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Transfer Learning-Based Classification of Fresh and Stale Fruits and Vegetables Using Deep Convolutional Neural Networks

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Abstract

In Food supply chains and household consumption the spoilage of fruits or vegetables and their quality degradation is a major challenge. Early identification of fresh and stale produce can help reduce food waste and improve food safety. We use deep learning to automatically learn and classify the fresh and stale fruits and vegetables using image data. A publicly available fruit and vegetable dataset has been used for this research work. Three transfer learning models, namely MobileNetV2, ResNet50, and EfficientNetB0, were employed to perform multi-class image classification.

Keywords: deep learning; image recognition; food spoilage; fresh fruit classification

1. Introduction

Fruits and vegetables are essential components of a healthy diet and play a significant role in global food systems. However, a considerable portion of fresh produce is lost every year due to spoilage and improper quality monitoring. According to global food waste reports, large quantities of fruits and vegetables are discarded during storage, transportation, and retail processes. Early detection of stale or spoiled produce is therefore important for reducing food waste, maintaining food quality, and ensuring consumer safety.

Traditional approaches to assess and evaluate the freshness of fruits and vegetables is though manual inspection by farmers, retailers, or consumers. This process become time consuming and nearly impossible when having bulk of fruits or vegetable carriers. As this process relies mainly on visual observation of factors such as color changes, texture deterioration, and surface damage. As the demand for efficient and automated food quality monitoring systems increases, computer vision and artificial intelligence have emerged as promising solutions.

Recently deep learning has been enhanced particularly after the introduction of convolution neural network image classification task has become very simpler and easier. As the demand for efficient and automated food quality monitoring systems increases, computer vision and artificial intelligence have emerged as promising solutions.

We also use in this research work transfer learning to automatically classify fresh and stale fruits and vegetables using image data. We use three well-known convolutional neural network architectures namely MobileNetV2, ResNet50, and EfficientNetB0 and compare the recognition results.

The main objective of this research is to investigate the capability of transfer learning models to accurately classify fruit and vegetable freshness from images. By analyzing the performance of multiple deep learning architectures. The proposed approach can support applications in smart agriculture, automated food inspection systems, and intelligent retail environments where rapid and reliable freshness detection is required.

We organized remaining paper in following sections:

- In Section 2, related work on fruit quality detection and deep learning-based classification methods is presented.
- In Section 3 the dataset and preprocessing techniques used in this study are briefly described.
- In Section 4 the proposed methodology and model architecture are explained.
- In Section 5 the experimental results and performance comparison of the models are presented.
- In Section 6 the paper is concluded, and the potential future research directions are discussed.

2. Literature Review

Computer Vision and deep learning has become very much enhanced and advanced during the last two decades. The algorithms and models have significantly improved and many researchers have been using and employing them to classify images in almost every domain and business of life from medical to marketing and from aerial to aquatic images.

In food supply chain also researchers have explored CNN, transfer learning and hybrid deep learning architectures to classify fruits and vegetables as fresh or stale. In [11] authors have proposed a deep learning-based framework to distinguish between fresh and stale fruits and vegetables using image data. They used simple CNN model to effectively learn visual patterns associated with freshness. Likewise, [12] developed a CNN-based classification system for detecting fresh and rotten fruits using transfer learning techniques. [13] investigated a compact CNN architecture integrated with micro cold storage monitoring systems for identifying stale fruits. In [14] also the authors used a CNN-based fruit freshness classification system with transfer learning to improve model generalization across different fruit types. Semantic segmentation was studied by [15] in this domain. [16] used and utilized texture-based features extracted through convolutional layers to identify signs of decay and deterioration. A CNN model was customized by [17] combining multiple pre trained models to classify fruits as fresh or spoiled. [18] developed a multi-task convolutional neural network capable of simultaneously detecting fruit freshness and identifying fruit types. The shared feature extraction architecture improved model efficiency while maintaining high detection accuracy. [19] proposed an integrated deep learning approach combining CNNs with bidirectional learning mechanisms to improve fruit and vegetable freshness detection. [20] designed a CNN-based deep learning framework to recognize fresh and rotting fruits using image datasets containing multiple fruit types.

Comparative studies also has been conduction by various authors in this domain like [21,22] evaluated different CNN architectures for classifying fruit quality.

Ref. [23] used YOLOv4 detection for classifying fruit quality assessment model. [24–27] developed a CNN-based model for predicting fruit freshness levels and detecting fruit types from images. [28–30] also developed CNN-based models for predicting fruit freshness levels and detecting fruit types from images.

3. Methodology

The methodology consists of four main stages as most deep learning methodology adopts [31–34]: dataset preparation, data preprocessing and analysis, model architecture and training, and performance evaluation.

3.1. Dataset Description

The experiments were conducted using the Fresh and Stale Fruits and Vegetables dataset, which contains images of six different types of produce: apple, banana, bitter gourd, capsicum, orange, and tomato. Each category contains two classes as shown in Figure 1 representing freshness levels: fresh and stale. Therefore, the dataset contains a total of twelve classes.

```
class_counts = {}

for cls in sorted(os.listdir(dataset_root)):
    cls_path = os.path.join(dataset_root, cls)
    if os.path.isdir(cls_path):
        count = len([
            f for f in os.listdir(cls_path)
            if f.lower().endswith(('.png', '.jpg', '.jpeg'))
        ])
        class_counts[cls] = count

df_counts = pd.DataFrame(list(class_counts.items()), columns=["Class", "Count"])
df_counts = df_counts.sort_values("Class")
print(df_counts)
```

```
               Class  Count
0        fresh_apple   1693
1       fresh_banana   1581
2  fresh_bitter_gourd   327
3     fresh_capsicum    990
4       fresh_orange   1466
5       fresh_tomato    981
6        stale_apple   2342
7       stale_banana   1467
8  stale_bitter_gourd   357
9     stale_capsicum    901
10      stale_orange   1595
11      stale_tomato    982
```

Figure 1. Dataset Count.

Each image represents a single fruit or vegetable captured under varying lighting conditions and backgrounds. These images provide sufficient visual variations for training deep learning models to recognize freshness characteristics such as color changes, surface texture, and spoilage patterns [35].

The distribution of images across the twelve classes is shown in Figure 2, showing that the dataset contains a relatively balanced number of samples for both fresh and stale categories. This help us understand visually the dataset composition, the number of images in each class [36–38].

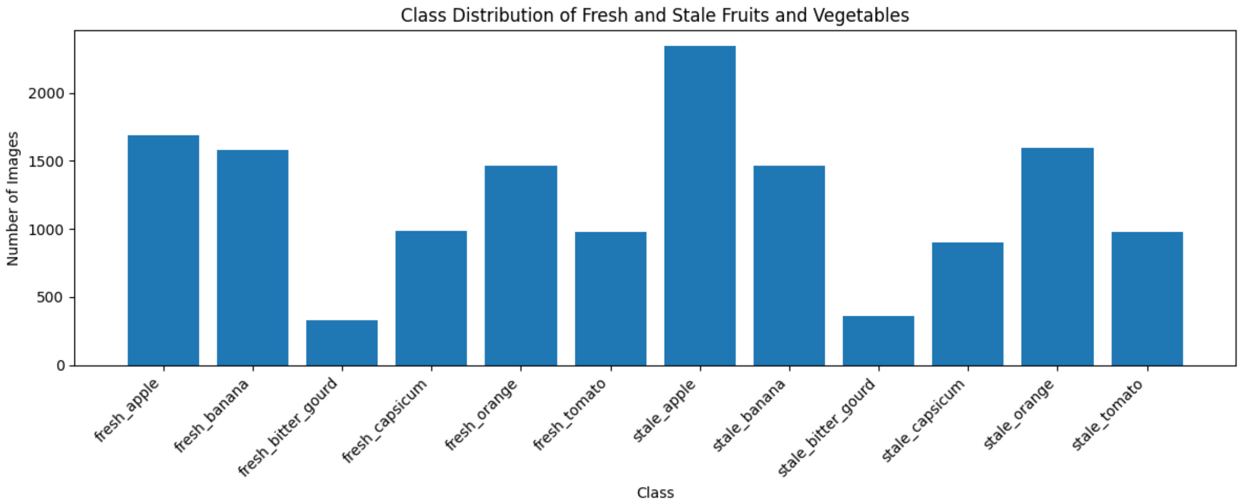

Figure 2. Distribution of Images in Each Class (Fresh vs Stale).

Representative images from each class are shown in Figure 3 so we can see visual examples of the variations between fresh and stale produce.

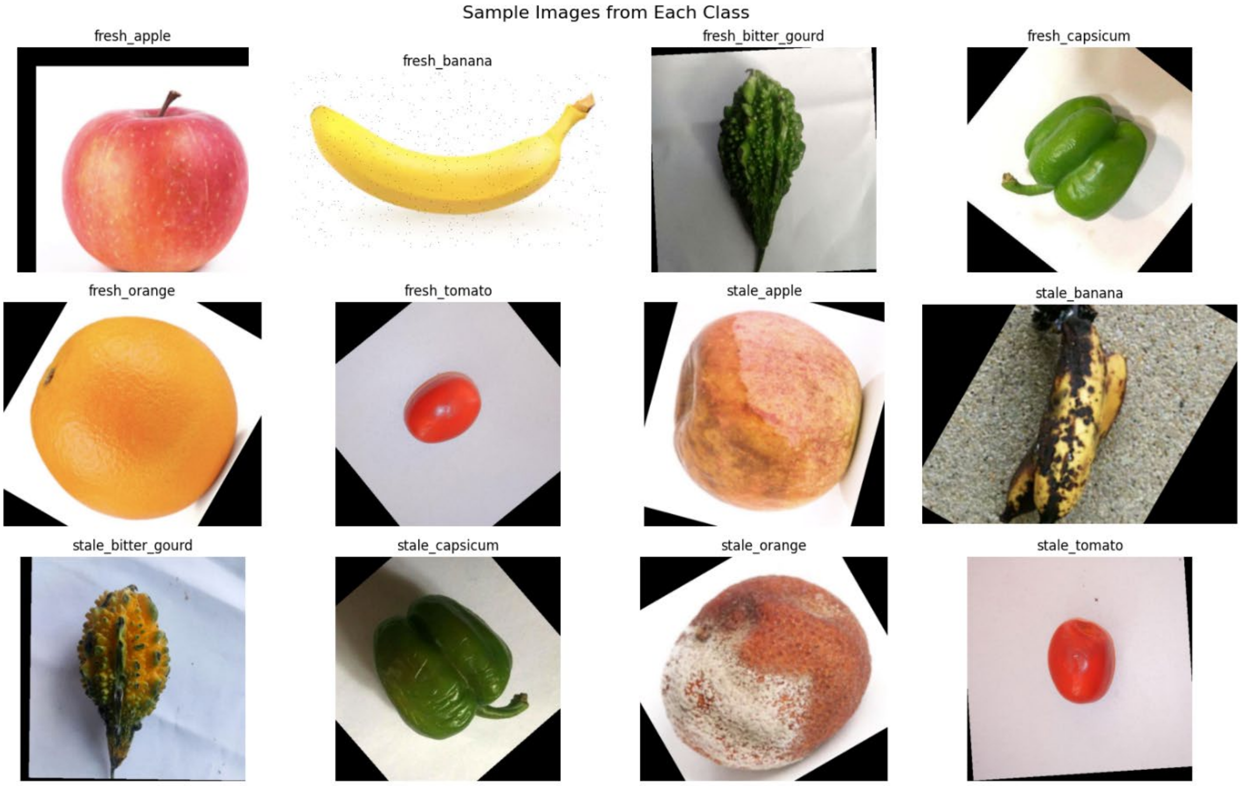

Figure 3. Sample images from different classes in the dataset.

3.2. Data Preprocessing and Analysis

Before training the deep learning models, several preprocessing and exploratory data analysis steps were performed to ensure data quality and improve model generalization [39–42].

First, the dataset was organized into a structured directory format where each class was stored in a separate folder. This format allows deep learning frameworks to automatically assign class labels during training [43–45].

Next, the spatial characteristics of the images were analyzed. The width and height distribution of the images were examined to determine the appropriate input size for the neural networks [46,47]. The distributions of image dimensions have been shown in Figure 4, we can see the variation in image resolutions within the dataset.

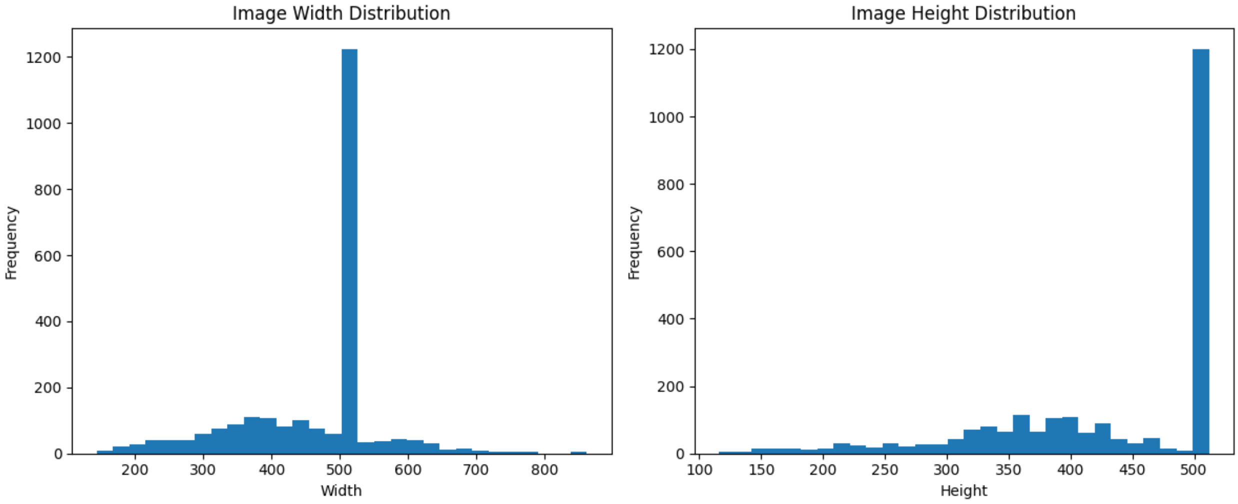

Figure 4. Distribution of image width and height across the dataset.

After the exploratory analysis, all images were resized to a uniform resolution of 224 × 224 pixels, which is the standard input size required by the selected deep learning architectures. Pixel values were normalized during preprocessing to improve training stability.

Several data augmentation techniques were applied during training which enhances model robustness and reduce overfitting. These techniques included random rotation, horizontal flipping, and zoom transformations. Examples of augmented and preprocessed images generated during the training process are shown and presented in Figure 6.

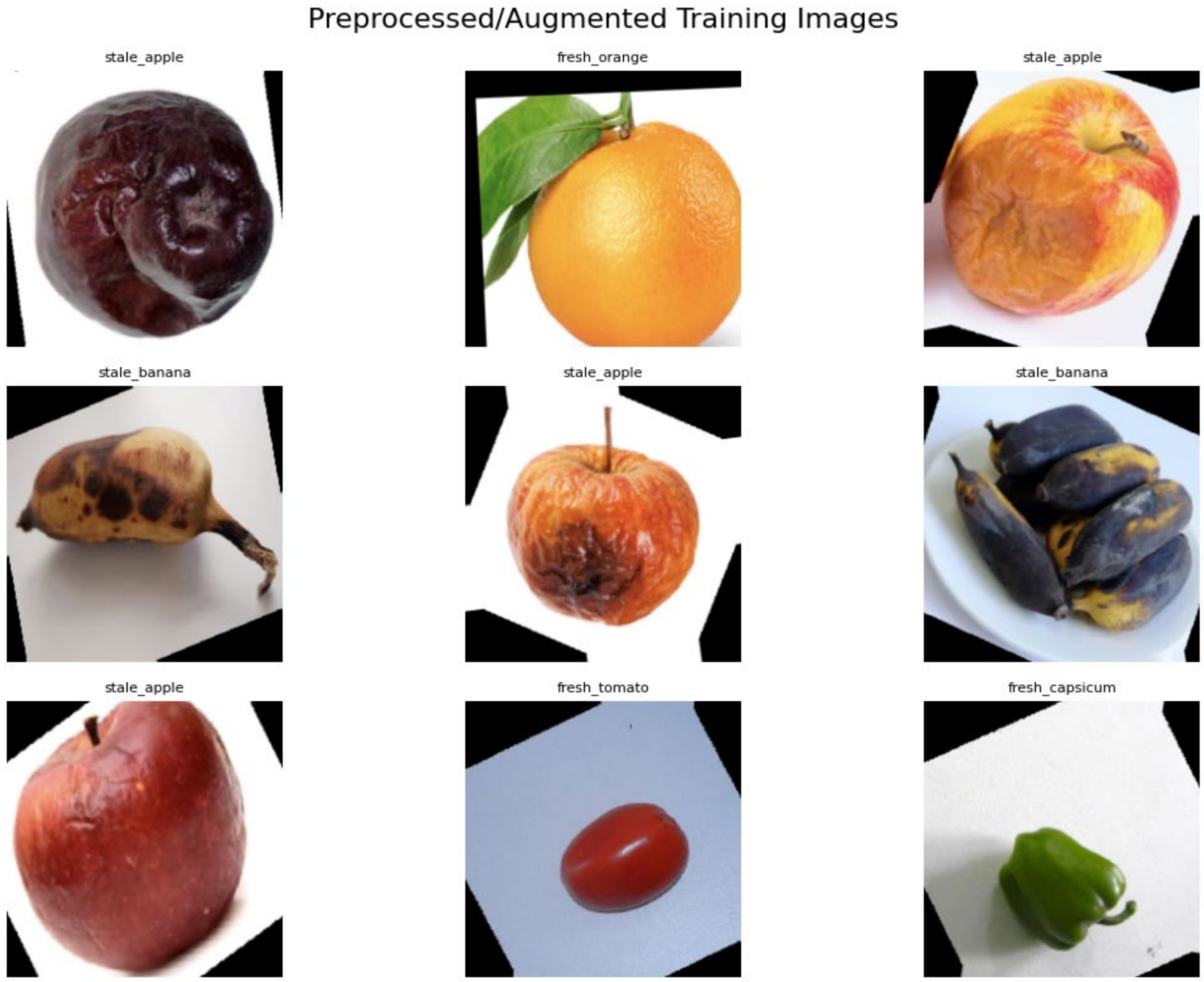

Figure 6. Examples of preprocessed and augmented training images used during model training.

3.3. Transfer Learning Models

We used three widely used deep convolutional neural network architectures to classify fresh and stale fruits and vegetables. This is called Transfer learning which enables models to take advantage of features learned from large-scale datasets such as ImageNet and then improve classification performance even with moderate-sized datasets.

The following architectures were evaluated in this study:

- **MobileNetV2**—This is a lightweight CNN designed for efficient computation and mobile applications.
- **ResNet50**—This is a deep residual network which utilizes and applies skip connections so that it can enable the training of very deep architectures.
- **EfficientNetB0**—This is a modern deep learning architecture having scales network depth, width, and resolution in a balanced manner to improve performance.

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For each architecture, the final fully connected layer was replaced with a new classification layer corresponding to the twelve classes in the dataset. The base convolutional layers of the pre-trained networks were initially frozen. This approach in transfer learning allow the models to utilize previously learned visual features while training only the newly added classification layers.

3.4. Model Training

The dataset was divided into training and validation sets using an 80:20 split. During training, images were loaded using an image data generator that applied preprocessing and augmentation operations in real time. The models were trained using the Adam optimizer with categorical cross-entropy as the loss function.

4. Results

The training and validation curves provide insight into the learning behavior of the models during training.

MobileNetV2 Performance

The MobileNetV2 model showed a rapid improvement in training accuracy during the first few epochs. The training accuracy increased from approximately 90% to over 98%, indicating that the network successfully learned discriminative features from the training images. The validation accuracy stabilized at approximately 88–89%. This demonstrated acceptable generalization performance. However, the validation loss gradually increased during later epochs, suggesting a slight overfitting tendency. Figure 7 shows MobileNetV2 accuracy and loss curves.

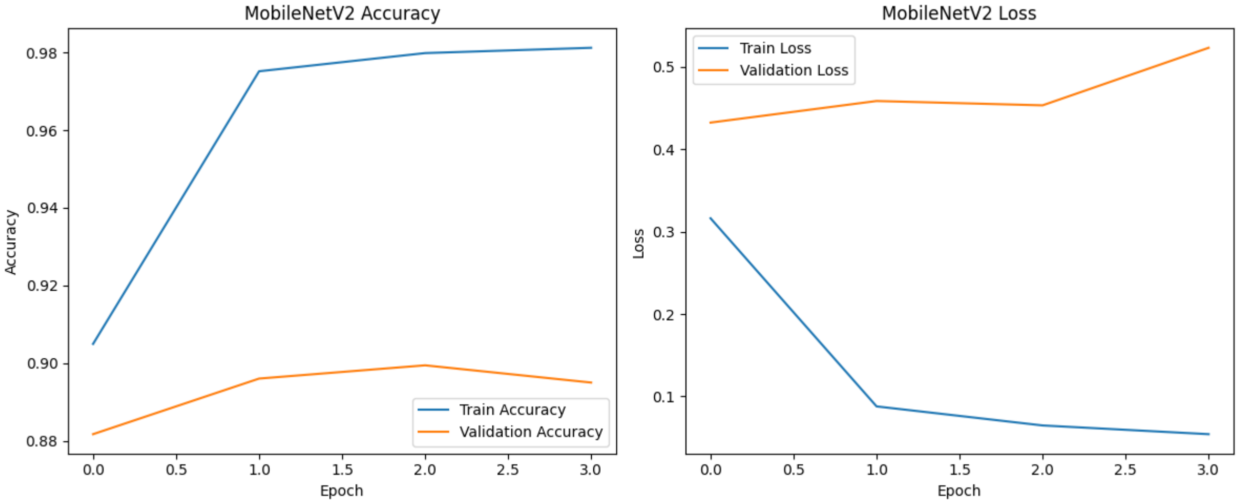


Figure 7. Training and Loss Curves for MovileNetV2.

ResNet50 Performance

ResNet50 also showed a strong learning capability due to its deeper architecture and residual connections. The model achieved training accuracy close to **99%**, while validation accuracy stabilized around **89–90%**. If we compare this to MobileNetV2, ResNet50 feels slightly better generalization performance and produced improved classification results for several fruit categories. Figure 8 shows training and loss curves for ResNEt50.

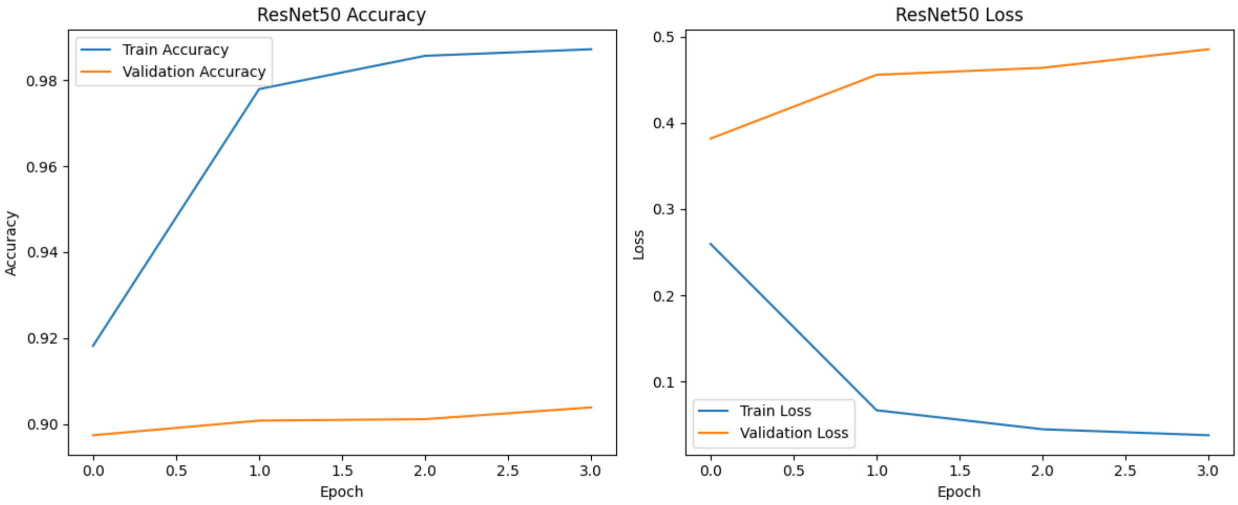


Figure 8. Training and Loss curves for ResNet50.

EfficientNetB0 Performance

EfficientNetB0 achieved the most stable training behavior among the three models. The training accuracy exceeded **98%**, while the validation accuracy reached approximately **90%**. EfficientNetB0 indicated better generalization by maintaining relatively stable validation loss values during training. Figure 9 shows training and loss curves for EfficientNetB0.

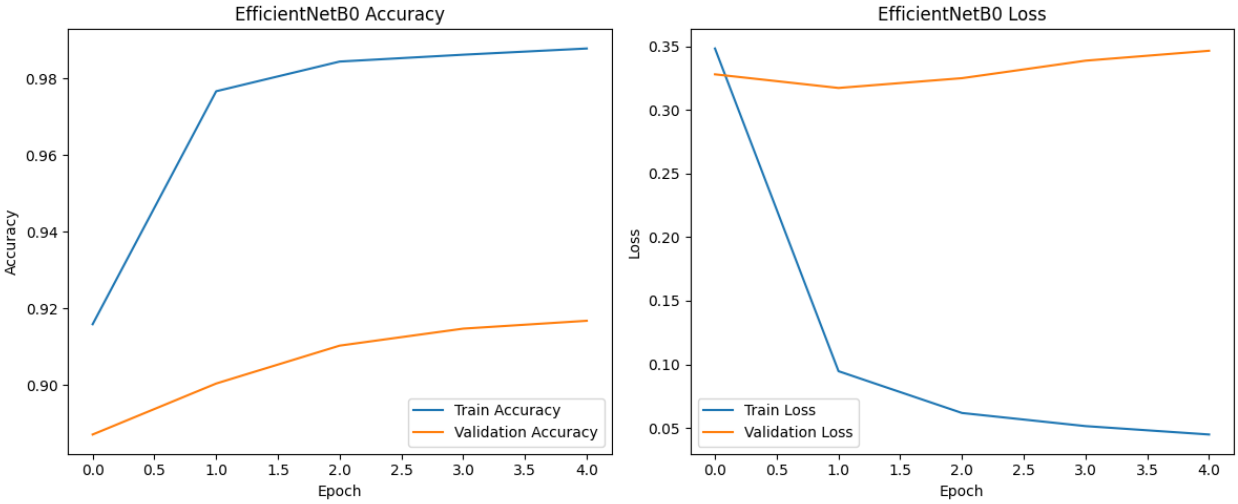
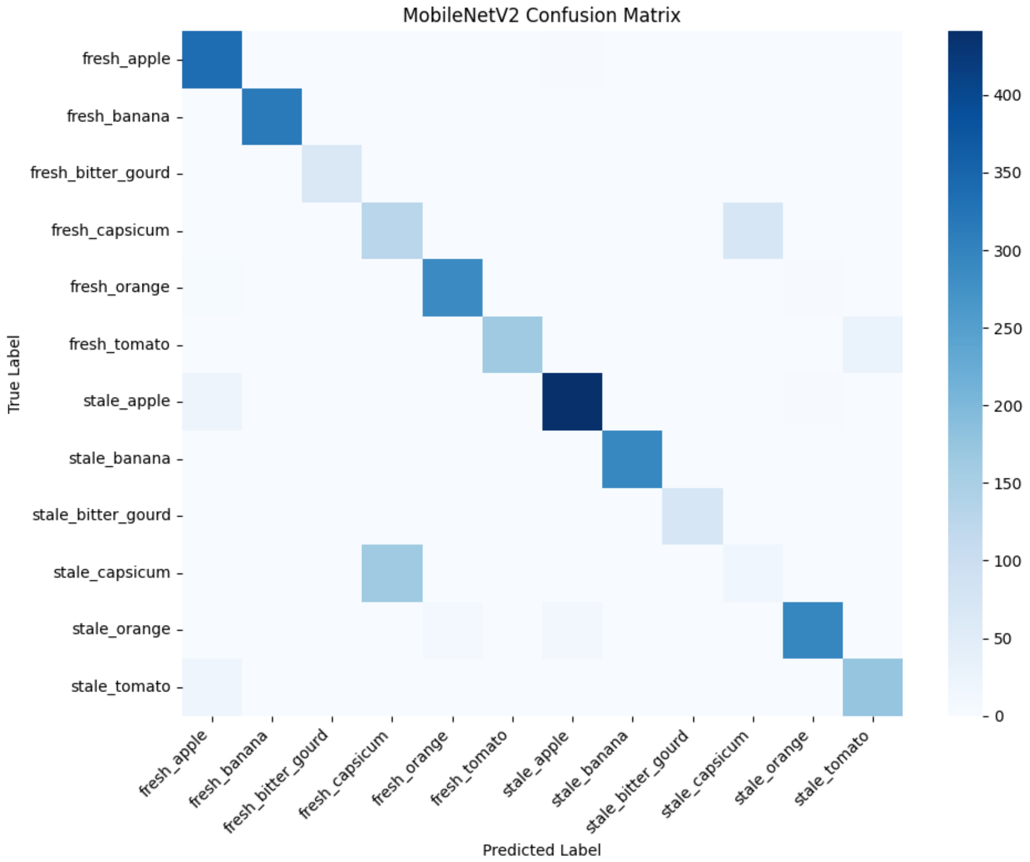


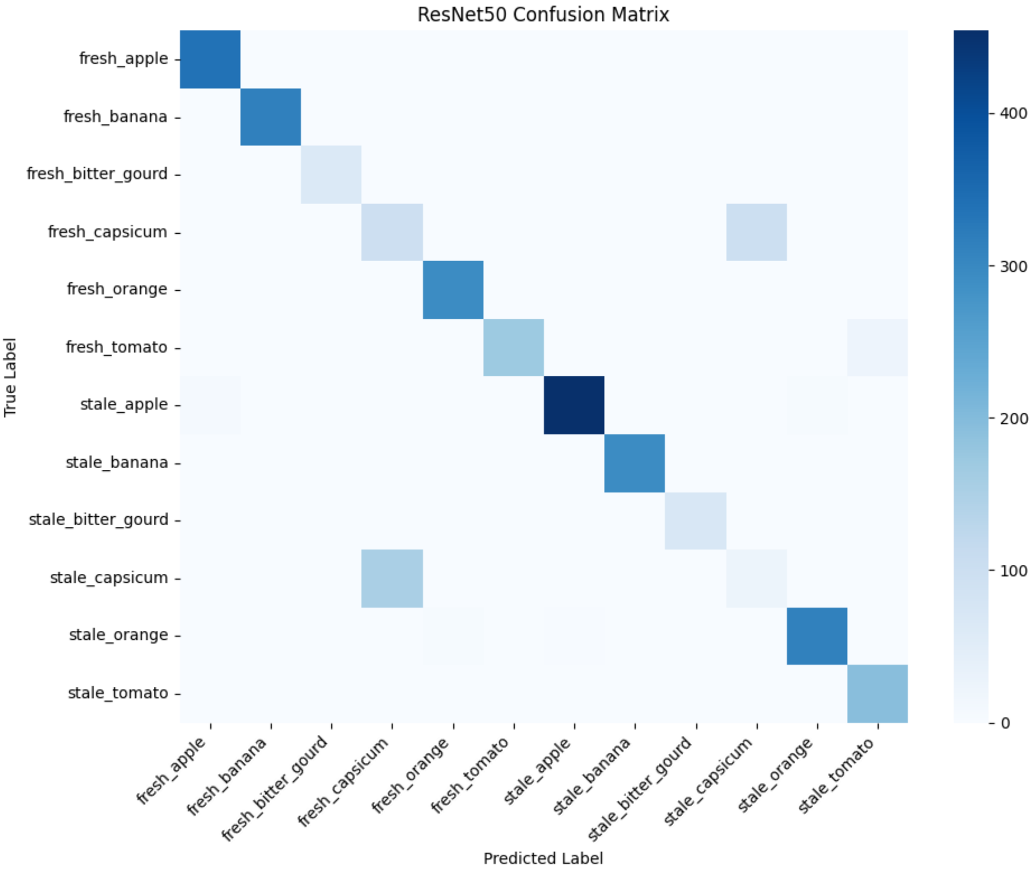
Figure 9. Training and Loss curves for EfficientNetB0.

4.1. *Confusion Matrix Analysis*

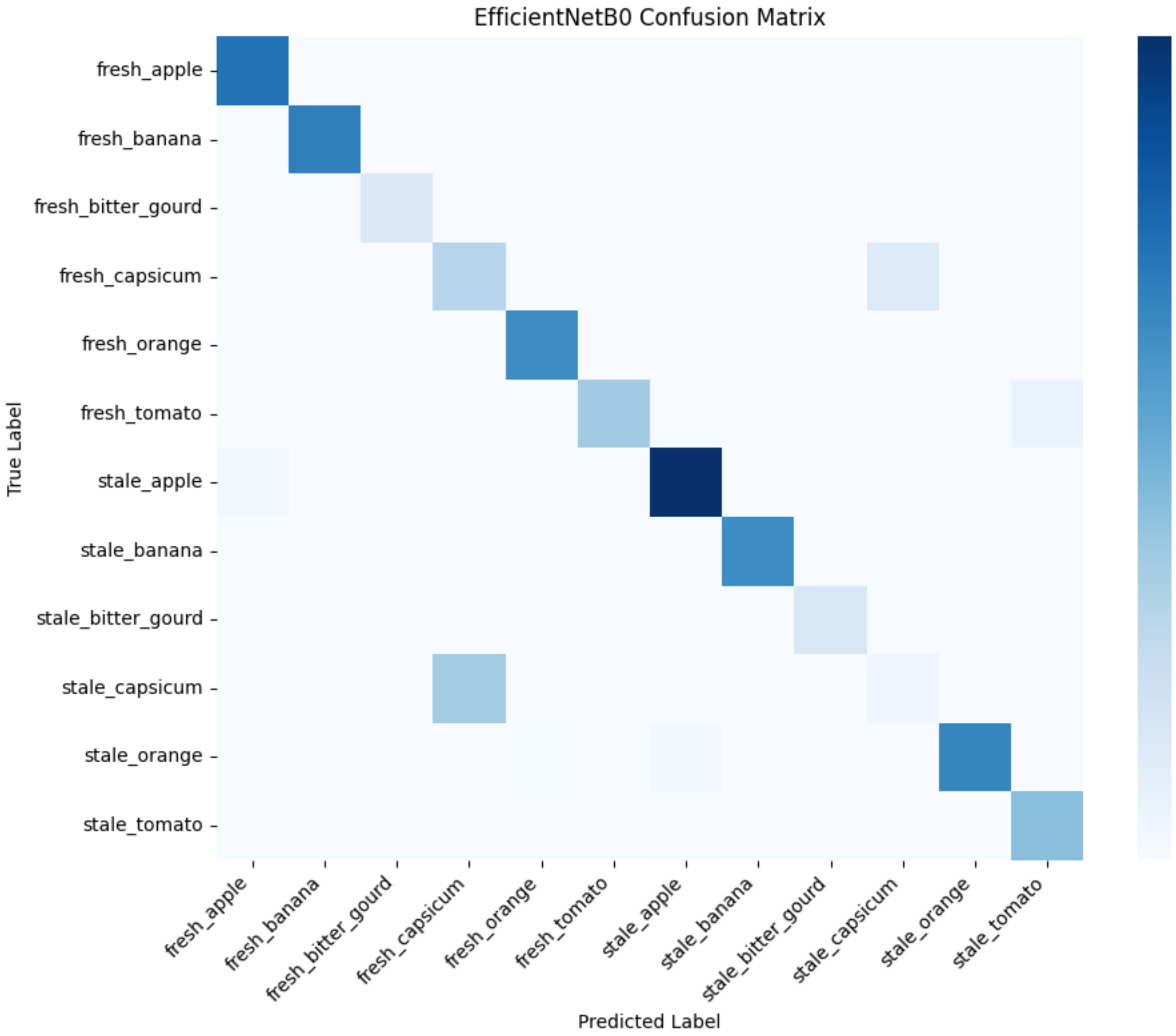
Confusion matrices were generated to analyze the classification performance of each model across the twelve classes. The results showed that most fruit categories were classified correctly with high accuracy. Classes such as fresh banana, fresh bitter gourd, stale banana, and stale bitter gourd achieved near-perfect classification across all models. These classes have distinctive visual features, making them easier for the models to identify. However, some misclassifications were observed between fresh capsicum and stale capsicum. Figure 10 (a-c) shows confusion metrics for all three models.



(**a**) Confusion Metrics for MobileNetV2



(**b**) Confusion Metrics for ResNet50

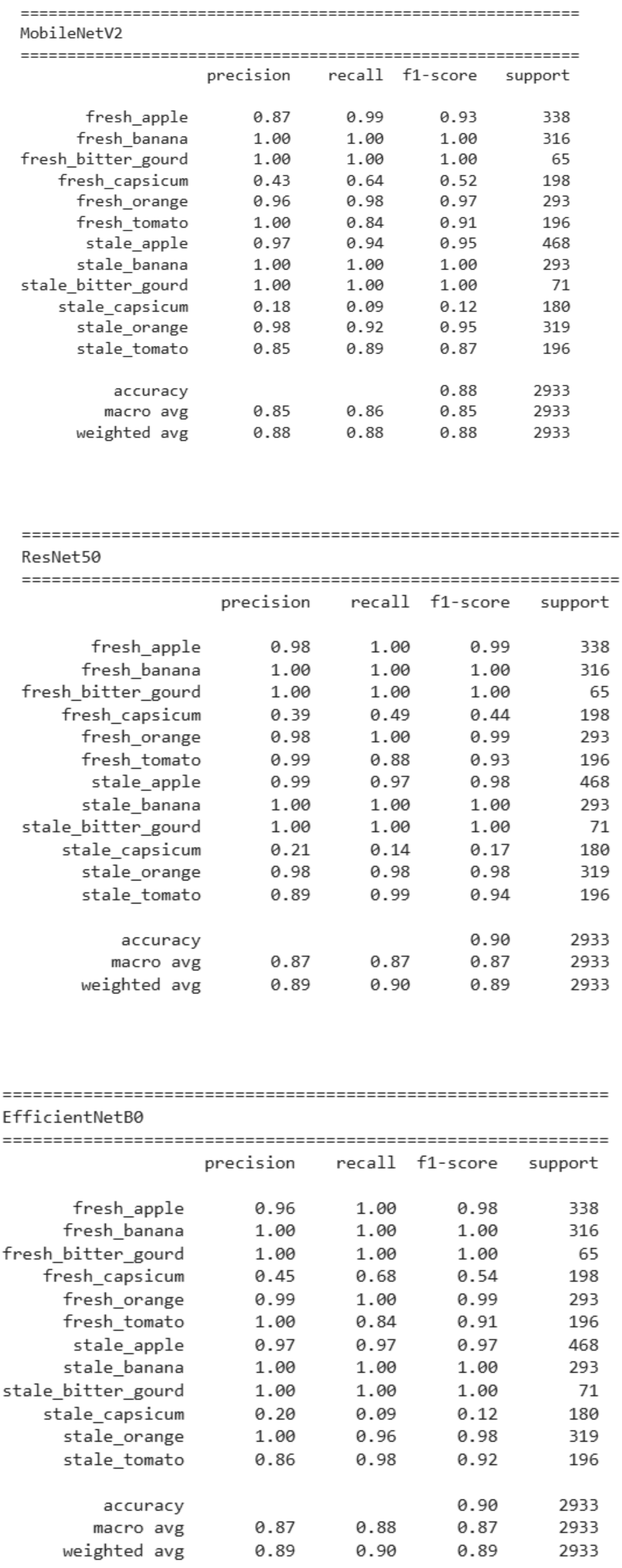


(**c**) Confusion Metrics for EfficientNetB0

Figure 10. Confusion Metrics for all three models.

4.2. Classification Performance

The classification reports further evaluate model performance using precision, recall, and F1-score metrics. The results show that most fruit classes achieved precision and recall values above 0.90, indicating strong classification performance. For the MobileNetV2 model, the overall accuracy reached 88%, with strong performance on categories such as fresh banana, stale banana, and stale orange. However, the model struggled slightly with capsicum classes, where precision and recall values were comparatively lower. ResNet50 improved the overall accuracy to approximately 90%, demonstrating stronger performance on several fruit classes including apple, orange, and tomato. EfficientNetB0 achieved similar performance to ResNet50 with an overall accuracy of approximately 90%. Figure 11 shows classification performance for three models.



```
============================================================
MobileNetV2
============================================================
                    precision    recall  f1-score   support

       fresh_apple       0.87      0.99      0.93       338
      fresh_banana       1.00      1.00      1.00       316
fresh_bitter_gourd       1.00      1.00      1.00        65
    fresh_capsicum       0.43      0.64      0.52       198
      fresh_orange       0.96      0.98      0.97       293
      fresh_tomato       1.00      0.84      0.91       196
       stale_apple       0.97      0.94      0.95       468
      stale_banana       1.00      1.00      1.00       293
stale_bitter_gourd       1.00      1.00      1.00        71
    stale_capsicum       0.18      0.09      0.12       180
      stale_orange       0.98      0.92      0.95       319
      stale_tomato       0.85      0.89      0.87       196

          accuracy                           0.88      2933
         macro avg       0.85      0.86      0.85      2933
      weighted avg       0.88      0.88      0.88      2933
```

```
============================================================
ResNet50
============================================================
                    precision    recall  f1-score   support

       fresh_apple       0.98      1.00      0.99       338
      fresh_banana       1.00      1.00      1.00       316
fresh_bitter_gourd       1.00      1.00      1.00        65
    fresh_capsicum       0.39      0.49      0.44       198
      fresh_orange       0.98      1.00      0.99       293
      fresh_tomato       0.99      0.88      0.93       196
       stale_apple       0.99      0.97      0.98       468
      stale_banana       1.00      1.00      1.00       293
stale_bitter_gourd       1.00      1.00      1.00        71
    stale_capsicum       0.21      0.14      0.17       180
      stale_orange       0.98      0.98      0.98       319
      stale_tomato       0.89      0.99      0.94       196

          accuracy                           0.90      2933
         macro avg       0.87      0.87      0.87      2933
      weighted avg       0.89      0.90      0.89      2933
```

```
============================================================
EfficientNetB0
============================================================
                    precision    recall  f1-score   support

       fresh_apple       0.96      1.00      0.98       338
      fresh_banana       1.00      1.00      1.00       316
fresh_bitter_gourd       1.00      1.00      1.00        65
    fresh_capsicum       0.45      0.68      0.54       198
      fresh_orange       0.99      1.00      0.99       293
      fresh_tomato       1.00      0.84      0.91       196
       stale_apple       0.97      0.97      0.97       468
      stale_banana       1.00      1.00      1.00       293
stale_bitter_gourd       1.00      1.00      1.00        71
    stale_capsicum       0.20      0.09      0.12       180
      stale_orange       1.00      0.96      0.98       319
      stale_tomato       0.86      0.98      0.92       196

          accuracy                           0.90      2933
         macro avg       0.87      0.88      0.87      2933
      weighted avg       0.89      0.90      0.89      2933
```

Figure 11. Classification Performance for Three Models.

4.3. Model Comparison

The overall validation performance of the three models is summarized in Table 1 and shown in Figure 12.

Table 1. Validation performance comparison of the evaluated models.

Model	Validation Accuracy	Validation Loss
EfficientNetB0	0.900	0.317
ResNet50	0.897	0.382
MobileNetV2	0.882	0.432

The comparison results indicate that EfficientNetB0 achieved the highest validation accuracy of 90.04%, followed closely by ResNet50 with 89.73% accuracy, while MobileNetV2 achieved 88.17% accuracy.

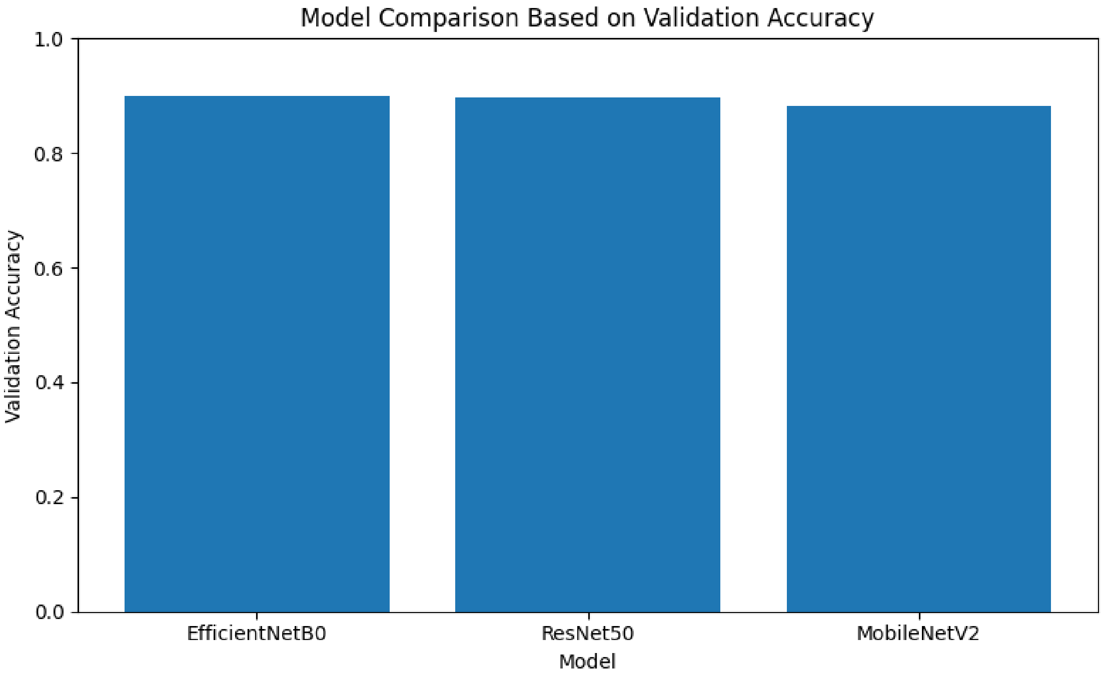


Figure 12. Comparison of validation accuracy across the evaluated deep learning models.

5. Conclusions

In this research work we aimed and showed that deep learning methods are efficient for checking fruit and vegetable freshness from images. We used three models: MobileNetV2, ResNet50, and EfficientNetB0.

The models learn patterns of color, shape, and texture in the images. The models identified fresh and stale items correctly in many cases. EfficientNetB0 shows the best accuracy in this experiment. ResNet50 also shows strong results. MobileNetV2 also performs well.

The confusion matrices show that many classes are predicted correctly. Some mistakes appear in capsicum images because fresh and stale capsicum look similar.

The work has shown that computer vision is useful for checking food quality. The method is helping to find fresh and stale fruits from images. This system is helping to reduce food waste. This system is also helping to improve food safety. In future work we are using YOLOv8 to detect fruit parts that are becoming stale. We are customizing the same dataset for this task. We are also using explainable AI to show the visual features used by the model. This process is helping to understand how the model is making predictions. Future work is also testing more fruits and vegetables to improve the system.

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