultural items with artificial intelligence for the quality of organic veggies. There are three steps in this essay: Collection of data, data preparation, and data modeling.

4.1. Collection of data

This paper is a collection of data from organic vegetable plantation owners in the Chaotha subdistrict, Kamalasai district, and Kalasin province. The two types of vegetables are iceberg lettuce and green cos. Three tiers of classification are based on size and color. The data collection process has been split into the following two parts:

- Step 1: To collect data from agricultural product packing plants, start by washing, culling, and trimming vegetables.

1) Separate the size of the vegetable into three levels, as shown in Fig. 1.

Table 1: Previous related works

Reference	Technique used	Research results
Africa et al. (2020)	Machine learning, machine vision	Proposed machine learning and machine vision methods for fruit identification and classification. Aimed to automate fruit evaluation and improve accuracy
Ezat et al. (2020)	CNN, Transfer learning	Concluded that CNN models, particularly deep learning algorithms, are efficient for image classification tasks. Outperformed other techniques in terms of accuracy
Orquia and Bibangco (2020)	Deep learning, fruit114Net	Compared pre-trained deep learning models for fruit classification. Fruit114Net showed potential as an alternative model
Saha and Neware (2020)	Image processing, deep learning	Proposed an approach for classifying sick oranges using image processing and deep learning techniques. Achieved an accuracy rate of 93.21% and aimed to maximize economic gains for farmers
Saleh and Liansitim (2020)	CNN, Color cue	Used CNN to classify ripe and immature palm oil fruit based on color cues. Achieved high accuracy in classification
Xue et al. (2023)	Convolution autoencoder, DenseNet, attention mechanism	Suggested a hybrid deep learning-based system for fruit classification. Improved fruit sorting efficiency and reduced costs in the fresh supply chain
Abisha and Bharathi (2023)	ML, DL, ANN	Used ML-based RF classifier and pre-trained models (VGG 16, RESNET, MobileNet, InceptionResNetV2, Inception, Xception) for plant flaw classification. Achieved zero misclassified classes and 100% accuracy
Baid and Dhole (2021)	CNN, SVM	Classified food photos using pre-trained CNN models and SVM classifiers. Achieved high accuracy using the Food-11 dataset.
Golchubian et al. (2021)	CNN, Image quality classification	Used CNN to accurately classify images based on quality Demonstrated the effectiveness of the trained CNN using a fresh dataset of photos
Reddy et al. (2023)	Classifier fusion	Used classifier fusion technique to enhance object recognition for small fruits. The suggested model successfully identified tiny fruits and improved object categorization
Rismiyati and Luthfiarta	Transfer learning, VGG16	Classified the quality of salak fruit using transfer learning and the VGG16 architecture. Achieved high accuracy in salak fruit classification
Villaseñor-Aguilar et al. (2021)	Expert systems, ANN, Fuzzy logic	AI can be a useful tool for assessing food and agricultural product quality. ANN model produced the best outcomes for modeling and real-time monitoring
Abou Baker et al. (2022)	Transfer learning	Discussed transfer learning as a technique for improving image classification tasks. Highlighted the importance of selecting the appropriate pre-trained model for target domains
Aherwadi et al. (2022)	DL algorithms	Proposed an automated fruit quality estimation system using DL algorithms. Used CNN model for banana fruit quality classification. Aimed to minimize harvest losses for farmers
Ashari et al. (2022)	Deep learning, CNN	Used deep learning algorithms for the maturity level classification of oil palm fresh fruit bunches. Achieved high accuracy in maturity level determination
Hidayat et al. (2022)	ResNet152V2	Classified different varieties of beef, mutton, and pork using ResNet152V2. Highlighted the importance of meat quality classification for various applications
Lee et al. (2022)	Clustering, image classification	Developed an application for identifying beef cuts, freshness, and marbling. Used clustering and image classification technologies. Provided details on beef cuts and quality
Mirra and Rajakumari (2022)	Deep learning algorithms	Used deep learning algorithms to classify fruits based on type and quality. MobileNetV2 achieved the highest accuracy for fruit quality classification
Liu et al. (2022)	YOLOX, Channel pruning	Suggested a deep learning-based method for shiitake mushroom quality classification. Achieved high accuracy using the YOLOX algorithm and channel pruning
Mirwansyah and Wibowo (2022)	Computer vision, Deep learning	Deep learning algorithms can improve fruit inspection and sorting, leading to higher productivity and efficiency in the fruit business.
Chen et al. (2022)	Neural networks	Developed model using TensorFlow and Keras for fruit quality classification. Proposed an innovative method using AI algorithms for classification
Khan and Afzal (2022)	GLCM, ANN	Suggested a method for classifying flowers using surface and color information. Achieved an overall accuracy of 96.0% using an artificial neural network classifier
Shelke et al. (2022)	Deep learning, Object detection	Proposed an automatic fruit quality monitoring system using deep learning and object detection. Increased speed and accuracy in the fruit sorting process
Gill et al. (2022)	CNN, RNN, LSTM	Proposed a novel method for fruit classification using CNN, RNN, and LSTM. Outperformed other methods like SVM, FFNN, and ANFIS.
Yadav et al. (2022)	TensorFlow, CNN	Explored the usage of TensorFlow and CNN for image classification. Demonstrated high accuracy in image categorization using deep learning
Alsirhani et al. (2023)	Deep transfer learning	Suggested a unique classification model for date fruits using deep transfer learning. Achieved high accuracy in data categorization.
Aranuwa and Fawehinmi (2022)	Deep learning, CNN	Used deep learning neural networks to classify human iris pictures. Achieved high accuracy in iris classification
Gill et al. (2023)	Machine learning, Deep learning	Developed a method for fruit classification using machine and deep learning approaches. Outperformed other methods and highlighted the challenges in fruit classification
Guo et al. (2023)	Deep transfer learning	The proposed deep transfer learning model for automatic water quality picture categorization. Achieved 99% accuracy and showed promise for real applications
Gupta et al. (2023)	CNN, Leaf segmentation	Developed an automated plant leaf disease detection and classification system using CNN and leaf segmentation techniques. Aimed to increase crop yield in agriculture
Mamat et al. (2023)	YOLO, Transfer learning	Developed an automated image annotation method for fruit identification and freshness categorization. Achieved high accuracy and demonstrated potential for improving fruit classification
Gulzar (2023)	Transfer learning, model modification	Transfer Learning, Model Modification Proposed TL-MobileNetV2 model for fruit classification Outperformed other well-known models with 99% accuracy. Emphasized the value of preprocessing techniques and model modification

Green cos small | Green cos medium | Green cos large | Iceberg lettuce small | Iceberg lettuce medium | Iceberg lettuce large

Fig. 1: Iceberg lettuce and green cos with separated sizes in three levels

2) Take photos of organic vegetables using a camera that is placed on top of the studio box. The distance between the camera and the organic vegetables is 40 centimeters. Place the organic vegetables in the studio box, as shown in Fig. 2.

Fig. 2: Take photos of organic vegetables

- Step 2: Images are divided into a training dataset, a testing dataset, and a validation dataset.

1) The image training dataset is divided into two types: Iceberg lettuce and green cos. The process of grouping the quality of organic vegetables uses three experts to determine the training dataset by dividing it into three groups: Small, medium, and large. Each group collected 3,239 images, as shown in Fig. 3.

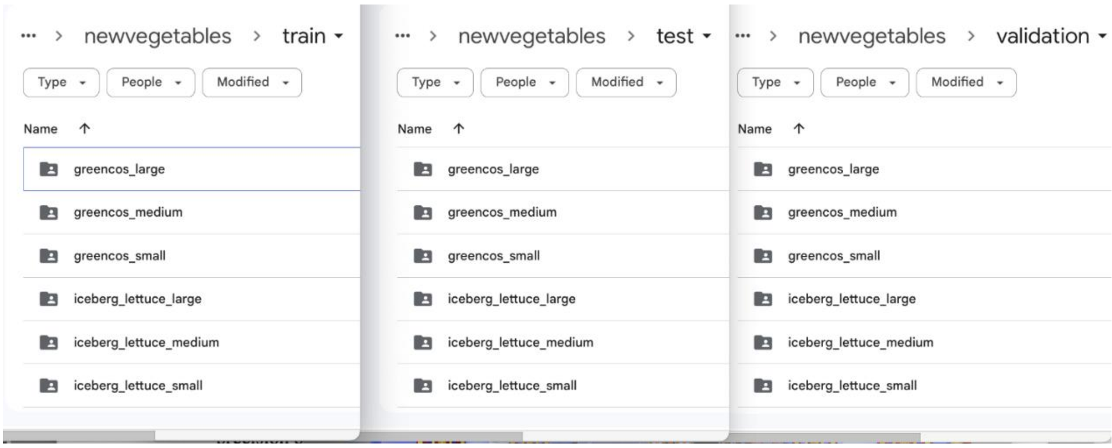

Fig. 3: Images training datasets

2) The image testing datasets, which are used separately from the training dataset, are divided into two types: Iceberg lettuce and green cos, and each type is divided into three groups: Small, medium, and large size. Each group collected 362 images.
3) The image validation datasets used to evaluate the accuracy of the model during training collected 362 images

4.2. Data preparation

In this process of processing images for the preparation of training datasets and testing datasets, resize each image to a size equal to 224 x 224 pixels (wide, high).

4.3. Data modeling

In terms of modeling, the process of training to create a model using image training datasets of two types of organic vegetables with a size of 224 x 224 pixels amounts to 3,239 images for use in training as follows:

- Iceberg_lettuce_small is an image for the training dataset class of 302 images.
- Iceberg_lettuce_medium is an image for the training dataset class medium with 252 images.
- Iceberg_lettuce_large is an image for the large training dataset class of 1029 images.
- Green_cos_small is an image for the training dataset class with a small amount of 302 images.
- Green_cos_medium is an image for the training dataset class medium with 341 images.
- Green_cos_large is an image for the training dataset class of 1018 images.
- In the process of training a model, it must be evaluated during training using image validation datasets. In this experiment, validation images were used for 362 images of two types of organic vegetables, as follows:

- Iceberg_lettuce_small is an image for the validation dataset class Small, which contains 54 images.
- Iceberg_lettuce_medium is an image for validation dataset class medium amounting to 28 images.
- Iceberg_lettuce_large is an image for the validation dataset class with a large number of 51 images.
- Green_cos_small is an image for the validation dataset class's small number of 70 images.
- Green_cos_medium is an image for validation dataset class medium amounting to 61 images.
- Green_cos_large is an image for the validation dataset class with a large number of 111 images.

Training model process using deep transfer learning. The working steps are shown in Fig. 4.

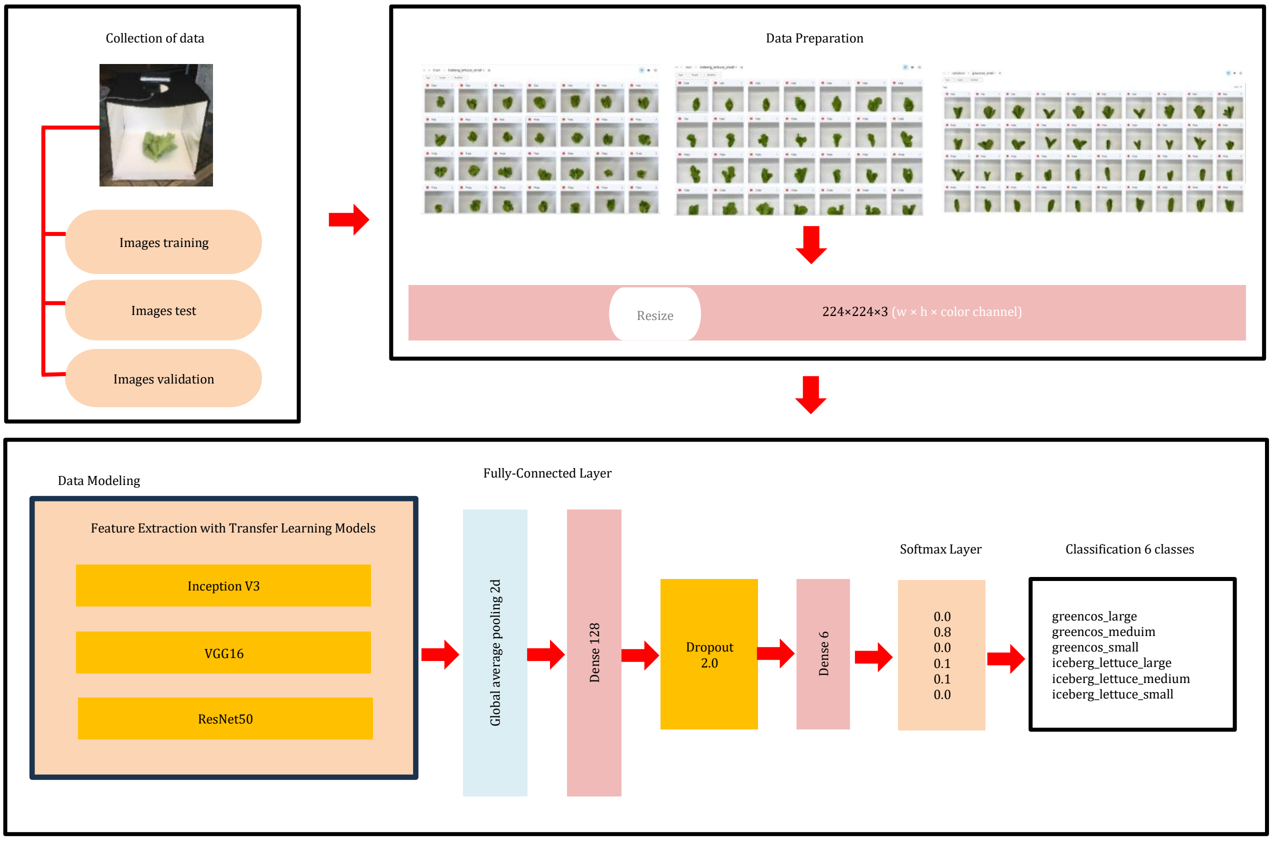

Fig. 4: Workflow training model process

Fig. 4 shows an overview of the system's operation. Consists of 3 parts: Collection of data, Data preparation, and Data modeling. The collection of data is the process of collecting training, test, and validation images. When the images are collected, they will be sent into the Data preparation section by resizing the image to a size of 224x224 pixels to reduce processing time and sent to the Data modeling section for extraction features of the image by transfer learning model using three models: Inception V3, VGG16, and ResNet50. Then, cut the top classification, leaving only feature extraction, add a dense layer of 128 nodes and a dropout layer of 0.2, and use an output layer of 6 classes through softmax to get the probability of the answer.

5. Results and discussion

The experimental findings indicate that the Inception V3, VGG16, and ResNet50 models, utilizing deep transfer learning based on CNN, have varied performance levels in classifying the quality of organic vegetables. The Inception V3 model reached an overall accuracy of 85%. Specifically, its accuracy for classifying small, medium, and large iceberg lettuces was 87%, 100%, and 93%, respectively. For green cos lettuce, the small size was classified with 88% accuracy, medium size with 48% accuracy, and large size with 98% accuracy.

The VGG16 model achieved an overall accuracy of 82%, with small, medium, and large iceberg lettuces being classified with accuracies of 78%, 100%, and 78%, respectively. For green cos lettuce, the accuracies were 60% for small size, 100% for medium size, and 88% for large size.

The ResNet50 model's overall accuracy was significantly lower, at 50%. For iceberg lettuce, the accuracies were 78% for small size, 0% for medium size, and 85% for large size. Green cos lettuce saw accuracies of 0% for both small and medium sizes and 0% for large sizes. These results, including the validation accuracies for each vegetable size and type, are detailed in Table 2.

The findings from this study reveal differences in the effectiveness of various models in classifying organic vegetables. The Inception V3 model displayed the highest level of accuracy for most categories, underscoring its capability for precise organic vegetable classification. Meanwhile, the VGG16 model showed commendable accuracy but was less effective in some specific categories. On the other hand, the ResNet50 model demonstrated a generally lower accuracy and particularly struggled with the accurate classification of small-sized green cos lettuce. These results are valuable as they expand our understanding of how deep transfer learning can be applied to classify the quality of organic vegetables effectively. Notably, the Inception V3 and VGG16 models show promise in improving the efficiency and accuracy of organic vegetable quality classification. The lesser performance of the ResNet50 model indicates areas that could benefit from further research and enhancement. For stakeholders such as policymakers, farmers, and industry participants, these insights are crucial. They guide decision-making and promote the adoption of deep transfer learning technologies. In summary, this research underscores the potential of CNN-based deep transfer learning for the precise and efficient classification of organic vegetable quality, contributing to advancements in global agricultural practices. The study also emphasizes the importance of comparing model results across different classes to understand test accuracy comprehensively.

The outcomes highlight the differing effectiveness of the models across various categories. A bar chart can illustrate this comparison, with the x-axis displaying the class names for iceberg lettuce in small, medium, and large sizes. The y-axis shows the accuracy levels of the models (Inception V3, VGG16, and ResNet50), as depicted in Fig. 5. The comparisons in research studies on classification using transfer learning. These studies demonstrate the effectiveness of deep transfer learning CNN-based approaches for classifying organic vegetables. While Alsirhani et al. (2023) achieved a slightly lower accuracy of 80% with the ResNet50 model, our current study and the work of Hidayat et al. (2022) showed higher accuracies with the Inception V3 (85%) and VGG16 (75%) models, respectively. These findings underscore the importance of selecting the appropriate transfer learning CNN architecture to achieve accurate classification results in organic vegetable quality assessment.

6. Conclusion

The study's results emphasize the superior accuracy of the Inception V3 model in classifying organic vegetables, achieving an accuracy rate of 85%. This model demonstrates consistently high accuracy across all categories, outperforming the VGG16 and ResNet50 models in terms of accuracy.

Importantly, our findings align with prior research conducted by Mohameth et al. (2020) and Mai et al. (2023), affirming the potential of transfer learning in enhancing accuracy and efficiency in agricultural product classification and sorting tasks. The impressive performance of the Inception V3 model further validates its superiority and bolsters the notion that leveraging advanced machine learning algorithms and computer vision techniques can yield significant benefits in agriculture.

Table 2: The accuracy of the model

Model	Total accuracy	Iceberg lettuce			Green cos		
		Small	Medium	Large	Small	Medium	Large
Inception V3	85%	87%	100%	93%	88%	48%	98%
VGG16	82%	78%	100%	78%	60%	100%	88%
Resnet50	50%	78%	0%	85%	0%	0%	0%

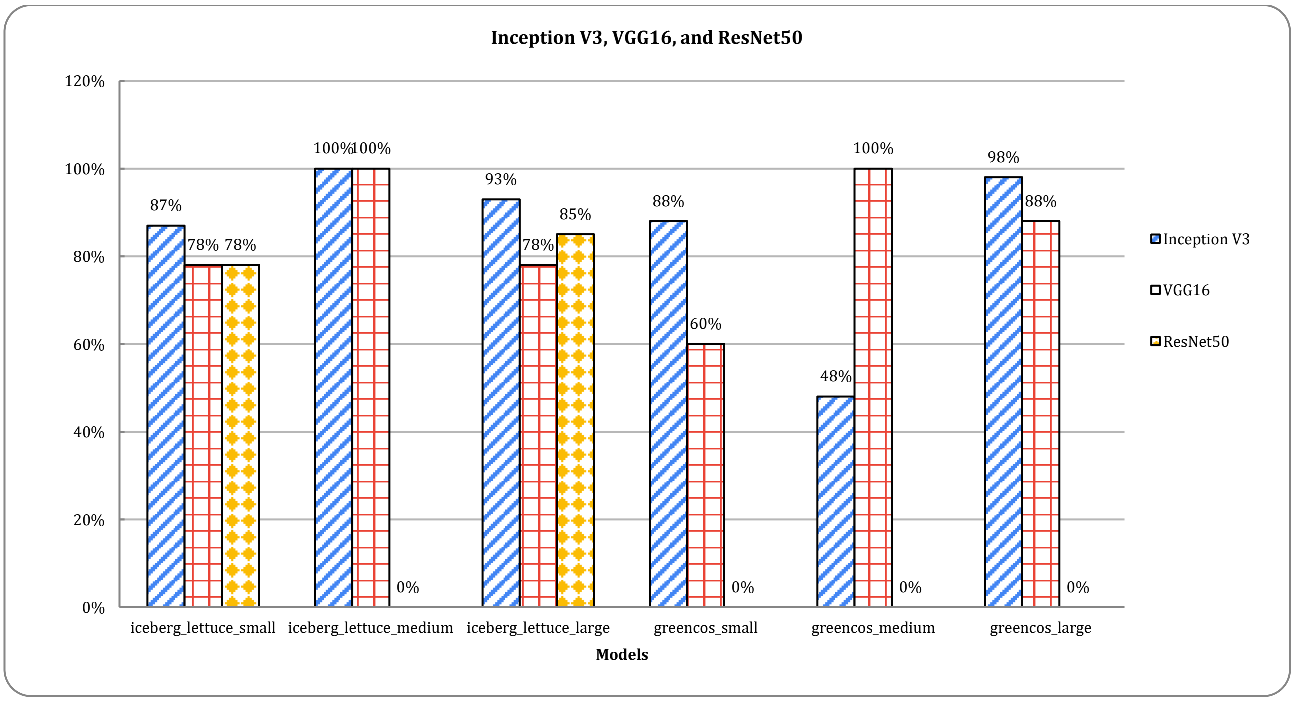

Fig. 5: Performance of the models

While our study contributes valuable insights, it is essential to acknowledge its limitations. We focused on specific organic vegetables and quality attributes, and our results are derived from a particular dataset. To enhance the generalizability of our findings, future research should encompass a broader range of agricultural products, incorporate diverse datasets, and consider additional variables.

The implications of our research are far-reaching, providing valuable guidance for decision-making and resource optimization in the agricultural sector. The exceptional performance of the Inception V3 model underscores its practicality and reliability in accurately classifying agricultural products, fostering the adoption of transfer learning within the industry. Our study offers researchers, policymakers, and stakeholders a reliable foundation upon which to drive advancements and improve the efficiency and accuracy of classification organic vegetables using deep transfer learning CNN-based.

7. Future works

- Exploring the potential of AI technology in other areas of agriculture, such as irrigation management, soil analysis, and plant disease diagnosis.
- The development of more advanced machine learning algorithms and computer vision techniques can enhance the accuracy and efficiency of AI-driven systems in agricultural product quality classification.
- The integration of AI technology with other emerging technologies, such as blockchain and the Internet of Things (IoT), can further optimize resource allocation and enhance sustainability in the agriculture industry.
- The implementation of AI-enabled systems in real-world agricultural settings can provide valuable insights into the practical challenges and opportunities of AI technology in agriculture, informing future research and development efforts.

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Compliance with ethical standards

Conflict of interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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