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A Comparative Analysis of Machine Learning Techniques for Fruit Defect Detection Systems

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Abstract

With evolving technologies in machine learning, significant advancements have been made in the livestock industry, helping to reduce waste, increase yield, achieve cost savings, and improve competitiveness in the marketplace. Fruit defect detection models support precision agriculture by providing valuable data for decision-making and enhancing overall efficiency through automated inspection processes. This study implements and comparatively evaluates machine learning models including MobileNetV2, a custom-designed convolutional neural network (CNN) model, ResNet50, and VGG16 to improve the accuracy of defect detection in fruits such as bananas, apples, and oranges. MobileNetV2 achieves competitive accuracy while ensuring computational efficiency, making it well-suited for environments with limited resources. The custom CNN model addresses the specific intricacies of fruit defect detection, showcasing adaptability across various fruit types. ResNet50 and VGG16, with their deep architectures, exhibit robust performance in capturing intricate features for enhanced defect identification. Comparative analysis employs metrics such as precision, recall, and F1 score to quantitatively assess each model's accuracy. This research contributes to the growing body of knowledge in fruit defect detection and serves as a valuable resource for practitioners implementing machine learning models tailored to specific fruit inspection needs, ultimately advancing precision agriculture and automated fruit quality assessment.

Keywords: MobileNetV2, ResNet50, VGG16, custom-made CNN model, fruit defect detection

INTRODUCTION

In the domain of agriculture, which is critical to the prosperity of nations and the livelihoods of a large portion of the population, the harvest of fruits and ensuring the quality and integrity of these yields are important tasks. This research project delves deeper into the critical domain of fruit defect detection in the farming sector, leveraging the life-changing capabilities of intelligent systems, machine learning (ML), and deep learning (DL) approaches. Focusing on three main fruits—apples, bananas, and oranges—the goal is to revolutionize how defects are identified and classified in fruits to avoid extra costs incurred later. India is a global agricultural powerhouse that currently faces the challenges of post-harvest losses and manual grading processes. With over 210 million acres of farmland and a diverse array of crops, there is a demand for automated systems to detect and categorize fruit defects [1]. The limitations of traditional methods are subjectivity, time-consuming processes, and susceptibility to human error, underscoring the

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urgency of integrating advanced technologies into the fruit defect inspection process [2]. The methodology involves the use of advanced neural network models, including a custom convolutional neural network (CNN) tailored specifically for fruit classification, MobileNetV2 for defect detection [3], ResNet50 for enhanced accuracy, and VGG16 for comprehensive feature extraction of the fruits [4]. These models collectively create a robust framework capable of discovering defects and providing accurate classifications of fruits, ensuring a more reliable and efficient grading of apples, bananas, and oranges [5]. In addition to powerful backend models, a simple frontend was developed using React JS, enabling seamless user interaction and image uploading [6]. This straightforward user interface empowers farmers and stakeholders to submit fruit images for the detection of defects effortlessly, bridging the gap between users and the system. As the research delves deeper into the subject, the aim is to address the immediate challenges of defect detection and contribute to the broader landscape of the agricultural domain [7]. Through the automation and optimization of the fruit defect detection process, this research aims to push the world towards sustainable and technologically driven agriculture, foster efficiency, reduce losses, and propel the industry into a future where precision meets productivity [8].

PROBLEM STATEMENT

A comparative analysis of the ML algorithms used for fruit defect detection systems to enhance the overall quality control of fruits in the agricultural sector swiftly and efficiently was conducted, and this analysis was applied to appraise the overall ripeness of fruits [9].

LITERATURE SURVEY

To increase the accuracy of defect detection in fruits, a comprehensive comparative examination was carried out by employing diverse machine learning models, namely MobileNetV2, a custom-designed CNN, ResNet50, and VGG16. This study aimed to examine bananas, apples, and oranges. The outcomes of this study reveal nuanced distinctions in the performance of these models, emphasizing their unique contributions to the fruit defect detection process.

MobileNetV2—Competitive Accuracy

MobileNetV2, known for its light-weight architecture, exhibits competitive accuracy in the realm of fruit defect detection.

- The ability of the model to maintain accuracy while being computationally efficient makes it a promising choice in resource-constrained environments.
- MobileNetV2's streamlined architecture stands notable. Its efficiency is particularly advantageous for edge devices, conserving energy and enabling faster inference. This aligns with the principles set forth by Sandler et al. who emphasized the significance of models that thrive in environments with limited computational resources.
- Dong K. and Yihan Ruan [3], "*MobileNetV2 Model for Image Classification*", presented at the 2nd International Conference on Information Technology and Computer Application (ITCA) in 2020, delves into the technical intricacies of MobileNetV2. It examines the architectural characteristics of the model, highlighting depth-wise separable convolutions and inverted residuals. The training strategies employed include data augmentation and optimization algorithms while enhancing the efficiency of the model. Additionally, it discusses practical applications, showcasing the model's effectiveness beyond controlled environments and providing a significant understanding of real-world utility.

Custom CNN Model—Addressing Intricacies

- A custom-designed CNN model takes the central stage to address the intricacies inherent in fruit defect detection.
- Tailored to the specific challenges posed by various fruit types, this model shows adaptability and precision in identifying nuanced defects.
- This adaptability ensures robust performance across a spectrum of fruit defect scenarios, showcasing its potential to contribute to precision agriculture [10]. In essence, the custom CNN

model serves as a specialized tool designed for the precise and nuanced task of fruit defect detection [11]. Its adaptability, coupled with its ability to capture fine-grained features, is a valuable asset for automated quality assessment in agriculture.
- The dataset consists of images for deep transfer learning based defect detection [5]. De Luna and Elmer P. Dadios contribute to the domain of agricultural technology. Their focus is on the function of deep transfer learning for defect detection in tomatoes by utilizing CNN. The authors are likely to delve into the specifics of the adopted CNN architecture, detailing layers, filters, and activation functions chosen for optimal defect identification. The transfer learning approach is explored, elucidating how pre-trained models enhance the network's capability to find defects in tomato fruit images. The creation and characteristics of the tomato fruit image dataset, which is a crucial aspect of training deep learning models, are discussed in detail.

ResNet50 and VGG16—Deep Architectures, Robust Performance
- ResNet50 and VGG16, which are renowned for their deep architecture, demonstrated robust performance in fruit defect detection.
- The depth of these models enables them to capture intricate features, contributing to enhanced accuracy in identifying defects across different fruit categories.
- ResNet50 and VGG16 prove their mettle by demonstrating versatility across diverse fruit types and defect scenarios. The depth of these architectures enables them to capture nuanced features, making them adept at discerning subtle variations that are indicative of defects. Their ability to learn hierarchical representation positions, ResNet50 and VGG16, is a powerful tool for automated fruit quality assessment.
- A Deep Neural Network based Disease Detection Scheme for Citrus Fruits [4] by Kukreja V. and Poonam Dhiman employ advanced architectures, specifically ResNet50 and VGG16. ResNet50's deep residual learning addresses vanishing gradients, thereby enhancing the model's ability to capture intricate disease-related features. VGG16's uniform design with small convolutional filters enables nuanced feature examination. This research is likely to delve into technical nuances, including pre-processing innovations, optimization algorithms, and transfer learning strategies. Rigorous evaluation metrics quantify model performance, contributing to a sophisticated understanding of the precision of disease detection in citrus fruits.

Comparative Study—Unveiling Model Variances
- This study systematically compared the working of MobileNetV2, custom CNN, ResNet50, and VGG16, shedding light on their strengths and weaknesses.
- Metrics such as precision, recall, and F1 score were utilized to quantitatively assess the accuracy of each model in the context of fruit defect detection.

Practical Implications for Fruit Defect Detection
- The knowledge acquired from this comparative study provides practical guidance for selecting the most suitable model based on the specific requirements and constraints.
- Considerations such as computational efficiency, adaptability to fruit nuances, and robustness play important roles in choosing the optimal model for real-world fruit defect detection applications.

This study contributes to the growing body of research on fruit defect detection and serves as an important resource for practitioners seeking to implement machine learning models tailored to their specific fruit inspection needs. The nuanced insights acquired by this comparative study pave the way for advancements in precision agriculture and automated fruit quality assessment.

METHODOLOGY
Dataset Preparation
A dataset consisting of 14,602 images of fruits was collected from a variety of sources, including Kaggle and self-collected Fresh and Rotten Fruit Images. These fruit images were captured with a white

background, and essential pre-processing procedures were applied to each image. The classification involved six labels: fresh apple, rotten apple, fresh banana, rotten banana, fresh orange, and rotten orange (Table 1).

The dataset was divided into two sets: a training set and a testing set, with 11,810 images assigned to train the model and the remaining images assigned for testing the model. Following data collection, the next crucial phase involves pre-processing the images to enhance data quality. A variety of pre-processing techniques are used to clean real-world data, which are usually random and noisy. Neglecting this important step before feeding the image data into the neural network can reduce the performance of the network.

Transfer Learning

Training deeper neural networks is difficult because of the high demand for computational power. Hence, a pre-trained ImageNet model was chosen. Because the dataset has a restricted set of visuals, and computational resources are constrained, the system implements transfer learning. This approach is very effective, as the created model displays outstanding performance on our testing set, especially after fine tuning.

Image Pre-processing

1. *Image resizing:* All images in the dataset are resized to a fixed resolution of 128×128 pixels. This is required because it ensures that all images have the same dimensions, which is required by the CNN models. CNNs expect input images of fixed size, as different resolutions can lead to inconsistent feature extraction and poor performance. Also resizing the images to a smaller resolution reduces the computational overhead during the training process. This does not make changes in the image of fruits; aspect ratio of the image is maintained. The appearance of the fruit does not get stretched.
2. *Pixel value normalization:* The pixel values of the images are normalized by dividing each value by 255, scaling the range from [0, 255] to [0, 1]. This method makes neural networks converge faster and more effectively. After Normalization, the model learns the different scales of the pixel values. The normalization of the fruit images scales all features to a common range. This allows the model to learn meaningful patterns from images.
3. *Data augmentation:* As the dataset was limited, the model may have been insufficient to learn from the limited data. Hence, to increase the diversity of the training data and improve the generalization ability of the model, various data augmentation techniques have been applied.
   a. *Random shearing:* This applies a controlled deformation to the images by shearing them along the x- and y-axes. This results in variations in fruit shape.
   b. *Random zooming:* Images are randomly zoomed in or out within a specified range, which helps the model to learn and recognize fruits with different variations in size.
   c. *Random horizontal:* Flipping: Images in the dataset are randomly flipped horizontally, which helps the model to learn and recognize the fruits regardless of their orientation.

Table 1. Number of images for each label.

Labels	Total images
Fresh apple	2088
Rotten apple	2943
Fresh banana	1962
Rotten banana	2754
Fresh orange	1854
Rotten orange	1998

Feature Extraction and Fine Tuning

Feature extraction involves the use of the last three unfrozen convolutional layers of the pre-trained network to obtain features from the new data. Fine tuning follows by freezing all layers, except the last ones. A custom classifier is added, featuring a two-layer ReLU network, followed by SoftMax activation. The joint training of the convolutional layer and the new classifier enhanced the overall model performance.

Training

Before building the model, the dataset was partitioned into two subsets, 80% for training and 20% for testing. The training of images is used to train the network, while the testing set, held back during training, assesses the model's efficacy and refines its hypothesis.

Model's Working

The process starts with the fruit classification model shown in Figure 1, which identifies the type of fruit (apple, orange, or banana) from the input image. Once the fruit type is determined, the corresponding classification model trained on a specific fruit dataset is employed. These fruit-specific models have been fine-tuned on a binary classification task, distinguishing between fresh and rotten fruits and then determining the color of the fruit ripeness.

The models analyzed the visual characteristics of the fruit image, such as color, texture, and shape, to predict the probability of the fruit being fresh, rotten, ripe, or unripe. This information is particularly valuable for quality control and ensuring that only fresh and undamaged fruits are selected for distribution and consumption.

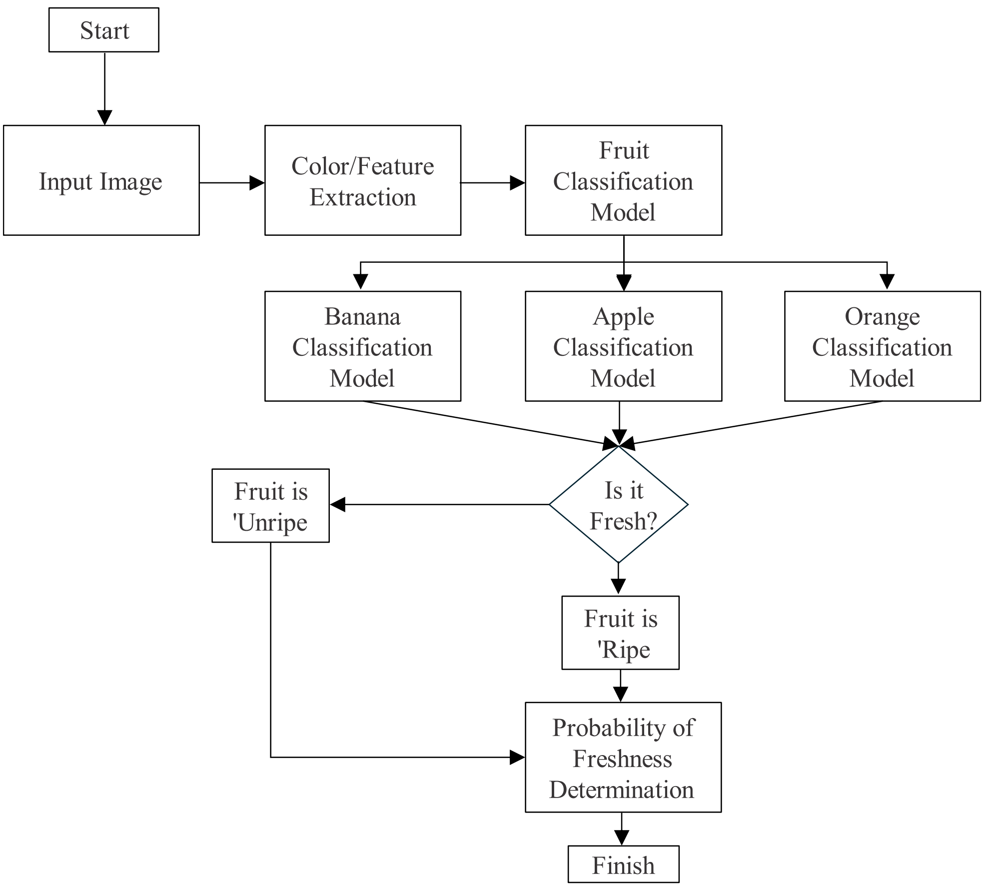

Figure 1. Working of ML model system.

RESULT AND ANALYSIS

Training Process

MobileNetV2 (Light-weight Model)

Trained for 25 epochs, proving to be a suitable duration for achieving satisfactory results despite its light-weight nature, as indicated by the results in Figures 2–4.

ResNet50 (Complex Model)

Initially showed lower accuracy; therefore, the number of epochs was increased from 25 to 35 to improve performance because of its complexity and depth, as indicated by the results shown in Figures 5–7.

VGG16 (Heavy-weight Model)

Satisfactory results within the first three to five epochs. Owing to the limited computational resources, fewer epochs were used, as indicated by the results shown in Figures 8–10.

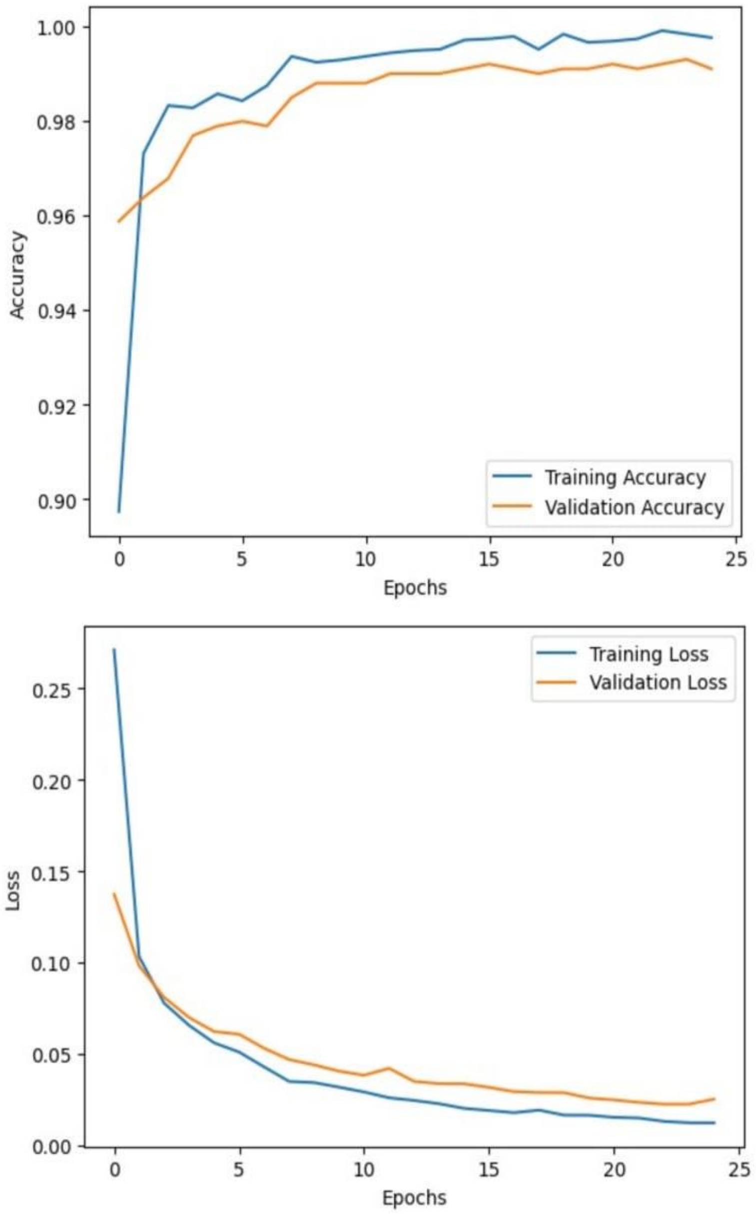

Figure 2. Training and validation loss, accuracy for MobileNetV2.

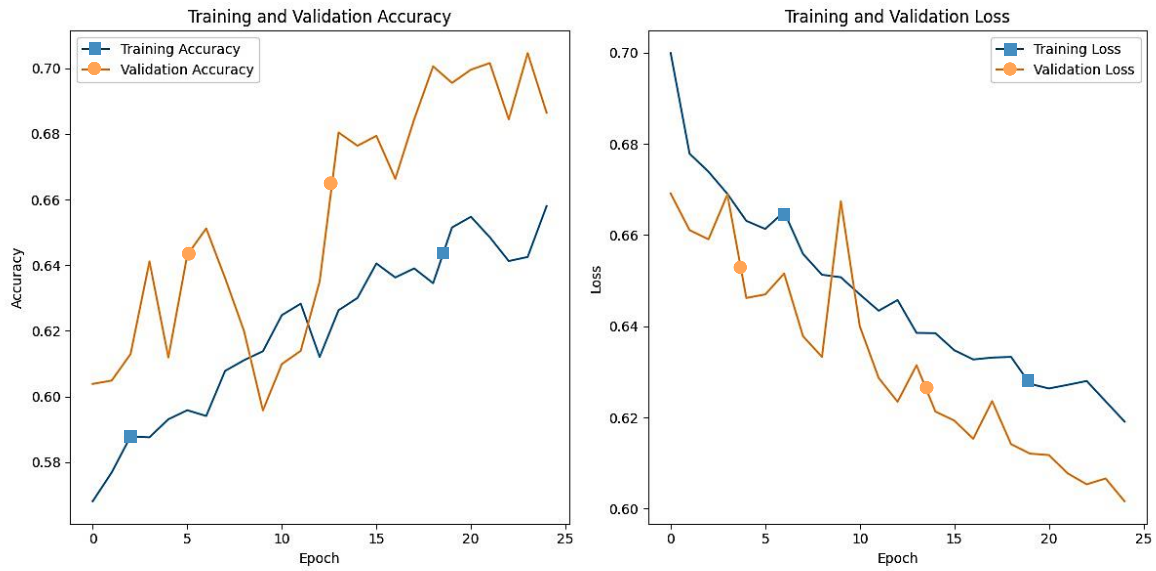

Figure 3. Training and validation loss, accuracy for ResNet50.

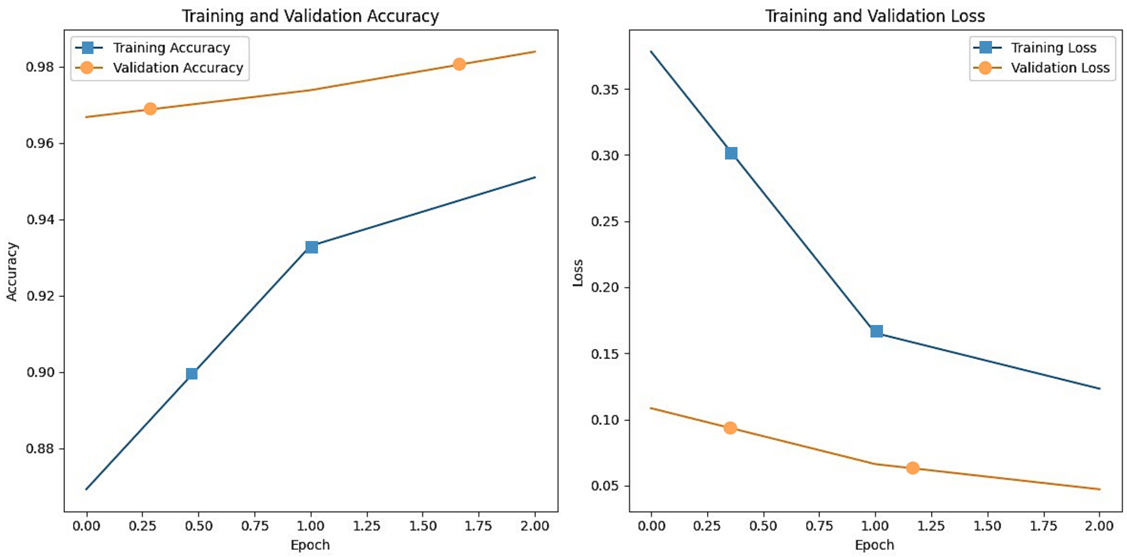

Figure 4. Training and validation loss, accuracy for VGG16.

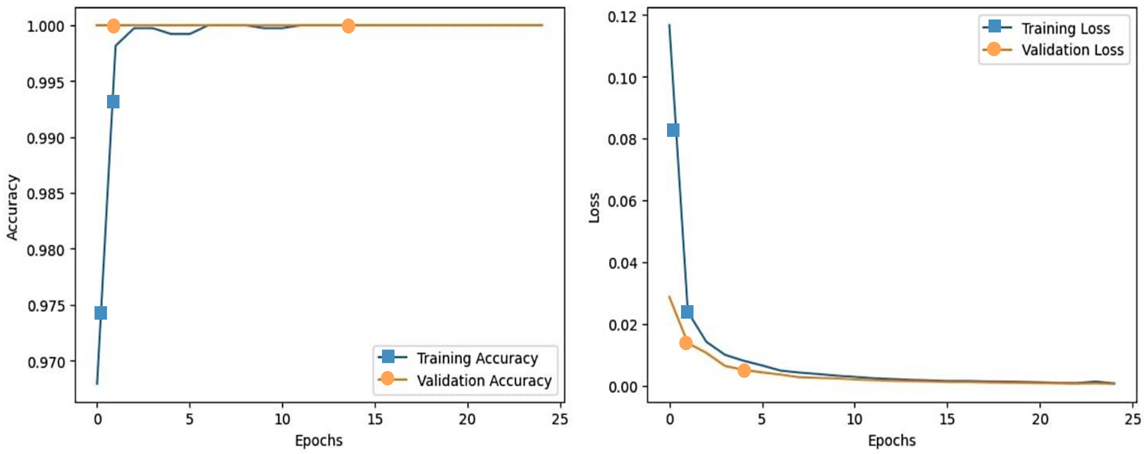

Figure 5. Training and validation loss, accuracy for MobileNetV2.

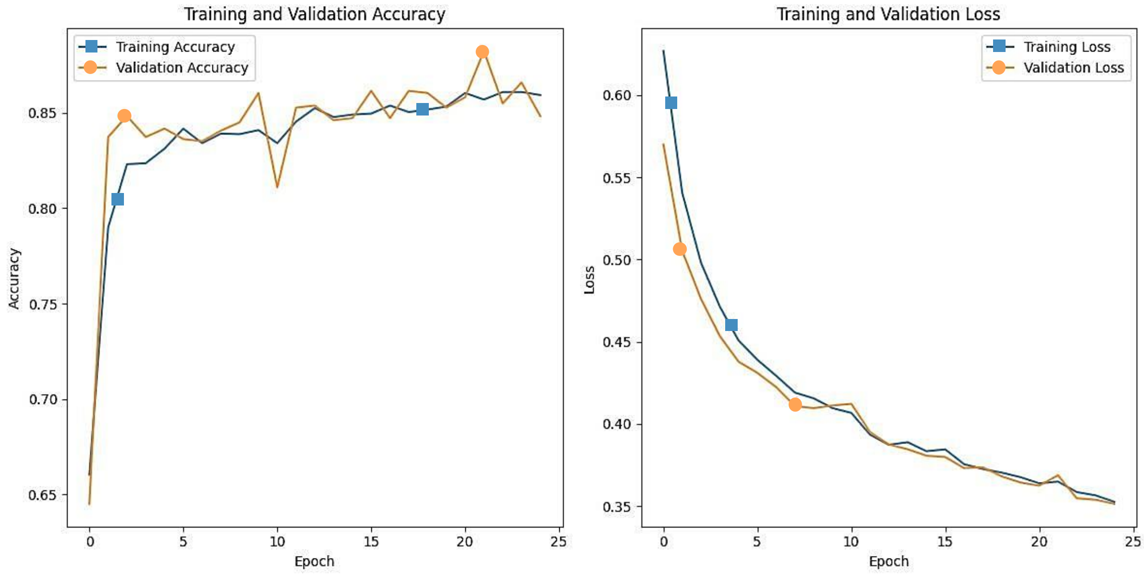

Figure 6. Training and validation loss, accuracy for ResNet50.

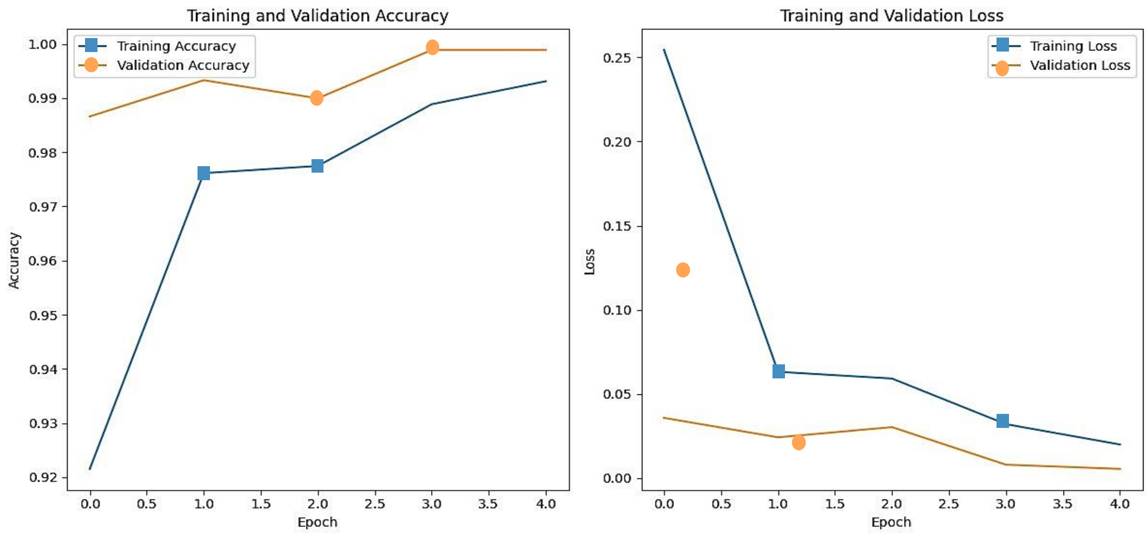

Figure 7. Training and validation loss, accuracy for VGG16.

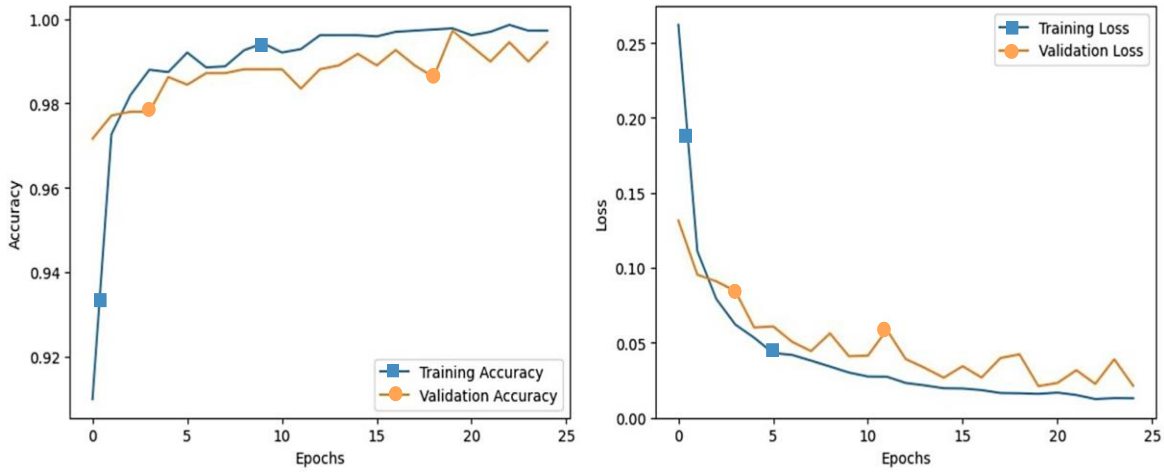

Figure 8. Training and validation loss, accuracy for MobileNetV2.

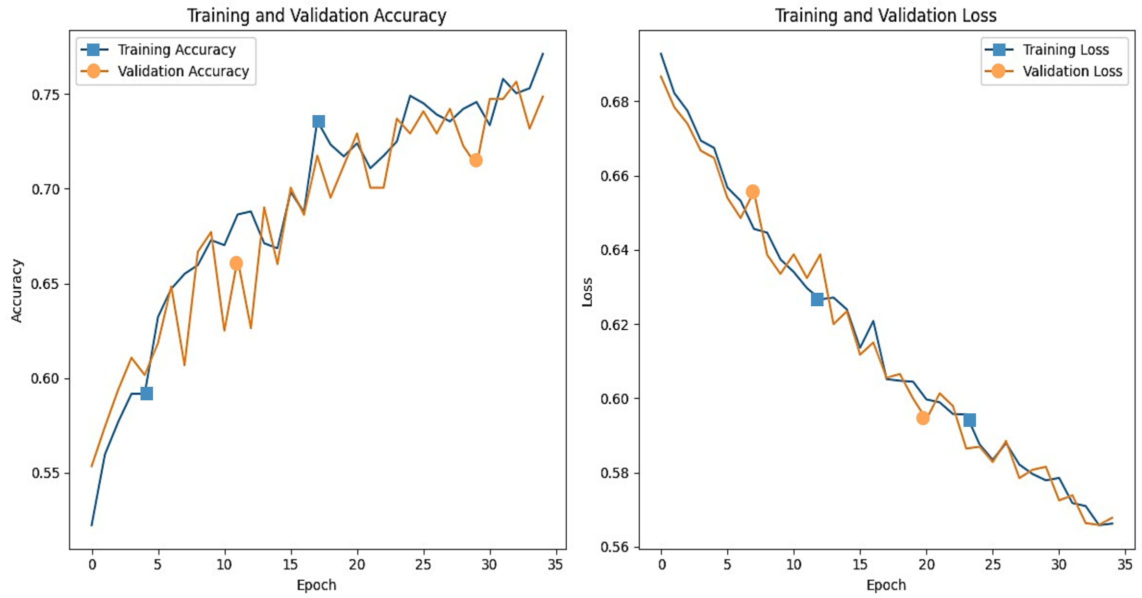

Figure 9. Training and validation loss, accuracy for ResNet50.

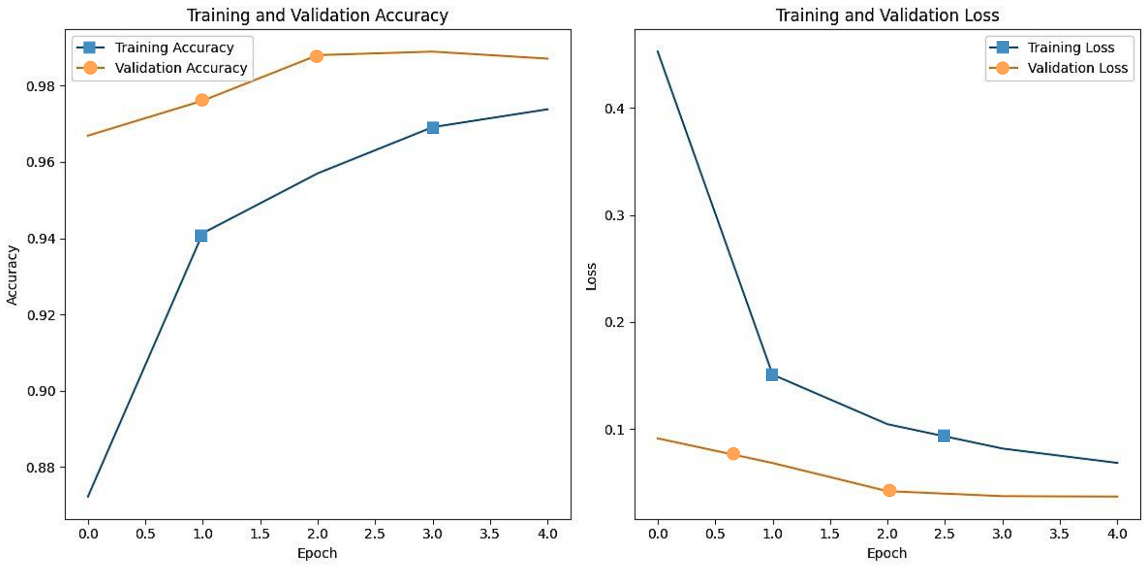

Figure 10. Training and validation loss, accuracy for VGG16.

Table 2. Classification accuracies.

Fruit	Model	Figure Number	Accuracy (%)
Apple	MobileNetV2	Figure 1	99.09
	Resnet50	Figure 2	68.55
	VGG16	Figure 3	98.39
Banana	MobileNetV2	Figure 4	100
	Resnet50	Figure 5	84.84
	VGG16	Figure 6	99.89
Orange	MobileNetV2	Figure 7	99.45
	Resnet50	Figure 8	75.13
	VGG16	Figures 9, 10	98.62

Observations

MobileNetV2

It achieved excellent accuracy, showcasing its efficiency and effectiveness even with light-weight architecture. The model achieved satisfactory results within 25 epochs, as presented in Table 2 and Figures 2–4.

ResNet50

It showed comparatively lower accuracies, indicating that its increased depth may require more epochs, signifying the importance of extended training for complex models, as shown in Table 2 and Figures 5–7.

VGG16

High accuracy was achieved for all fruits, demonstrating its effectiveness in this task. The quick convergence within a few epochs suggests its suitability for limited computational resources, as shown in Table 2 and Figures 8–10.

DISCUSSION

The results showed that MobileNetV2 did the best job in recognizing fruits because it was designed to be light-weight and efficient, which means it is suitable for applications where speed and resources are limited. However, it may not be suitable to spot more complicated defects. ResNet50 and VGG16 did not perform as well because they had deeper architectures, which required more data to show their full potential. With more time and tweaking, they performed better.

The choice of the right model depends on what is needed. If working with devices that do not have much power, MobileNetV2 is the way to go. However, if more computing power is required, ResNet50 or VGG16 might be better. To make these models even better at spotting defects, try to use larger and more varied datasets, use different ways of changing the data to train the models, or even combine the strengths of different models.

CONCLUSION

This research paper has successfully employed advanced data-driven models to enhance quality control, focusing on apples, bananas, and ranges. This study performed a comparative assessment of three prominent CNN architectures-MobileNetV2, ResNet50, and VGG16-for the crucial task of defect detection in these major fruits.

The methodology employed was a systematic approach that encompassed several key steps. These include dataset preparation, strategic partitioning to ensure balanced representation, and meticulous pre-processing to ensure data quality. Additionally, image pre-processing and feature extraction are critical in extracting relevant information from fruit images.

The results of this comprehensive process were evaluated in terms of the classification accuracies and losses for each model, providing a quantitative assessment of their performance in identifying defects. The conclusive findings of this research highlight MobileNetV2's consistently superior performance across the three CNN architectures. A particularly noteworthy achievement of 100.00% accuracy for bananas indicates an exceptional capability in detecting defects in this specific fruit. These outcomes yield resourceful insights into precision agriculture and automated fruit quality assessment, emphasizing the practical implications of real-world image recognition tasks. These insights could significantly impact the agricultural sector by enabling the precise and automated quality assessment of fruits.

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