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Evaluating pretrained CNNs for distinguishing fresh vs rotten fruits and vegetables

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Abstract

Accurately distinguishing between fresh and rotten fruits and vegetables is essential for reducing waste, ensuring food safety, and maintaining quality standards in agriculture and supply chain management. This research utilized the fruit and vegetable diseases dataset from Kaggle, which included images of 14 types of produce in both healthy and rotten states. In this study, the performance of four pre-trained convolutional neural network models was evaluated: MobileNetV3 Small, EfficientNetV2 Small, DenseNet121, and ShuffleNetV2_x1_5. Among these, ShuffleNetV2_x1_5 demonstrated the highest performance, achieving an overall accuracy of 94.61% and a cross-validation mean accuracy of 96.43% with minimal standard deviation. The model's efficiency and robust feature extraction capabilities make it highly suitable for real-time applications in agricultural monitoring and robotics, offering a significant advancement in the automation of produce quality assessment.

Key words: MobileNetV3 Small, EfficientNetV2 Small, DenseNet121, ShuffleNetV2_x1_5, image classification, fruit and vegetable diseases

Introduction

The accurate distinction between fresh and rotten fruits and vegetables is of paramount importance across various sectors, including agriculture, supply chain management, and food safety. The early detection of spoilage not only reduces waste but also ensures consumer safety and helps maintain stringent quality standards. In agriculture, identifying spoilage at an early stage can prevent the spread of diseases, thus leading to healthier crops and more robust yields. Similarly, in the supply chain, differentiating between fresh and rotten produce enables better decision-making regarding storage, transportation, and inventory management. For consumers and retailers, ensuring the freshness of fruits and vegetables is critical to enhancing customer satisfaction and trust (Nerella *et al.*, 2023; Shobana *et al.*, 2022; Arvind *et al.*, 2022).

Given these significant implications, this research focuses on evaluating pre-trained Convolutional Neural Network (CNN) models for the accurate classification of fresh versus rotten produce. Utilizing the Fruit and Vegetable Diseases Dataset sourced from Kaggle, which includes images categorized into 28 directories representing healthy and rotten images of 14 different types of produce, this study employs several state-of-the-art pre-trained models such as MobileNetV3 Small, EfficientNetV2 Small, DenseNet121, and ShuffleNetV2_x1_5 (Sharmila *et al.*, 2023). These models, known for their efficiency and high accuracy in image classification tasks, are fine-tuned and tested on this comprehensive dataset to develop a reliable system for detecting the freshness of fruits and vegetables.

The field has seen various approaches to this problem. For instance, Palakodati *et al.* (2020) explored transfer learning models like VGG16, VGG19, MobileNet, and Xception, achieving an impressive accuracy of 97.82% in classifying fresh and rotten fruits. Similarly, Miah *et al.* (2021) employed models such as InceptionV3, which achieved the highest accuracy of 97.34% on a diverse dataset. Other studies, like those by Karakaya *et al.* (2019) and Mishra and Singh (2024), have utilized Support Vector Machines (SVMs) and CNN architectures like VGG16, demonstrating high classification accuracy in distinguishing fresh from rotten produce.

Furthermore, the integration of advanced deep learning techniques in fruit classification has been highlighted in several studies. For example, Chakraborty *et al.* (2021) demonstrated the effectiveness of MobileNetV2 in achieving over 99% accuracy in both training and validation stages. Similarly, Amin *et al.* (2023) proposed a fruit freshness classification method using AlexNet with transfer learning, achieving near-perfect accuracies across multiple datasets. Other studies, such as those by Mukhiddinov *et al.* (2022) and Göksu *et al.* (2023), have explored enhancements to existing models, such as the YOLOv4 model and ResNet50, to improve precision and robustness in fruit and vegetable classification tasks. Studies have demonstrated the effectiveness of machine learning techniques like CNN and SVM for automating fruit freshness classification. Models was achieved with an impressive accuracy in distinguishing fresh and rotten fruits, including apples, bananas, and oranges (Sia and Baco, 2023). Hybrid approach highlights the potential of SVM as a reliable alternative for enhancing fruit freshness assessment (Yashadhana *et al.*, 2023).

In this research, by leveraging a well-structured data set alongside sophisticated deep learning models, we aim to develop a reliable system for detecting rotten and fresh fruits and vegetables. The outcomes of this study have the potential to significantly impact agriculture, supply chain management, and food safety, contributing to reduced waste, enhanced quality control, and improved consumer trust.

Materials and method

Data preparation and transformation: The dataset for this research, sourced from Kaggle, was the Fruit and Vegetable Diseases Dataset, designed for developing deep learning models for detecting diseases in fruits and vegetables. The dataset comprises images categorized into 28 directories, each representing healthy and rotten images for 14 different types of produce (Table 1). To prepare the data, source directories were defined for each category, linking the type and condition of produce with specific directory names to ensure a structured dataset. A base path indicated the root directory, and separate paths were created for training, validation, and testing datasets. Corresponding directories were created within these paths to organize the data. The images were then processed by accessing the source directories, splitting the images into training, validation, and test sets, and copying them into their respective destination directories. This careful organization and distribution ensured the dataset's consistency and quality, facilitating effective training, validation, and testing of the machine learning models.

The training, validation, and test sets consisted of 12130, 2598, and 2609 images, respectively. Data transformation was applied using the predefined transformations associated with each pretrained model to standardize the image preprocessing steps. For the MobileNetV3 Small model, images were resized to 232x232 pixels and then cropped to 224x224 pixels, with pixel values normalized using a mean of [0.485, 0.456, 0.406] and a standard deviation of [0.229, 0.224, 0.225], and bilinear interpolation was used. The EfficientNetV2 Small model involved resizing and cropping images to 384x384 pixels, with the same normalization values and bilinear interpolation. For DenseNet121, images were resized to 256x256 pixels and cropped to 224x224 pixels, again normalizing with the same mean and standard deviation and using bilinear interpolation. The ShuffleNetV2_x1_5 model required images to be resized to 232x232 pixels and cropped to 224x224 pixels, with the same normalization parameters and bilinear interpolation applied. These transformations ensured that the images were preprocessed to match the input requirements of each pretrained model, optimizing the performance of the deep learning models by maintaining consistency in the data fed into the models.

Table 1. Dataset distribution across training, validation, and test sets for fresh and rotten fruit and vegetable classes

Classes	Train	Validation	Test
Fresh Apple	223	48	48
Rotten Apple	405	87	87
Fresh Banana	557	119	120
Rotten Banana	399	85	86
Fresh Bell pepper	422	90	91
Rotten Bell pepper	413	89	89
Fresh Carrot	422	90	91
Rotten Carrot	404	87	87
Fresh Cucumber	411	88	89
Rotten Cucumber	394	84	85
Fresh Grape	140	30	30
Rotten Grape	140	30	30
Fresh Guava	140	30	30
Rotten Guava	140	30	30
Fresh Jujube	140	30	30
Rotten Jujube	140	30	30
Fresh Mango	1117	240	240
Rotten Mango	1563	335	335
Fresh Orange	214	46	46
Rotten Orange	413	89	89
Fresh Pomegranate	140	30	30
Rotten Pomegranate	140	30	30
Fresh Potato	422	90	91
Rotten Potato	408	87	88
Fresh Strawberry	1122	240	241
Rotten Strawberry	1099	235	236
Fresh Tomato	195	42	42
Rotten Tomato	407	87	88
Total	12130	2598	2609

Proposed model: ShuffleNet v2_x1_5 was selected as the primary model architecture for its superior performance metrics, showing high accuracy and robust cross-validation results essential for the task of classifying rotten fruits and vegetables from fresh ones based on image data. The architecture's efficiency stems from its innovative use of depthwise separable convolutions, which separate spatial and channel-wise operations to significantly reduce computational complexity while preserving feature representation (Fig. 1). Integrated channel shuffle operations promote information exchange across different groups of channels, enhancing the model's capability to capture diverse features across various produce types. Moreover, residual connections within each stage ensure smooth gradient propagation during training, thereby improving convergence and stability. The model architecture culminates with global average pooling to aggregate spatial information and a fully connected layer with softmax activation for final classification, consistently achieving top accuracy and demonstrating superior performance in cross-validation with minimal standard deviation. By using ShuffleNet's efficient feature extraction and processing capabilities, this architectural choice not only enhances accuracy but also supports real-time deployment in agricultural monitoring

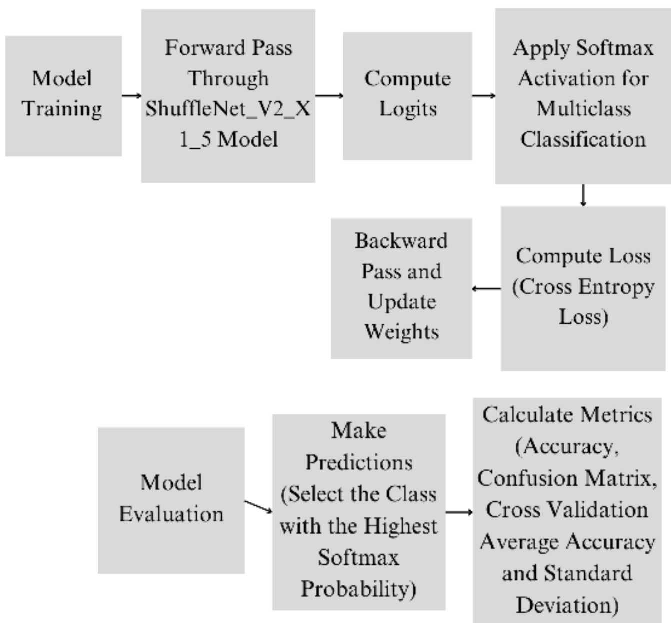

Fig. 1. Training and evaluation of the proposed model

systems and mobile applications, addressing resource constraints while maintaining high predictive performance.

Experimental Setup: The experimental setup (Fig. 2) involved training the models locally using Visual Studio Code on a workstation equipped with an Intel Core i9 processor and an NVIDIA GeForce RTX GPU. The training code was implemented in PyTorch, using its deep learning capabilities and extensive neural network modules. Each selected model MobileNetV3 Small, EfficientNetV2 Small, DenseNet121, and ShuffleNet v2_x1_5 was created with pretrained weights from torchvision models and finetuned for 10 epochs. During training, the optimizer used was Adam with a learning rate of 0.01. This optimizer efficiently adjusted the model's weights based on the gradients computed during backpropagation, optimizing the cross-entropy loss function. This loss function was important in calculating the discrepancy between predicted and actual class distributions, guiding the model towards improved classification accuracy. The training process involved passing batches of preprocessed images through each model. Initially, the images were loaded from predefined directories, resized, and normalized to ensure consistent input dimensions and data quality. The forward pass through the models involved applying the respective convolutional and pooling layers to extract hierarchical features, followed by flattening and passing through fully connected layers to compute class probabilities. The softmax activation function at the output layer transformed logits into probabilities, facilitating class prediction based on the highest probability. After training, evaluation of the models involved several steps to ensure a comprehensive assessment of their performance. This included computing the mean and standard deviation of 5-fold cross-validation accuracy with each fold consisting of 10 epochs, which provided insights into the models' generalization capabilities across different subsets of the dataset (Fig. 3). Additionally, metrics such as overall accuracy on the test set and confusion matrices were calculated. These matrices detailed the models' performance across different classes, highlighting specific areas of strength or weakness in classification.

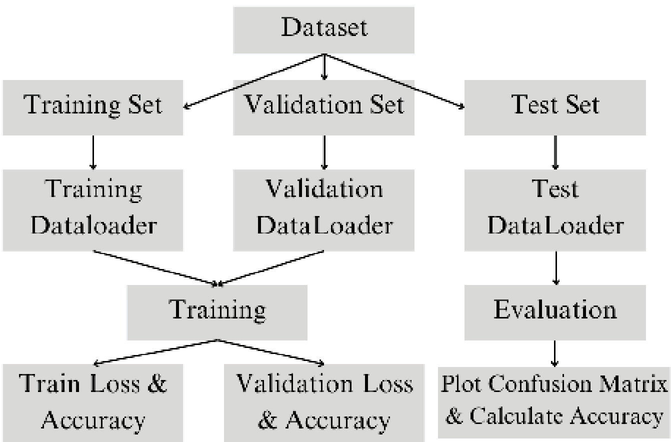

Fig. 2. Experimental setup

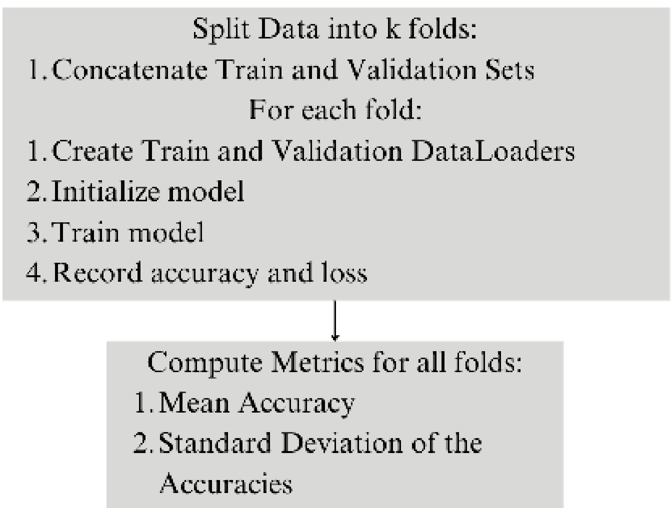

Fig. 3. K-Fold cross-validation setup

Results and discussion

In this study, four convolutional neural network architectures were evaluated: MobileNet V3 small, EfficientNet V2 small, ShuffleNet_V2_X1_5, and DenseNet121. The primary metrics for comparison were overall accuracy, cross-validation mean accuracy, and cross-validation accuracy standard deviation.

For MobileNet V3 small, an overall accuracy of 93.88% was achieved. The cross-validation mean accuracy was 95.28% with a standard deviation of 0.0051. This model, despite its relatively high accuracy, showed a significant discrepancy between the training and validation loss curves. The divergence in the loss curves indicated potential overfitting, making this architecture less favorable despite its solid performance metrics.

EfficientNet V2 small yielded an overall accuracy of 94.80% and a cross-validation mean accuracy of 95.01%, with a standard deviation of 0.0043. While this model demonstrated a high level of accuracy, the loss curve increased towards the end of training, suggesting instability in the training process.

DenseNet121 achieved an overall accuracy of 94.49% with a cross-validation mean accuracy of 95.07% and a standard deviation of 0.0085. Although the accuracy was competitive, the fluctuations observed in the loss curves indicated inconsistent training behavior. The higher standard deviation also pointed to less reliable performance across different validation folds.

ShuffleNet_V2_X1_5 demonstrated an overall accuracy of 94.61%. The cross-validation mean accuracy was 96.43% with a minimal standard deviation of 0.0027. The selection of ShuffleNet_V2_X1_5 was primarily based on its superior cross-validation mean accuracy and the lowest standard deviation among all tested models. These metrics indicated not only a high level of accuracy but also consistent performance across different validation sets. Moreover, the training process for ShuffleNet_V2_X1_5 showed smoother loss and accuracy curves when compared to the other models.

The absence of significant divergence between the training and validation loss curves highlighted a more stable and generalizable training process. This contrasted with the performance of MobileNet V3 small, which showed a divergence in the loss curves, EfficientNet V2 small, which had an increasing loss towards the end of training, and DenseNet121, which displayed considerable fluctuations in its loss curves (Fig. 4). Thus, ShuffleNet_V2_X1_5 was chosen for its highest cross-validation mean accuracy and minimal standard deviation, ensuring robust and reliable performance. The stability observed in the loss and accuracy curves further supported the decision, making ShuffleNet_V2_X1_5 the optimal choice among the evaluated models.

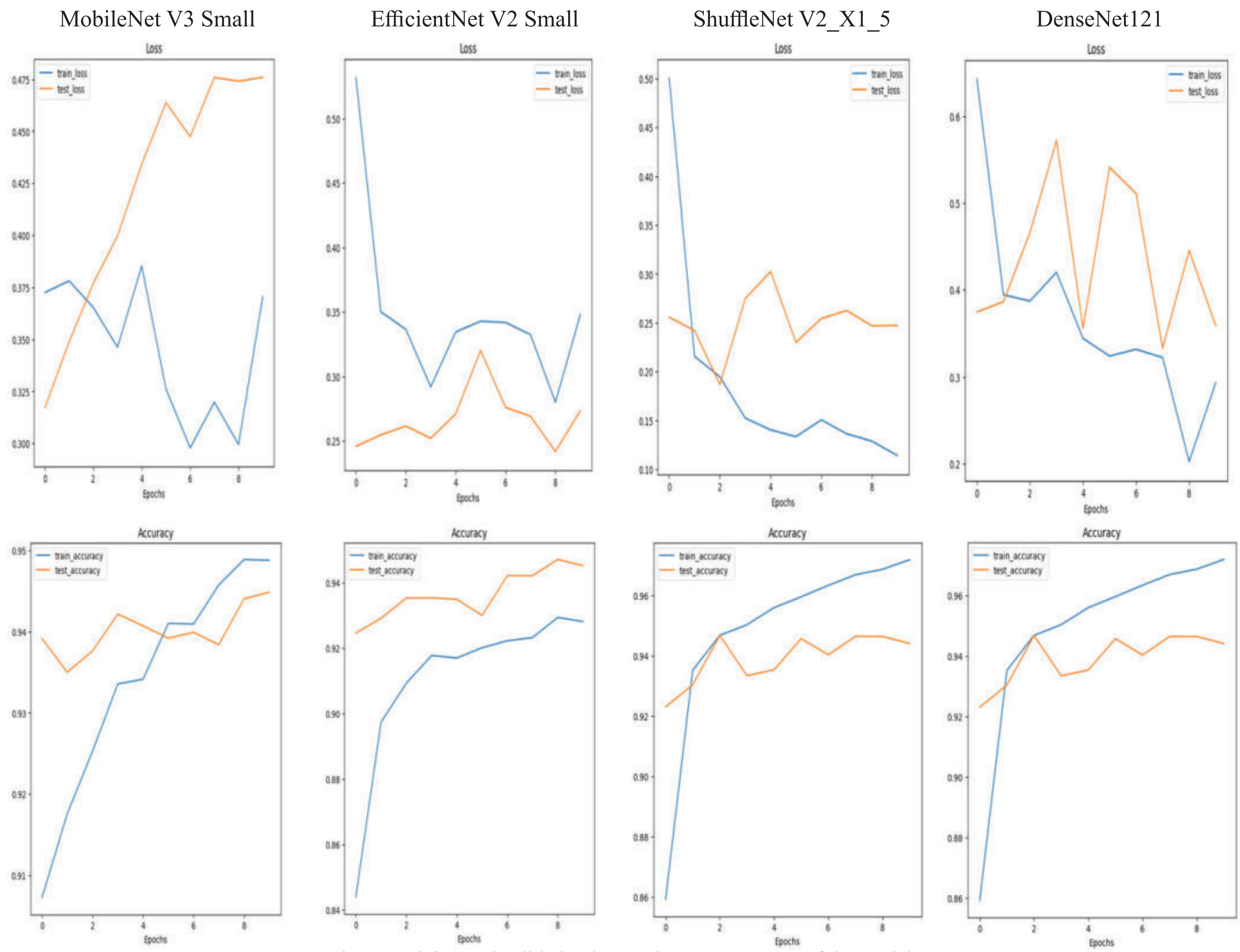

Fig. 4. Training and validation loss and accuracy curves of the models

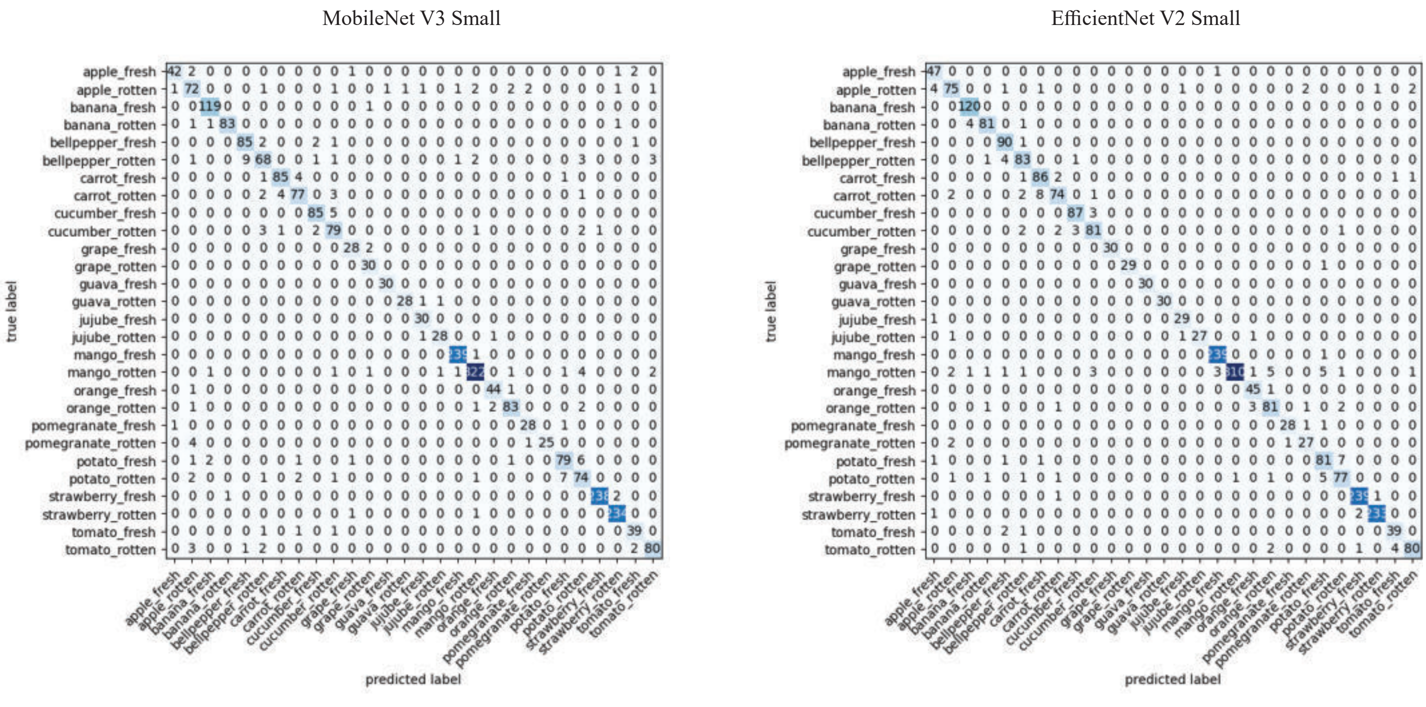

Fig. 5. Confusion matrices of the models

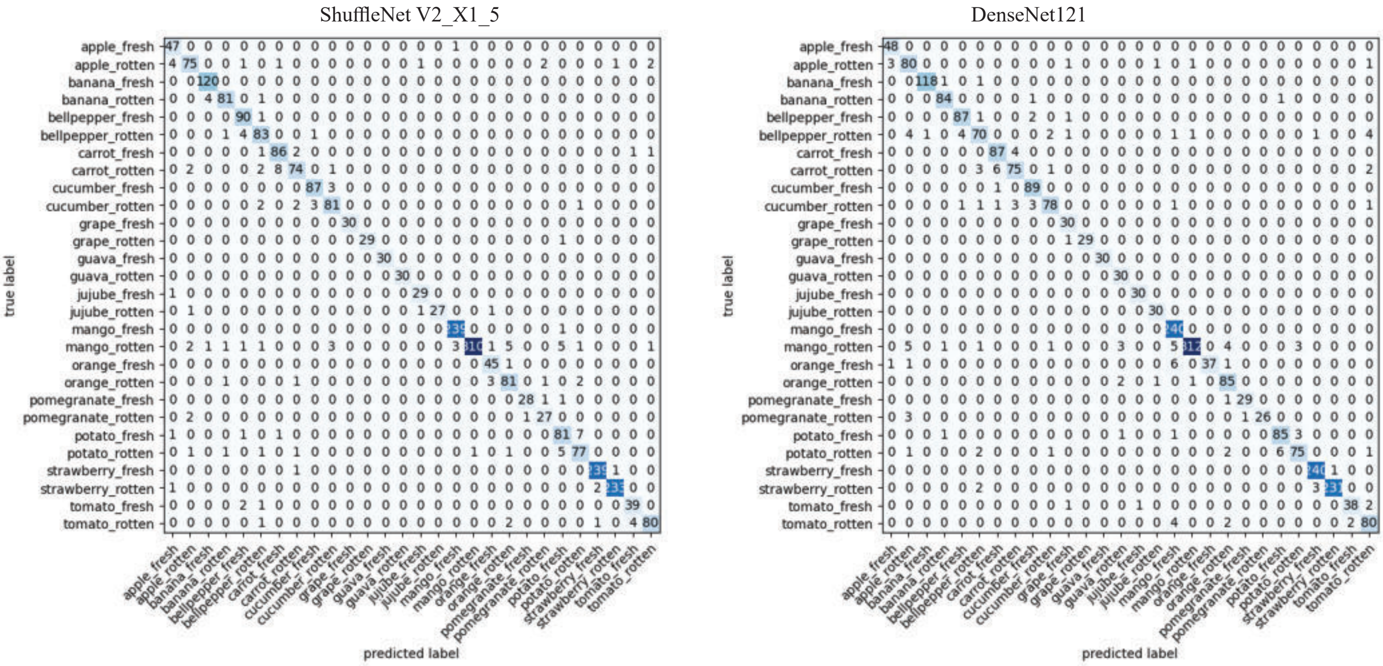

Fig. 5. Confusion matrices of the models (contd..)

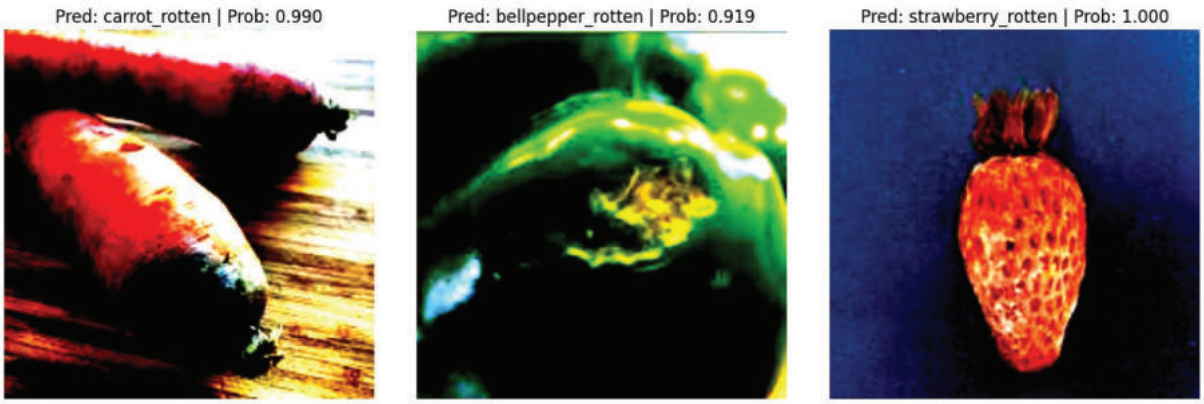

Fig. 6. Predictions and prediction probabilities on transformed images

Fig. 4 indicates training and validation loss and accuracy curves of the models, Fig. 5 presents the confusion matrices of the models and Fig. 6 shows the predictions and prediction probabilities on transformed images used in this research.

The results demonstrated that ShuffleNetV2_x1_5 outperformed the other models, achieving the highest overall accuracy of 94.61% and a cross-validation mean accuracy of 96.43% with minimal standard deviation. This model's robust performance can be attributed to its efficient depthwise separable convolutions and channel shuffle operations, which enhance feature extraction while maintaining computational efficiency (Mukhiddinov *et al.*, 2022). The stability of ShuffleNetV2_x1_5 was further evident in its smooth loss and accuracy curves, contrasting with the fluctuations and potential overfitting observed in the other models (Amin *et al.*, 2023; Sharmila *et al.*, 2023).

This research underscores the importance of selecting the appropriate CNN architecture for specific tasks in agricultural monitoring and supply chain management. The superior performance of ShuffleNetV2_x1_5 suggests its potential for real-time applications, offering a significant advancement in the automation of produce quality assessment (Rodriguez *et al.*, 2021). The study also highlights the need for further refinement and integration of such models into comprehensive systems to support continuous monitoring and early detection of spoilage, ultimately contributing to improved food safety and sustainability (Patel and Patil, 2023; Miah *et al.*, 2021).

This research highlights the potential of deep learning models in automating the detection of rotten fruits and vegetables, which is critical for enhancing quality control and reducing waste in the food supply chain. Among the models evaluated, ShuffleNetV2_x1_5 proved to be the most effective, offering the highest accuracy and consistent performance across validation sets. The model's architecture, featuring efficient depth wise separable convolutions and channel shuffle operations, enables robust feature representation and stability during training. These attributes make it an ideal candidate for deployment in real-time monitoring systems and mobile applications, addressing the need for efficient and reliable produce quality assessment tools. Future work should focus on further refining these models and integrating them into comprehensive systems for continuous monitoring and early spoilage detection, thereby advancing food safety and sustainability practices.

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