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Advanced Fruit Quality Assessment using Deep Learning and Transfer Learning Technique

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Abstract

Ensuring the quality of fruits is essential for consumer satisfaction and food industry standards. Accurately identifying and classifying high-quality fruits is essential for maintaining good health and nutrition. The subjective and labor-intensive nature of traditional techniques of evaluating quality highlights the need for automated solutions. This study utilized transfer learning with Four pre-trained convolutional neural network (CNN) models—MobileNetV2, ResNet50, VGG16, and EfficientNetB0 —to detect the quality of five fruits: apple, banana, strawberry, orange, and mango. All models were trained and tested with a public labeled fruit images dataset, and their performance was evaluated in terms of accuracy, precision, recall, and F1-score. Our results demonstrate that ResNet50 consistently achieves the highest accuracy across all fruit types, surpassing MobileNetV2, EfficientNet and VGG16. Additionally, our models' performance is benchmarked against state-of-the-art techniques, underscoring the superior accuracy and reliability of ResNet50 in automated quality control systems within the agricultural and food sectors..

Keywords: Fruit Quality Detection; Convolutional Neural Networks; Transfer Learning; ResNet50; MobileNetV2; VGG16; EfficientNet; Image Classification; Food Industry.

1 | Introduction

Ensuring the quality of fruits is fundamental to consumer satisfaction and the overall success of the food industry. High-quality fruits contribute significantly to health and nutrition, making accurate detection and sorting is crucial task [1]. Traditional methods of quality assessment often rely on human inspection, which can be labor-intensive, subjective, and at risk for errors [2]. These methods typically involve manual inspection such as assessing various visual attributes. While these methods can be effective, they are time-consuming and can suffer from variability in human judgment [3]. Mechanical systems have been developed to address some of these challenges, using sensors and physical criteria to sort fruits. However, these approaches are often limited in their ability to detect subtle quality differences and may not be adaptable to different types of fruits and quality parameters [4]. This underscores the necessity for automated solutions that can provide consistent, reliable, and efficient quality control [5].

Fruit quality detection presents several challenges due to the inherent variability in fruit appearance. Factors and the presence of blemishes or defects can vary widely even within the same fruit type. Seasonal changes,

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growing conditions, and post-harvest handling further complicate the assessment process [6, 7]. These variations make it difficult to develop a one-size-fits-all solution using traditional methods. Advanced AI techniques, particularly deep learning models, offer a promising solution by learning to recognize and adapt to these complex patterns, thus improving the accuracy and robustness of quality assessments [8, 9].

Recent advances in AI and machine learning have revolutionized the field of fruit quality detection [10]. Convolutional neural networks (CNNs), a class of deep learning models particularly well-suited for image processing tasks, have shown great promise in automating the quality assessment process [11]. These models can analyze images of fruits and identify various quality attributes with high accuracy. By training on large datasets of labeled fruit images, CNNs learn to recognize patterns and features associated with quality, leading to more consistent and objective assessments and accurate differentiation between fresh and rotten fruits [12]. Furthermore, Transfer learning, a technique where a pre-trained model is fine-tuned for a specific task, plays a crucial role in this advancement. By using models pre-trained on large datasets such as ImageNet, we can leverage learned features and patterns, significantly reducing the time and computational resources required for training. This method also helps in achieving higher performance with limited labeled data, as the model starts with already learned general features that are refined for the specific task of fruit quality detection which leading to more accurate results [13].

In this study, we focus on leveraging pre-trained CNN models through transfer learning to detect the quality of five fruits: apple, banana, strawberry, orange, and mango, these models are used for differentiating between fresh and rotten fruits. Transfer learning allows us to use pre-trained models and fine-tune them for our specific task. This approach significantly reduces the time and computational resources required for training while achieving high performance. We evaluate four pre-trained models: MobileNetV2, ResNet50, VGG16, and EfficientNet. Comparing their accuracy, precision, recall, and F1-score. Furthermore, these models are compared against state-of-the-art techniques to determine the most effective model for fruit quality detection. By this work, we aim to highlight the potential of AI in enhancing automated quality control systems in the agricultural and food sectors.

1.1 | Contributions and Paper Organization

This paper presents several significant contributions to the field of fruit quality detection using artificial intelligence and deep learning techniques. The primary contributions of this study are as follows:

- This study applies transfer learning with four pre-trained convolutional neural networks (CNN) models: MobileNetV2, ResNet50, VGG16, and EfficientNetB0 for quality detection. And provides a comprehensive comparison of the performance between them in detecting the quality of five different fruits: apple, banana, strawberry, orange, and mango.
- The study benchmarks the performance of these pre-trained models against state-of-the-art techniques in fruit quality detection, highlighting the strengths and performance of each model using a set of evaluation metrics such as accuracy, precision, recall, and F1-score.
- Focusing on developing a general model capable of assessing the quality of various types of fruits. And address the limitations related to model generalization and computational efficiency.
- Our results show that ResNet50 consistently achieves the highest accuracy across all fruit types, demonstrating its potential as the most effective model for this task. This highlights its applicability and reliability for real-world use in the agricultural and food sectors.
- The findings of this study have significant practical implications, offering a pathway to integrate AI-driven solutions into existing quality control systems in the agriculture and food industries. This can lead to more efficient, consistent, and objective quality assessments.

The remainder of this paper is organized as follows. Section 3 reviews existing literature on fruit quality detection, focusing on traditional methods and recent AI advancements. Section 4 presents the proposed work, it details the methodology and the transfer learning approach using MobileNetV2, ResNet50, VGG16, and EfficientNet models. The Experimental analysis including the dataset description and utilized evaluation metrics is shown in section 5, Section 6 shows and interprets the results, compares them with state-of-the-art techniques, and discusses the models' practical applications. Finally, the Conclusion and Future Work section summarizes the key findings and suggests directions for future research is presented in section 7.

2 |Literature Review

In this section, we explore the existing literature on the application of machine learning and computer vision technologies for evaluating fruit quality. Current research indicates that most used methods for automatic fruit freshness detection rely on feature engineering. This involves extracting features from colored images of fruits at various stages of freshness and using machine learning techniques to assess the freshness of fruits based on these extracted features. By analyzing existing research, we aim to pinpoint gaps in knowledge and highlight significant findings, methodologies, and advancements in the field of fruit quality detection and freshness assessment.

Authors in [14], proposed a Novel model named YOLOAPPEL for identifying and classifying the quality of apple fruit into three classes: normal, damaged, and red delicious apple using Augment YOLOv3 deep learning model. This model utilizes an extra spatial pyramid pooling and incorporates a swish activation function which helps preserve crucial feature information during training and leads to improved results. This model supports a multi-class detection and recognition system, achieving a higher mean average precision (mAP) compared to other models. However, this approach is specifically tailored to apples, and its applicability to other types of fruits remains untested. Additionally, the model's robustness under varying environmental conditions and lighting scenarios needs further exploration. The YOLO model was also used in [15] to classify the ripeness of oil palm fruit and the results indicate the effectiveness of YOLO models in image classification The mAP result achieved for oil palm fruit was 98.7%.

Authors in [16], proposed A multimodal data fusion framework has been developed for assessing pineapple quality using deep learning techniques using features extracted from thermal imaging. They show how the features derived from these thermal images correlate with the fruit's quality attributes, thereby enhancing the effectiveness of the deep learning models in quality determination. Three different types of deep learning architectures, including VGG16, ResNet, and InceptionV3 were used to build the multimodal data fusion framework to distinguish different pineapple varieties. The results demonstrated the effectiveness of multimodal deep learning data fusion with thermal imaging which can improve the recognition accuracy and the model performance up to 0.9687. Thermal imaging was invested in another study [17] to measure the mango fruit's surface temperature. It was analyzed and utilized to train an enhanced deep-learning model to predict the damaged mango. The model achieved a classification accuracy of 99.6 %. Despite the high accuracy, and the generalizability of thermal imaging techniques, these methods' applicability to different imaging modalities has not been extensively studied.

Authors in [18], applied transfer learning techniques and used a set of pre-trained models to classify fruits based on their freshness, this approach gets advantages of the deep architecture of the pre-trained models with a set of different classifiers such as Random Forest and SVM. All models were trained on A dataset comprising images of fruits such as apples, bananas, and guavas taken from various angles and under different lighting conditions was used to facilitate classification into six categories, including fresh and rotten. The results showed that the inception model integrated with SVM results in the highest accuracy among all other integrations. Another study [19] proposed a CNN architecture model to classify the banana fruit maturity to 3 categories: ripe, unripe, and over-ripe, and compared the results against the pre-trained AlexNet model, this study utilized three different datasets from different sources and the results concluded that The suggested CNN model is the most appropriate DL algorithm for bananas' fruit maturity for all three datasets of banana images. While promising, the adaptation of this approach to other fruit types and maturity stages needs further investigation.

A new dataset for classifying fresh fruits and vegetables was created in this research [20], which was aimed at developing an Improved method. The authors developed an optimized YOLOv4 model for this task and compared the results with the previous YOLO model series. The results showed that, compared to the original YOLOv4 and YOLOv3, the experimental evaluation of the proposed model can yield a greater average precision. The same dataset is used in [21], where a new deep learning model is proposed for detecting the freshness of multiple vegetables and fruits more accurately via the fusion method, in this model, deep features extracted from fruits and vegetable images using three pre-trained models named GoogleNet, DenseNet-201, and ResNeXt-101 are fused and fed to SVM classifier to distinguish between fresh and rotten fruits and vegetables. The study used three classifiers SVM, LDA, and Bagging, but SVM achieved the best accuracy through most fruits and vegetable types. Moreover, In [22], The authors present a generalized machine-learning model for evaluating fruit quality named Vision Transformers (ViT). A variety of fruit datasets are used in the construction and training of the ViT model, which allows it to differentiate between images of fresh and rotting fruit based only on appearance. The model showed amazing performance in correctly classifying the quality of different fruits such as Appel, Orange, Guavas, and Mango. Despite effectiveness of all these methods, the computational complexity and resource requirements of such fusion methods need to be addressed to make them practical for real-time applications.

While these studies have made significant strides in automating fruit quality assessment and classification, there remains a need for robust generalization across different fruit types. Some of these studies lack high classification accuracy, and others are tailored to only one type of fruit or do not consider the large computational requirements. In light of these identified gaps, this paper focuses on developing a general model capable of assessing the quality of various types of fruits. The proposed approach aims to address the limitations related to model generalization, environmental robustness, and computational efficiency by utilizing lightweight models, making it suitable for real-time applications in diverse agricultural settings.

3 | Methodology

The methodology of this study is designed to leverage advanced deep learning techniques for effective fruit quality detection. We utilize convolutional neural networks (CNNs) and apply transfer learning to pre-trained CNN models. This approach allows us to benefit from pre-existing knowledge and features extracted from large-scale datasets, enhancing the accuracy and efficiency of our models.

3.1 | Convolutional Neural Networks

CNNs are powerful deep-learning models for image-based tasks, making them highly suitable for fruit quality detection [23]. CNNs excel at automatically extracting relevant features from images, such as color, shape, texture, and size, which are crucial for assessing fruit quality. CNN networks are composed of multiple layers, including convolutional layers, pooling layers, and fully connected layers [24]. Each one has a specific role in the network. First convolution layers use filters to extract features from the input image. Increasingly complicated characteristics can be learned by stacking many convolutional layers. Then a pooling layer is commonly incorporated after convolution layers, these layers reduce the amount of computation required while maintaining crucial information by downsampling the output of convolutional layers. Which makes the model focus on the most important features. Finally, the output is fed to fully connected layers which generate the final output on the model. These components made CNN models have a superior performance in various image classification tasks, including fruit quality assessment.

3.2 | Transfer Learning

Transfer learning is a machine learning approach where a model developed for a particular task is reused as the starting point for a model on a second task, instead of starting from scratch. The primary advantage of transfer learning is that it allows models to leverage previously learned features, which can significantly reduce the amount of data and computational resources required to achieve high performance on the new task. The core idea behind transfer learning is that the features learned in one task can be beneficial for another related task.

A typical transfer learning process involves these steps starting with selecting a model that was trained on a large dataset for a specific task (e.g., image classification on ImageNet). Then the pre-trained model is used to extract features from new data. These features are generic and transferable to other tasks. The next step involves model adaption and Fine-tuning process, this step includes modification of the pre-trained model to suit the new task. It involves replacing the final layers of the model to match the number of output classes in the new task. And freeze all or most of the pre-trained models' layers, to prevent it from changing the pre-trained parameters of the model. In addition, some new layers including the new final layer are added to the model and trained on the new dataset. To make the model work effectively with the new task.in some cases, the pre-trained layers could be partially or fully unfrozen. Letting the pre-trained weights slightly change to better suit the new work. Thus, by utilizing transfer learning methodology. Is crucial in advancing deep learning models used for fruit quality detection, where it enables the development of highly accurate and efficient models.

3.3 | Proposed Approach

The proposed approach for fruit quality detection involves selecting a pre-trained CNN-based model. Each pre-trained model is concerned with a set of preprocessing steps that are applied to the images to make the train it effective. Then adding some new layers to this model to tailor the models to our specific task.

In this work, we employ four pre-trained CNN models: MobileNetV2, ResNet50, and VGG16. Each of these models has been previously trained on the ImageNet dataset and is adapted for the task of fruit quality detection. MobileNetV2 is a lightweight CNN architecture introduced in [25], it involves a combination of depth-wise separable convolutions and pointwise convolutions for efficient feature extraction. ResNet50 is utilizes residual connections allowing information to flow directly from earlier layers to later ones which improves training stability and performance, making it highly effective for image classification tasks [26]. The third model is VGG16, which was developed by Simonyan and Zisserman [27]. It is a simple, effective, and more computationally intensive CNN model. and finally, EfficientNet [28], was developed by researchers at Google. It employs a compound scaling method where depth, width, and resolution are scaled uniformly to ensure balanced growth across all dimensions, leading to more efficient models.

For each pre-trained model, we modify the architecture to fit our specific task. This modification involves removing the last layer of the pre-trained model, which became the base model now, and then a set of new layers are added to this base model, these layers are trained on our dataset to make the model work well with the new task. In this work, a set of layers includes the Global Average Pooling Layer which replaces the fully connected layers to reduce the number of parameters and computational load. And a final fully connected layer with the number of neurons equal to the number of classes in our dataset, this layer will serve as the new output layer of the new model. The final model structure is illustrated in Figure 1, which shows the integration of data preprocessing, the pre-trained base model, and the additional layers. This comprehensive approach leverages the strengths of pre-trained models while tailoring them to the specific requirements of fruit quality detection, ensuring both efficiency and high performance.

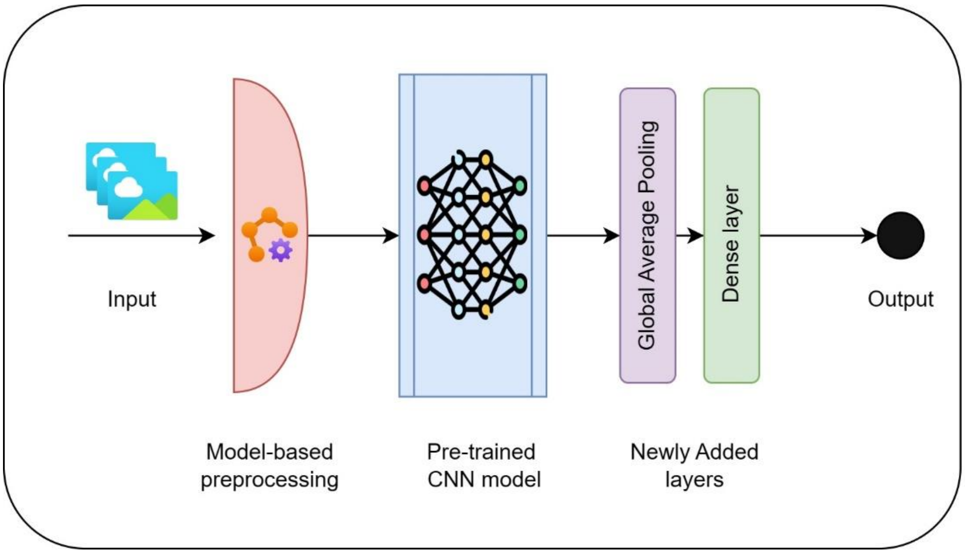

Figure 1. Model architecture.

4 | Experimental Analysis

In this section, we present a comprehensive analysis of the experiments conducted to evaluate the performance of various pre-trained CNN models in fruit quality detection. We provide detailed descriptions of the dataset used, the evaluation metrics employed, and the experimental setup.

4.1 | Dataset Description

This research utilized a curated dataset containing labeled images of five different fruits: apple, banana, strawberry, orange, and mango. This data set is a part of the dataset which was created and used in [20], it was collected from several sources, including Fruit360, Kaggle, Bing Images, Google Images, and Sriram R.K. It was initially created for the vegetable and fruit freshness classification task the whole data is available at fruits-and-vegetables-dataset.

In this paper, we will focus on Fruit images. Each fruit has two categories: fresh and rotten fruits. Each fruit category has a balanced number of images to provide robust training and testing samples. It contains approximately 6000 images divided into 10 categories. The dataset description is presented in Table 1 highlighting the balance between fresh and rotten images for each fruit category. In addition, Figure 2 shows a random sample image from the dataset.

Table 1. Dataset description and image distribution.

Fruit	Fresh images	Rotten images	Total
Appel	612	588	1200
Banana	624	576	1200
Mango	605	593	1198
Orange	609	591	1200
Strawberry	603	596	1199

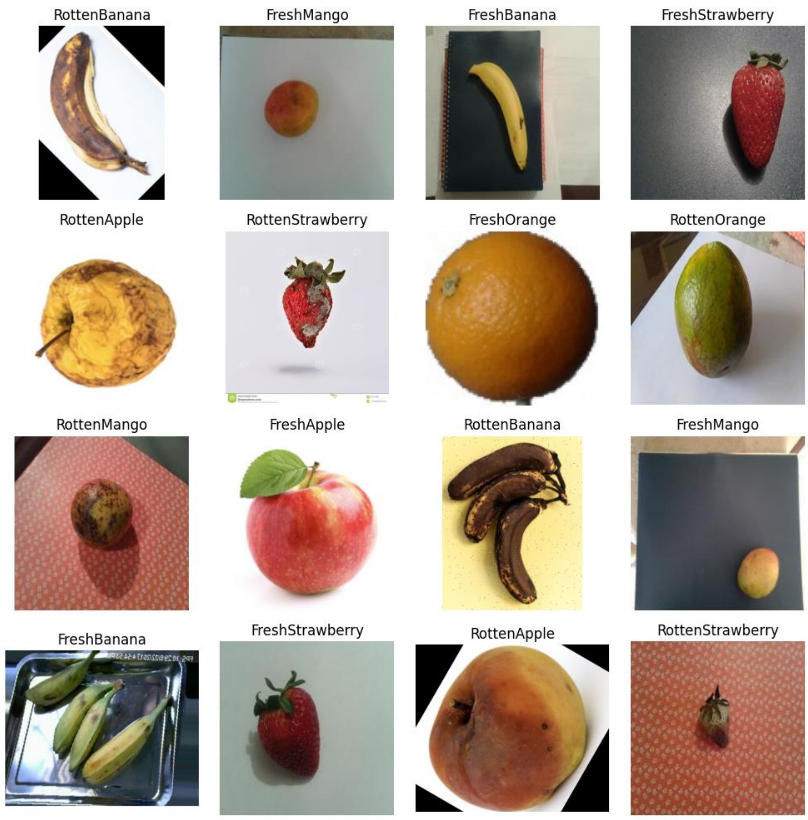

Figure 2. Sample image from the dataset.

4.2 | Dataset Preprocessing

First, as shown in the sample images and mentioned earlier, the images were collected from various sources, resulting in different sizes. The initial step was to resize the images to match the input size requirements of the pre-trained models used. Then the dataset is divided into Training, Validation, and Test datasets with a ratio of 70%, 15%, and 15% respectively. Following this, data augmentation techniques were applied to the dataset to enhance the model's robustness and performance. Data augmentation included operations such as random rotations, flips, shifts, and zoom adjustments. These techniques help in artificially increasing the size and diversity of the training dataset, thereby improving the model's ability to generalize to new, unseen images [29]. Finally, the last step in data processing involved model-specific preprocessing, tailored to optimize the data for each pre-trained model used in the study (MobileNet, ResNet50, Vgg16, and EfficientNet). This preprocessing step ensures that the input data is in a format that maximizes compatibility and performance with the respective model architectures. For instance, preprocessing may include normalizing pixel values, converting color channels, or applying other transformations specific to each model's requirements. This ensures that the models can effectively learn and extract meaningful features from the input images [30-33].

4.3 | Performance Metrics

The performance of the models in fruit quality detection was evaluated using several key metrics: accuracy, precision, recall, and F1-score. These metrics provide a comprehensive assessment of the models' ability to classify fruits into fresh and rotten categories effectively.

- Accuracy – Calculate the proportion of correctly predicted instances relative to the total number of instances evaluated.

$$\text{Accuracy} = \frac{(\text{TP} + \text{TN})}{(\text{TP} + \text{FP} + \text{TN} + \text{FN})} \tag{1}$$

- Precision – Focuses on the precision of positive predictions, for assesses the precision of positive predictions among all predicted positives.

$$\text{Precision } = \frac{TP}{(TP + FP)} \tag{2}$$

- Recall - Focuses on capturing all relevant instances, to ensure the model's ability to correctly identify all relevant instances.

$$\text{Recall } = \frac{TP}{(TP + FN)} \tag{3}$$

- F1 Score – Is the harmonic mean of precision and recall, it ensures a balancing assessment that considers both false positives and false negatives for comprehensive performance evaluation.

$$F1 \text{ Score } = 2 \times \frac{\text{recall } \times \text{ precision}}{\text{recall } + \text{ precision}} \tag{4}$$

These metrics were calculated individually for each type of fruit and were also averaged across all classes to provide an overall performance measure for each model. We conducted these evaluations using a dedicated validation dataset to ensure unbiased assessment and to gauge how well the models generalize to new, unseen fruit samples.

4.4 | Environment Setup

All experiments were conducted on the Kaggle platform utilizing an Nvidia Tesla P100 GPU with 30 GB of RAM. The experiments were implemented using Python version 3.10.13. The deep learning models were developed and trained using TensorFlow version 3.10.13 [34] and Keras API. Specifically, the models were trained using the Adam optimizer with a learning rate set to 0.001, a batch size of 32, and trained for 100 epochs. Adam combines the benefits of two other popular optimization algorithms, namely AdaGrad and RMSProp [35], which makes it a suitable one for most image classification tasks. To prevent overfitting, early stopping was employed with a monitoring criterion of 'val_loss' and patience of 5 epochs.

5 | Results and Discussion

This section presents the experimental results of our fruit quality detection models and provides a detailed discussion of their performance. The results are evaluated using accuracy, precision, recall, and F1-score metrics for each fruit type: apple, banana, strawberry, orange, and mango. These measures offer an extensive understanding of the model's performance, reliability, and capability for generalization. To validate the effectiveness of the proposed approach, we compare the performance of our models with four existing state-of-the-art techniques including using support vector classifiers (SVM) with a combining of deep features extracted by a set of pre-trained models architecture [21], An improved YOLOv4 model [20], Vision Transformers model (ViT) [22], and a pre-trained AlexNet model [19].

5.1 | Experiment's Results

To ensure a fair comparison against the existing state-of-the-art techniques, all these techniques were implemented and trained in the same environment as the proposed models, to ensure dependable results and consistent comparisons. Tables 2-6 show the results of all models for apple, banana, mango, orange, and strawberry fruits. Respectively, Figure 3 shows the comparison of all models' performances.

Table 2. Performance metrics for Apple quality detection.

Model	Accuracy	Pression	Recall	F1-Score
MobileNet	0.9832	0.9834	0.9831	0.9832
Resnet50	**0.9888**	**0.9888**	**0.9888**	**0.9888**
Vgg16	0.9236	0.9430	0.9203	0.9315
EfficientNet	0.9609	0.9618	0.9604	0.9608
SVM &deep features [21]	0.9330	0.9355	0.9342	0.9329
Improved YOLOv4 [20]	0.9162	0.9163	0.9160	0.9161
ViT [22]	0.8045	0.8059	0.8054	0.8044
Deep CNN [19]	0.8045	0.8064	0.8032	0.8046

Table 3. Performance metrics for banana quality detection.

Model	Accuracy	Pression	Recall	F1-Score
MobileNet	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Resnet50	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Vgg16	0.9933	0.9931	0.9934	0.9933
EfficientNet	0.9934	0.9925	0.9942	0.9933
SVM &deep features [21]	0.94774	0.9505	0.9429	0.9460
Improved YOLOv4 [20]	0.9342	0.9331	0.9331	0.9331
ViT [22]	0.7789	0.8210	0.7187	0.7675
Deep CNN [19]	0.7763	0.8224	0.8006	0.8114

Table 4. Performance metrics for mango quality detection.

Model	Accuracy	Pression	Recall	F1-Score
MobileNet	0.9833	0.9840	0.9831	0.9833
Resnet50	**0.9889**	**0.9892**	**0.9888**	**0.9889**
Vgg16	0.9778	0.9781	0.9777	0.9778
EfficientNet	0.9789	0.9792	0.9788	0.9789
SVM &deep features [21]	0.9500	0.9524	0.9504	0.9500
Improved YOLOv4 [20]	0.9778	0.9779	0.9782	0.9780
ViT [22]	0.7778	0.8176	0.7822	0.7025
Deep CNN [19]	0.7722	0.7994	0.7742	0.7822

Table 5. Performance metrics for orange quality detection.

Model	Accuracy	Pression	Recall	F1-Score
MobileNet	0.9889	0.9891	0.9889	0.9889
Resnet50	**1.0000**	**1.0000**	**1.0000**	**1.0000**
Vgg16	0.9889	0.9894	0.9886	0.9889
EfficientNet	0.9900	0.9902	0.9898	0.9899
SVM &deep features [21]	0.9167	0.9201	0.9177	0.9166
Improved YOLOv4 [20]	0.9556	0.9583	0.9565	0.9555
ViT [22]	0.9278	0.9277	0.9279	0.9278
Deep CNN [19]	0.8611	0.8619	0.8617	0.8611

Table 6. Performance metrics for strawberry quality detection.

Model	Accuracy	Pression	Recall	F1-Score
MobileNet	0.9833	0.9834	0.9833	0.9834
Resnet50	**0.9944**	**0.9944**	**0.9945**	**0.9945**
Vgg16	0.9611	0.9615	0.9613	0.9611
EfficientNet	0.9889	0.9890	0.9890	0.9889
SVM &deep features [21]	0.9500	0.9511	0.9503	0.9500
Improved YOLOv4 [20]	0.8944	0.8958	0.8941	0.8943
ViT [22]	0.7556	0.8250	0.7603	0.7913
Deep CNN [19]	0.7556	0.7786	0.7571	0.7511

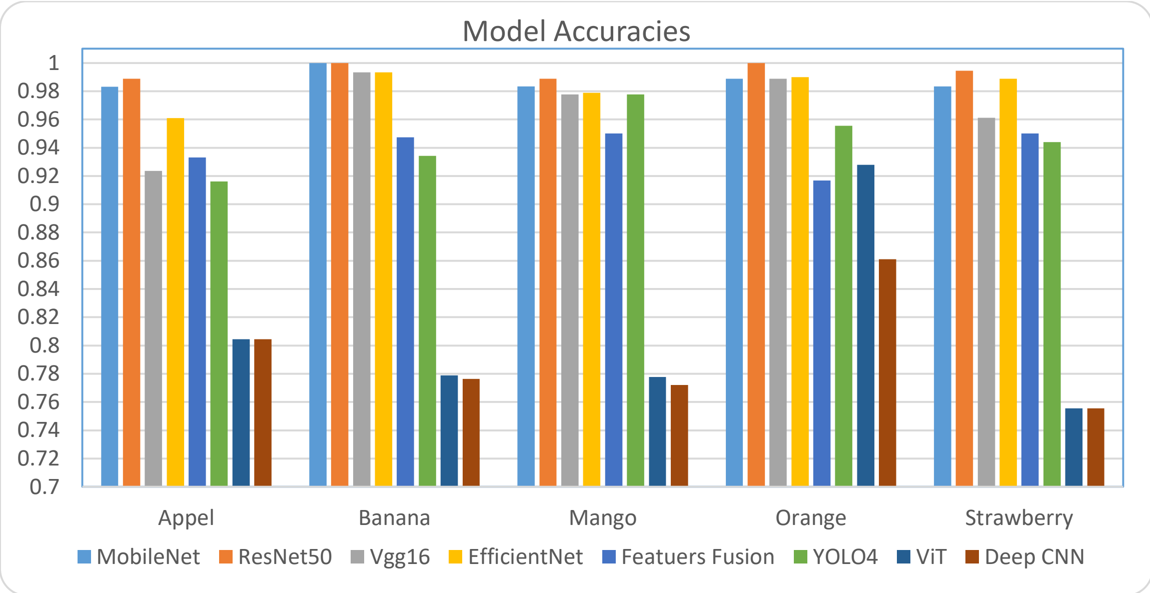

Figure 3. Comparison of model accuracies across all fruit types.

5.2 | Discussion

The Results reveal that ResNet50 consistently outperforms the other models in terms of accuracy, precision, recall, and F1-score for all fruit categories. This demonstrates its robustness and capability in handling complex image features and variations, making it the most effective model for fruit quality detection in our study. MobileNetV2 also showed strong performance, particularly achieving perfect scores with bananas and oranges. Its lightweight architecture and efficient computational requirements make it suitable for deployment on devices with limited resources. However, for other fruit types, its performance, while still strong, was not as good as ResNet50. EfficientNet, known for its balanced scaling and efficiency, provided competitive results but still fell short of ResNet50. Efficient Net's compound scaling method, which simultaneously scales up network width, depth, and resolution, offers significant efficiency improvements. However, ResNet50's deeper architecture and residual connections allowed it to capture more complex features, leading to better overall performance. In contrast, VGG16 performed the least well among the evaluated models. Its relatively lower accuracy, especially with apples, suggests that it might not be as effective in capturing the intricate features necessary for high-quality fruit detection. This could be attributed to its larger parameter size and older architecture compared to more modern networks like ResNet50 and EfficientNet.

When compared to state-of-the-art methods like [19-22], ResNet50 demonstrated superior performance. Models like YOLOv4 and ViT, although effective in their specific domains, did not achieve the best performance compared ResNet50 model in fruit quality detection. in addition, Models like AlexNet and Ensemble deep features with SVM, although considered a CNN-based pre-trained models, not match

ResNet50's accuracy in this specific task. This suggests that for the specific task of fruit quality detection, ResNet50's architecture and feature extraction capabilities are particularly well-suited.

The application of data augmentation techniques was critical in enhancing the model's ability to generalize and handle diverse and unseen data. By using it the models were better equipped to handle different variations in the fruit images. Furthermore, the specific preprocessing steps for each model ensured that the input images were appropriately scaled and normalized, contributing to the high performance observed.in addition, The use of transfer learning allowed us to leverage pre-trained weights from large datasets like ImageNet, significantly reducing the training time and computational resources required. This approach was particularly effective for ResNet50, which benefited from the extensive pre-training on diverse image data, leading to superior performance in our fruit quality detection task.

6 |Conclusion and Future Work

In this paper, we have proposed a transfer learning-based deep learning model for automated fruit quality detection, focusing on five fruits: apple, banana, strawberry, orange, and mango. We leveraged the power of four pre-trained convolutional neural network models—MobileNetV2, ResNet50, VGG16, and EfficientNet—to determine the most effective approach for this task. The methodology involved extensive data preprocessing, to prepare the images for training. We fine-tuned each pre-trained model by adding a global average pooling layer and a dense layer suited to the number of fruit quality classes. The models were trained and evaluated on a robust dataset, and their performance was measured using accuracy, precision, recall, and F1-score metrics. The experimental results demonstrated that ResNet50 consistently outperformed the other models, achieving the highest accuracy across all fruit types. MobileNetV2 and EfficientNet also showed strong performance, particularly for bananas and oranges, where they achieved perfect scores. In contrast, VGG16 showed lower performance relative to other pre-trained models. To validate our approach, we compared the performance of our models with existing state-of-the-art techniques in fruit quality detection. Our findings indicate that ResNet50 not only achieved superior performance in our experiments but also outperformed several contemporary methods reported in the literature. These findings underscore the potential of deep learning and transfer learning techniques in enhancing the efficiency and accuracy of automated fruit quality detection systems. By leveraging pre-trained models, we can significantly reduce the time and computational resources required for training while achieving high performance. This approach offers a promising solution for improving quality control processes in the agricultural and food industries.

Future work could explore the integration of more diverse datasets, including different fruit varieties and additional quality attributes. Moreover, investigating other advanced deep learning architectures and fine-tuning strategies could further enhance the accuracy and robustness of fruit quality detection systems. The insights gained from this study contribute to the growing body of knowledge on the application of AI in agriculture.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors.

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