


Article

Harnessing the Power of Transfer Learning in Sunflower Disease Detection: A Comparative Study

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Abstract: Sunflower is an important crop that is susceptible to various diseases, which can significantly impact crop yield and quality. Early and accurate detection of these diseases is crucial for implementing appropriate management strategies. In recent years, deep learning techniques have shown promising results in the field of disease classification using image data. This study presents a comparative analysis of different deep-learning models for the classification of sunflower diseases. Five widely used deep learning models, namely AlexNet, VGG16, InceptionV3, MobileNetV3, and EfficientNet were trained and evaluated using a dataset of sunflower disease images. The performance of each model was measured in terms of precision, recall, F1-score, and accuracy. The experimental results demonstrated that all the deep learning models achieved high precision, recall, F1-score, and accuracy values for sunflower disease classification. Among the models, EfficientNetB3 exhibited the highest precision, recall, F1-score, and accuracy of 0.979. Whereas the other models, AlexNet, VGG16, InceptionV3 and MobileNetV3 achieved 0.865, 0.965, 0.954 and 0.969 accuracy respectively. Based on the comparative analysis, it can be concluded that deep learning models are effective for the classification of sunflower diseases. The results highlight the potential of deep learning in early disease detection and classification, which can assist farmers and agronomists in implementing timely disease management strategies. Furthermore, the findings suggest that models like MobileNetV3 and EfficientNetB3 could be preferred choices due to their high performance and relatively fewer training epochs.

Keywords: disease classification; sunflower diseases; artificial intelligence; convolutional neural networks; transfer learning; precision agriculture; adjustable learning



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1. Introduction

Sunflower (*Helianthus annuus*) is a widely cultivated crop across various regions of the world due to its economic significance and versatility. It is grown in diverse climates ranging from temperate to subtropical regions, making it adaptable to a wide range of environmental conditions. Sunflower cultivation spans continents, including North America, Europe, Asia, Africa, and South America, with major producing countries including Russia, Ukraine, Argentina, the United States, and China. The global production of sunflower seeds during the year 2022–2023 is around 51.17 million metric tons [1]. The biggest producer is Russia with 16.5 million metric tons followed by Ukraine with 10 million metric tons, European Union with 9.48, Argentina with 4.6, Turkey 1.9, and rest 8.6 million metric tons [1]. The cultivation of sunflowers serves numerous purposes, such as animal feed production, oil extraction for different applications (culinary and industrial applications), and as a source of raw materials for biofuel production [2]. The widespread cultivation of sunflower reflects its agricultural significance and the recognition of its economic value in different regions of the world.

Sunflower seed cultivation is critical in many ways, including economic, agricultural, nutritional, and environmental considerations. Sunflower seeds are high in oil and have numerous applications, making them a valuable crop around the world [3]. Sunflower seeds are an excellent source of oil that is edible, frequently referred to as sunflower oil. Given its pleasant flavor, high smoke point, and nutritional benefits, sunflower oil is frequently utilized in cooking, frying, and salad dressings. Sunflower cultivation has various agricultural advantages as well. Sunflowers are well-known for their ability to take nutrients from the soil, making them an excellent rotation crop. Farmers can improve soil fertility and prevent pest and disease accumulation by planting sunflowers in rotation with other crops [4]. Sunflowers are an adaptive crop that can adapt to a wide range of climates and flourishing conditions, helping to increase agricultural biodiversity. Sunflower farming enhances biodiversity by providing a habitat for various beneficial insects, birds, and pollinators [4].

Sunflowers are prone to various diseases that can significantly influence the productivity, growth, and quality of crops. To avoid the adverse effect of diseases on productivity, it is important to identify and manage these diseases at the right time. There are some diseases commonly found in sunflowers such as Downy Mildew (*Plasmopara halstedii*), Sclerotinia Head Rot (*Sclerotinia sclerotiorum*), Rust (*Puccinia helianthi*), Phoma Black Stem (*Phoma macdonaldii*), Powdery Mildew (*Erysiphe cichoracearum*). It is very important to identify such diseases at the right time to avoid many things such as the effect on yield production, environmental impact, crop rotation, and future planning. Identifying such diseases needs a trained expert or a person who has knowledge. However, when talking about developing countries the farmers are illiterate and are not sound when it comes to technology usage. Such issues further negatively impact yield production. Identification and detection of sunflower diseases in developing countries are manually performed by the farmers through visual observation. It can't be done by a layman but by a person who has a lot of experience in such an area. Nevertheless, such observations are highly likely error prone. Moreover, it is not possible to identify the diseases regularly through visual inspection, which results in significant financial losses [5]. There are different methods to detect diseases in plants such as the use of spectrometers. Spectrometers are more accurate than traditional methods to classify diseased leaves from healthy ones [6]. Furthermore, molecular techniques like the polymerase chain reaction and the real-time polymerase chain reaction can be employed to detect plant illnesses [7–9]. Such methods demand qualified people to operate and are time-consuming, expensive, and difficult. Therefore, a system easy to use, and works on images will be more practical than any traditional system.

Automated disease recognition systems have gained popularity recently thanks to developments in computer vision and machine learning approaches. These systems use deep learning algorithms to detect diseases quickly and accurately by analyzing massive amounts of visual data [10,11]. Deep learning has gained a lot of attention lately due to its promising results in terms of improving accuracy. Deep learning has been incorporated into many domains because of its remarkable ability to solve complex problem. Such as Computer Vision [12], Object Detection and Recognition [13], Image Segmentation [14], Image Generation [10], Healthcare [15,16], Finance [17], Autonomous Systems [18], Education [19,20], Natural Language Processing (NLP) [21]. Bantan et al. [22] proposed a CNN-based sunflower seed classification model. The dataset is containing seven different varieties of sunflower seeds. Their proposed model achieved 98% accuracy in terms of identifying different varieties of sunflower seeds. Kurtulmus et al. [23] tried to use three different deep learning models such as AlexNet, GoogleNet, and ResNet to find their accuracy in terms of identifying sunflower seeds. They stated that GoogleNet has achieved 95% accuracy. In study [24], the authors have proposed a deep learning model based on VGG16 to classify fourteen different types of seeds. The VGG16 model has been modified by adding five more layers before the classifying layer to improve the performance of the model. From the results, it can be inferred that the proposed model has achieved 99% accuracy. Sirohi et al. [25] proposed a hybrid deep learning model

for classifying sunflower diseases. They created their dataset containing four different classes such as *Alternaria* leaf blight, Downy mildew, *Phoma* blight, and *Verticillium* wilt. Their hybrid model is based on VGG16 and MobileNet. Their proposed hybrid model has achieved 89.2% accuracy in identifying different types of diseases in sunflowers and they claimed that their model outperformed other models. Albarrak et al. [26] proposed a model based on MobileNetV2 to classify different types of date fruits. They trained the model on a dataset containing eight different types of date fruits found in Saudi Arabia. Their proposed model has achieved 99% accuracy and has outperformed state-of-art models.

Chen et al. [27] proposed a model based on YOLOv4 to detect sunflower leaf diseases. The modified version of YOLOv4 is obtained by collecting three effective layers of three versions of MobileNet model and used that to replace the feature layer of the original YOLOv4. Doing so has helped to improve the accuracy of the model and outperformed the original YOLOv4. Malik et al. [5] proposed a deep learning model for sunflower disease identification. They used a dataset collected from the Internet. The proposed model is based on MobileNet and VGG16. They claimed that the model based on VGG16 has achieved 81% accuracy whereas the model based on MobileNet has an accuracy of around 86%. Carbone et al. [28] proposed a model for sunflower-weed segmentation classification. They created a dataset containing both RGB and NIR data. their proposed model has shown an IoU performance of 76.4%. Dawod et al. [29] proposed a R-CNN-based model to classify Foliar diseases in sunflowers. They have perfumed the segmentation before they classified the different classes of foliar lesions. Gulzar [30] proposed a MobileNetV2-based modified model to classify forth different types of fruits. The modified proposed model has achieved 99% accuracy and has outperformed state-of-art models such as VGG16, AlexNet, and other models. whereas in another study Aktas et al. [31,32] trained AlexNet and InceptionV2 models to classify open and closed pistachios and achieved 96.13% and 96.54%, respectively. In another study, Dowod et al. [33] proposed a model to classify foliar diseases in sunflowers based on ResNet architecture. They claimed that by doing the segmentation, the results in terms of accuracy have increased by far and avoid many wrong predictions which usually happen without segmentation. Song et al. [34] trained their model based on remote sensing images to recognize the sunflower growth periodically. Their proposed model, PSPNet achieved 89.01% accuracy. Furthermore, Barrio-conde et al. [35] have a deep learning-based model to classify High Oleic Sunflower Seed Varieties. They used around 6000 images of six different types of sunflower seeds to train their model. The model achieved 100% accuracy for two of the classes whereas, for the remaining classes, the model achieved 89.5% accuracy. Sathi et al. [36] have conducted a study to classify sunflower diseases used a dataset containing 1428 images of three classes. They have trained and tested four CNN models based on the said dataset. they concluded that ResNet50 model was identified as optimal model with accuracy 97.88%. Ghosh et al. [37] have proposed a hybrid model for recognition of sunflower diseases. The hybrid model is the combination of VGG19 and small CNN model. they have trained around eight CNN models and out of those the proposed model has outperformed all the other models in detecting sunflower diseases.

The study investigated the classification of sunflower diseases using deep learning techniques, specifically employing five popular convolutional neural network (CNN) models: AlexNet, VGG16, InceptionV3, MobileNetV3, and EfficientNetB3. The contribution of this study is as follows:

- **Improved Disease Detection:** The study highlights the use of deep learning models, such as AlexNet, VGG16, InceptionV3, MobileNetV3, and EfficientNet, for the classification of sunflower diseases. These models have demonstrated high precision, recall, F1-score, and accuracy in detecting and classifying various sunflower diseases. This contribution improves the early detection of diseases, allowing farmers to implement timely management strategies and minimize crop yield and quality losses.
- **Comparative Analysis of Deep Learning Models:** The study provides a comparative analysis of different deep learning models, allowing researchers and practitioners to assess their performance in sunflower disease classification. By evaluating the

precision, recall, F1-score, and accuracy of each model, the study offers valuable insights into their effectiveness and helps in selecting the most suitable model for sunflower disease detection tasks.

- **Potential Benefits for Farmers and Agronomists:** The study’s results emphasize the potential of deep learning models in early disease detection and classification, offering significant benefits to farmers and agronomists. By utilizing these models, farmers can quickly identify and categorize sunflower diseases, enabling them to implement timely and appropriate disease management strategies. This contribution has practical implications in enhancing crop productivity and minimizing economic losses in sunflower farming.
- **General Applicability to Other Crops:** While this study specifically focuses on sunflower disease detection, the findings have broader implications for other crops as well. Deep learning models trained on image data can be adapted and applied to different plant species, aiding in disease identification and classification across various agricultural contexts. The study’s comparative analysis provides valuable insights that can be utilized in similar studies on different crops, benefiting farmers and researchers in multiple agricultural domains.
- **Reduced Training Epochs:** The study suggests that models like MobileNetV3 and EfficientNetB3 offer high performance while requiring relatively fewer training epochs. This finding is beneficial in terms of computational efficiency and time-saving during the training process. By reducing the required training time, farmers and researchers can expedite the development and deployment of disease detection models, facilitating faster decision-making and implementation of appropriate management strategies.

2. Material and Methods

Figure 1 provides a summary of the overall methodology used in this study. The images of sunflower leaves and blooms that are available online were used for four-class classification of healthy and infected groups. Pre-trained networks like AlexNet [38], VGG16 [39], InceptionV3 [40], MobilenetV3 [41], and EfficientNet [42] are used for the classification. Prior to the splitting dataset into training, validation, and testing sets, images were resized according to model requirements which are given in Figure 1.

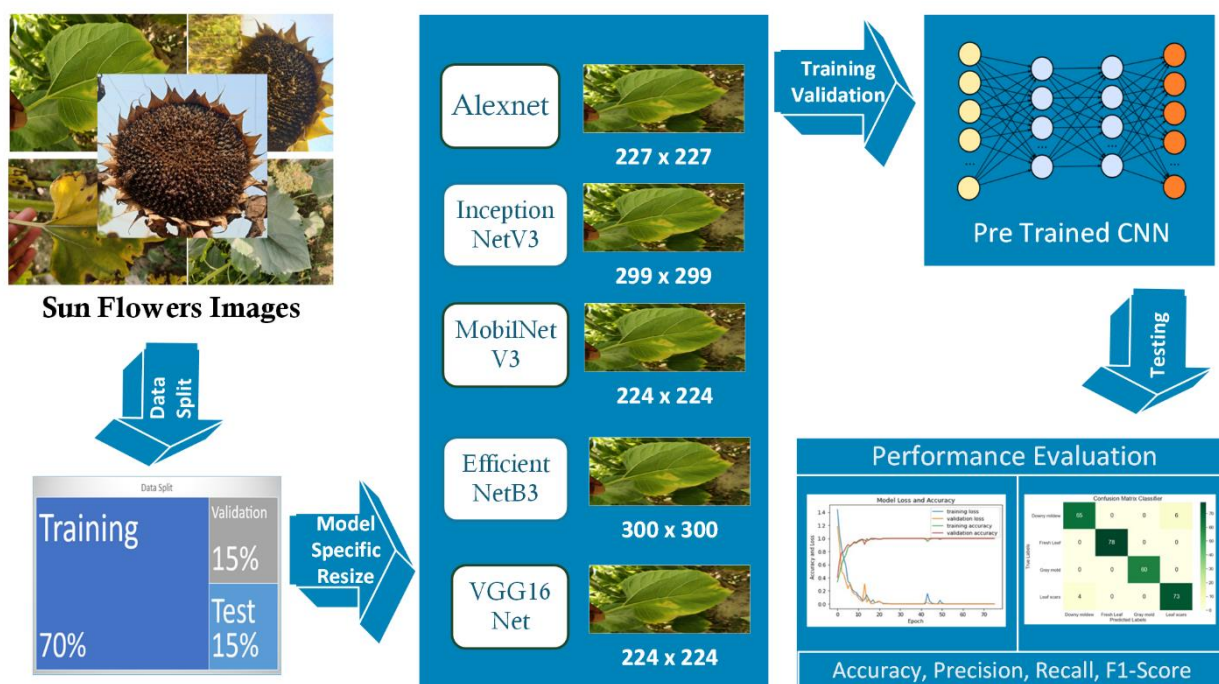


Figure 1. A diagram of the proposed approach.

2.1. Dataset

In this study, a public dataset [43] containing images of a total of 1892 images of healthy and infected sunflower leaves and blooms was used. The National Institute of Textile Engineering and Research in Bangladesh is the host institution for the dataset, which is publicly accessible online. The dataset originally containing images of a total of 467 images was created by researchers using sunflowers from the Bangladesh Agricultural Research Institute (BARI) demonstration farm at Gazipur. All the images were reported to be captured manually using a digital camera at a resolution of 512×512 pixels. Researchers later used original images to create 1892 augmented images. A dataset containing augmented images was split into training, validation, and testing subsets using a ratio of 70:15:15. The number of images per class and its distribution by subclasses are shown in Table 1. Whereas Figure 2 shows the sample of each class of diseases found in sunflowers.

Table 1. Dataset distribution.

Class Name	Training Set	Validation Set	Testing Set	Number of Images Per Class
Downy Mildew	329	70	71	470
Fresh Leaf	360	77	78	515
Gray Mold	278	60	60	398
Leaf Scars	356	76	77	509
Total	1323	283	286	1892

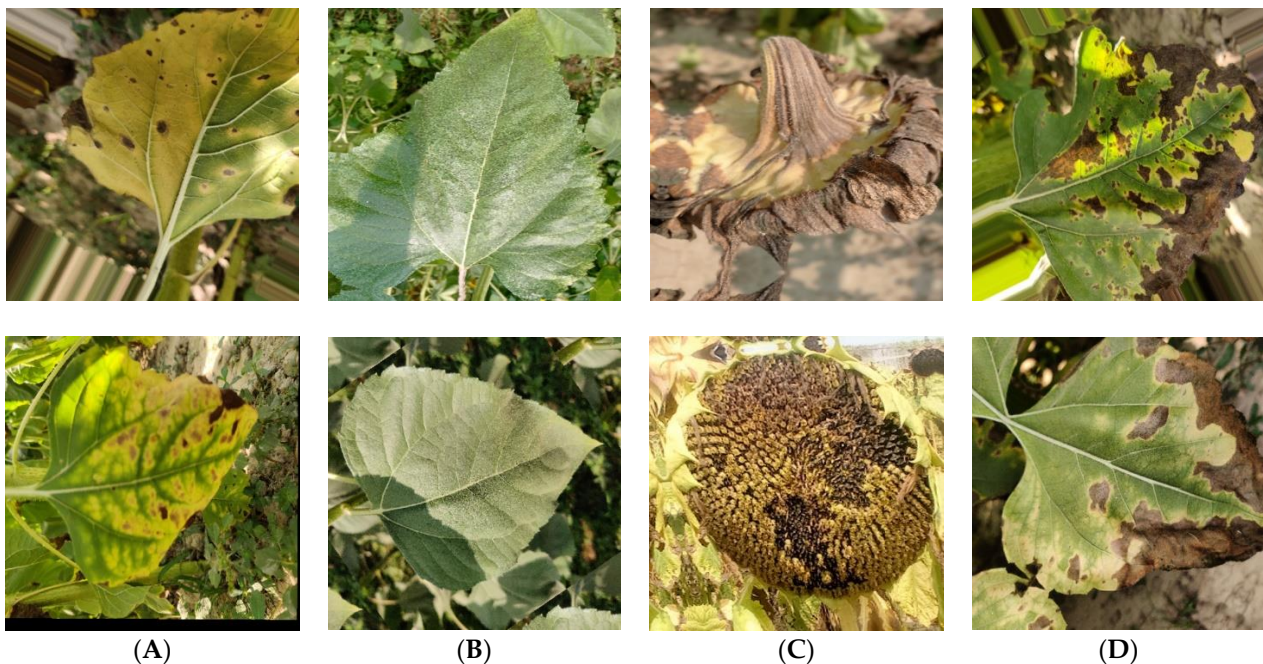


Figure 2. Sample images of four classes. (A) Downy Mildew, (B) Fresh Leaf, (C) Gray Mold, (D) Leaf Scars.

2.2. State-of-Art Models

In this study, we have selected start-of-art models which are very well-known for image classification. Due to their high popularity, we have selected AlexNet [38], VGG16 [39], InceptionV3 [40], MobilenetV3 [41], and EfficientNet [42] for this comparative study.

2.2.1. AlexNet

AlexNet [38] is a groundbreaking convolutional neural network (CNN) architecture that won the ImageNet Large Scale Visual Recognition Challenge in 2012. Figure 3 shows the architecture of AlexNet. It introduced several key innovations that revolutionized

deep learning and image recognition. AlexNet consisted of eight layers, including five convolutional and three fully connected layers. It employed the rectified linear unit (ReLU) activation function, local response normalization, and dropout regularization to improve performance and prevent overfitting. Notably, AlexNet utilized multiple GPUs for parallel processing, significantly reducing training time. With a top-5 error rate of 15.3% on the ILSVRC 2012 dataset, AlexNet outperformed previous approaches by a large margin. Its success propelled the development of more complex CNN architectures and accelerated the advancement of deep learning in computer vision tasks. The influential principles and design choices of AlexNet continue to shape the field of deep learning, making CNNs the standard model for image classification.

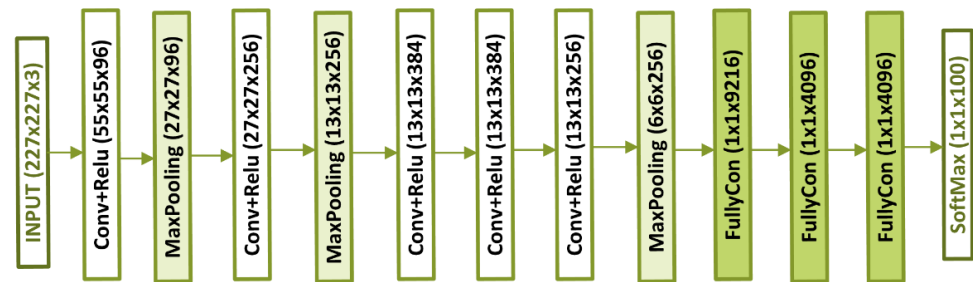


Figure 3. AlexNet Architecture.

2.2.2. VGG16

VGG16 [39] is a popular convolutional neural network (CNN) model known for its simplicity and effectiveness in image classification. Figure 4 shows the architecture of VGG16. Developed by the Visual Geometry Group (VGG) at the University of Oxford, VGG16 consists of 16 layers, including 13 convolutional layers and three fully connected layers. It follows a uniform architecture with small 3×3 filters and max pooling layers. VGG16's depth and small filter size contribute to its impressive performance. Despite its simplicity, VGG16 achieved outstanding results on the ImageNet dataset, surpassing previous models in accuracy. However, its large number of parameters makes it computationally expensive and memory-intensive, limiting its usage in resource-constrained environments. Nevertheless, VGG16's impact has been significant, serving as a benchmark for subsequent CNN architectures and influencing the development of deeper networks. Its simplicity and effectiveness have made it a widely studied and referenced model in the field of deep learning.

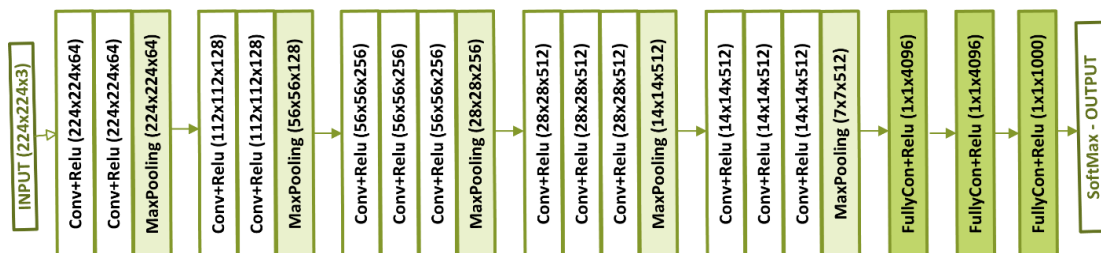


Figure 4. VGG16 architecture.

2.2.3. InceptionV3

The InceptionV3 [40] model is a deep convolutional neural network (CNN) architecture developed by Google researchers for image recognition tasks. Figure 5 shows the architecture of InceptionV3. It builds upon the original Inception architecture and is known for its high accuracy and computational efficiency. InceptionV3 utilizes inception modules, which incorporate different filter sizes to capture both local and global information while reducing the computational cost. Additional techniques like batch normalization, factorized convolution, and regularization contribute to improved performance and prevent overfitting. InceptionV3 has achieved impressive results in various image recognition

challenges, including winning the ImageNet Large Scale Visual Recognition Challenge in 2015. Its balance between accuracy and efficiency has made it a popular choice in computer vision applications. Furthermore, InceptionV3 has influenced subsequent iterations of the Inception architecture, such as InceptionV4 and Inception-ResNet, which have introduced advanced techniques to further enhance performance. The model’s impact on deep learning is substantial, inspiring researchers to explore more sophisticated and efficient CNN architectures for image recognition tasks.

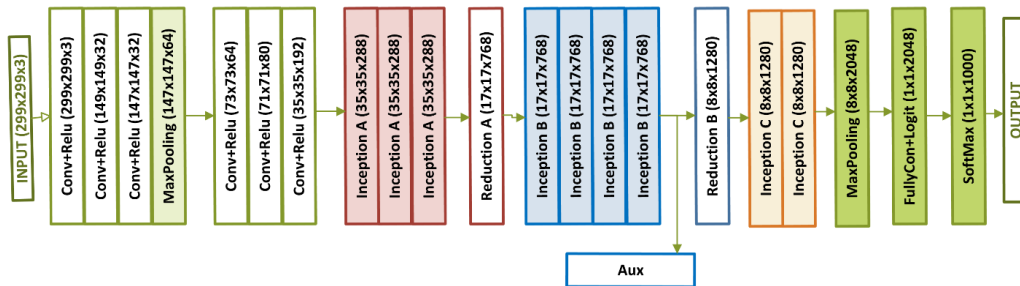


Figure 5. InceptionV3 architecture.

2.2.4. MobileNetV3

MobileNetV3 [41] is a highly efficient convolutional neural network (CNN) model designed for mobile and resource-constrained devices. Figure 6 shows the architecture of MobileNetV3. It builds upon the success of the original MobileNet architecture by introducing several improvements. Developed by Google, MobileNetV3 utilizes depth-wise separable convolutions, which split the standard convolutional operation into separate depth-wise and pointwise convolutions. This reduces computational complexity while maintaining high accuracy. It also incorporates inverted residuals and linear bottleneck layers to further enhance efficiency. MobileNetV3 achieves a good balance between accuracy and efficiency, making it suitable for real-time applications on devices with limited computational resources. It has been widely adopted in mobile vision applications, enabling tasks such as image classification, object detection, and semantic segmentation. MobileNetV3’s contributions to efficient CNN architectures have played a crucial role in enabling deep learning on mobile devices and expanding the reach of AI-powered applications.

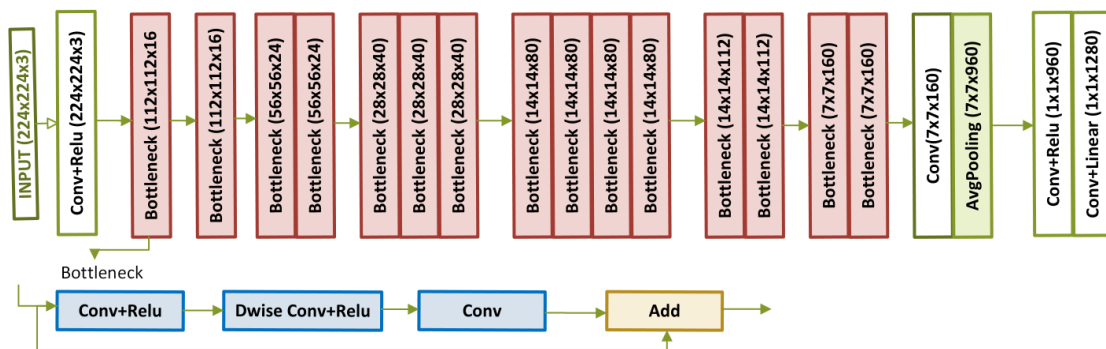


Figure 6. MobileNetV3 Architecture.

2.2.5. EfficientNet

EfficientNet [42] is a state-of-the-art convolutional neural network (CNN) model renowned for its exceptional efficiency and accuracy trade-off. Figure 7 shows the architecture of EfficientNet. Developed by researchers at Google, EfficientNet introduces a compound scaling method that optimizes the model’s depth, width, and resolution simultaneously. By systematically scaling up these dimensions, EfficientNet achieves superior performance while keeping computational requirements in check. This approach ensures efficient resource utilization and enables the model to perform well across a wide range

of resource constraints. EfficientNet has consistently achieved top-tier performance on various benchmark datasets, surpassing previous models in both accuracy and efficiency. Its versatility and scalability have made it popular in computer vision tasks such as image classification and object detection. The EfficientNet architecture serves as a guiding principle for developing efficient and effective CNN models, empowering the deployment of deep learning models on devices with limited computational capabilities. EfficientNet-B0 in the base mode which consists of 237 layers. Moving from EfficientNet-B0 to EfficientNet-B7 number of layers is increasing reaching 813.

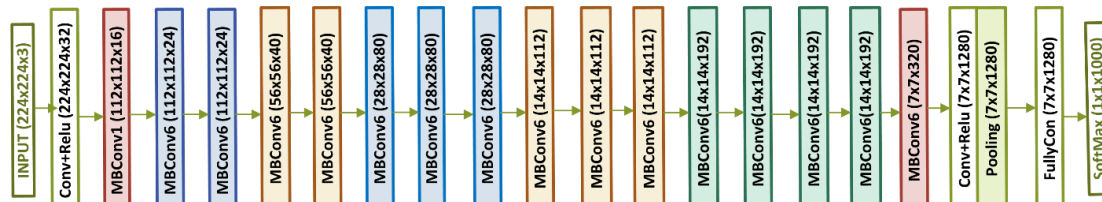


Figure 7. EfficientNetB0 baseline architecture.

2.3. Model Tuning

Transfer Learning: Transfer learning is a powerful technique in deep learning where pre-trained models are used as a starting point for solving new tasks. In this study, we have incorporated transfer learning for all our state-of-the-art models (AlexNet, VGG16, InceptionV3, MobileNetV3, and EfficientNet). By leveraging transfer learning, we have initialized all the networks with weights pertained on large-scale image classification dataset (ImageNet). Fine-tuning the SOTA models helps in accelerating the training and improves the performance.

2.4. K-Fold Validation

Cross-validation is a popular technique for estimating the skill of machine learning models. Because it has a lower bias, it is widely used to compare and select models for a given predictable modelling problem [44]. The entire procedure of the K-Fold cross validation algorithm used in this study is listed in following steps:

1. Shuffle the entire dataset and split data set into training and test dataset with the ration of 08:20.
2. Split training set into 4 subsets. Create a loop to train model 4 times.
3. In first loop first subset is used for validation and the last 3 parts are used for training. Train and test the model.
4. In second loop second subset is used for validation and the remaining 3 parts are used for training. Train and test the model.
5. In third loop third subset is used for validation and the remaining 3 parts are used for training. Train and test the model.
6. In last loop last subset is used for validation and the first 3 parts are used for training. Train and test the model.
7. Summarize the overall performance of all models of all trained K-Folds.

2.5. Experimental Environment Settings and Performance Evaluation Metrics

This research aims to propose an optimal model which identifies and classifies different types of images. The proposed model was implemented using Python (v. 3.8), OpenCV (v. 4.7), Keras Library (v. 2.8) were used on Windows 10 Pro OS, with system configuration using an Intel i5 processor running at 2.9 GHz, an Nvidia RTX 2060 Graphical Processing Unit and 16 GB RAM.

Several metrics were employed to evaluate the performance of classifying sunflower blooms and leaves, including accuracy, precision, recall, and F1-score, which are frequently used indicators [30]. Accuracy is the ratio of samples from all classes that can be correctly

identified, Recall is the ratio of correctly classified positives among all actual positives, and Precision is the ratio of correctly identified positives versus all expected positives [45]. The metrics were calculated using Equations (1)–(4).

$$\text{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{True Positive} + \text{True Negative} + \text{False Positive} + \text{False Negative}} \quad (1)$$

$$\text{Recall} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}} \quad (2)$$

$$\text{Precision} = \frac{TP}{\text{True Positive} + \text{False Positive}} \quad (3)$$

$$\text{F1 - Score} = 2 \times \frac{\text{Recall} \times \text{Precision}}{\text{Recall} + \text{Precision}} \quad (4)$$

3. Results

The performance of all classifiers, such as AlexNet, VGG16, InceptionV3, MobilenetV3, and EfficientNet, models were evaluated with evaluation metrics as mentioned in Section 2.5. The convergence graphs of performed training were also given to track the accuracies and losses of training with epoch. Transfer learning was employed for the training processes, and ImageNet weights were used to initialize the weights models. To produce results that can be compared, each training procedure was completed using the same settings, such as batch size, dataset split ratio, learning rate, and optimizer. The number of the epoch was set to 300, the early stop parameter was set to 30, the batch size was set to 32, the initial learning rate was set to 0.0005, and the SGD optimizer was chosen as the optimizer during the training process. Figure 8 displays the training accuracy, validation accuracy, training loss, and validation loss vs. the number of epochs for all models after using transfer learning considered in this study.

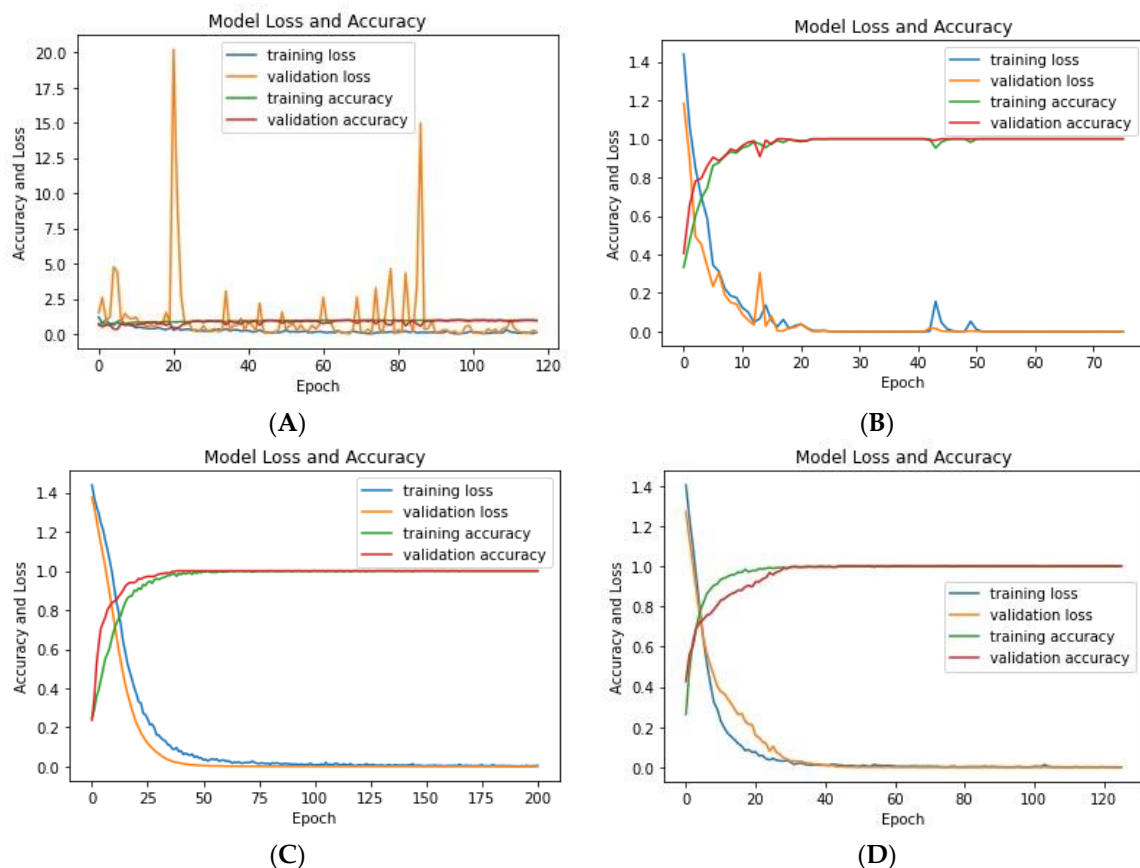
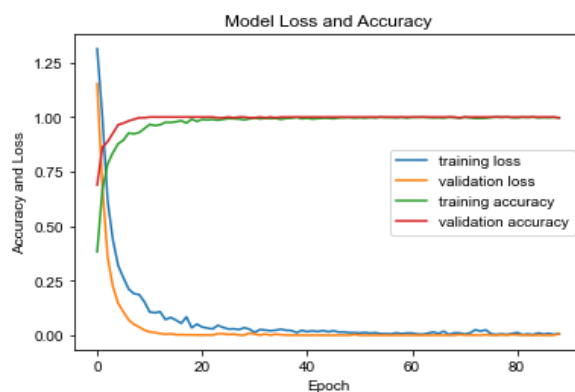


Figure 8. Cont.



(E)

Figure 8. Convergence Curves of Models: (A) AlexNet, (B) VGG16, (C) InceptionV3, (D) MobileNetV3, (E) EfficientNetB3.

Initially, the number of epochs was set to 300 for all the models but it is important to note that the early stop parameter was also deployed to avoid the wastage of time when there is no positive/negative change occurring to the model training. From Figure 8, it can be depicted that each model has taken different epochs to train and validate. It took 117, 76, 201, 126, and 89 epochs to AlexNet, VGG16, InceptionV3, MobileNetV3, and EfficientNetB3 respectively. From Figure 8A it can be detected that the training accuracy of AlexNet started at 40% at the initial iterations and gradually increased and remained around 85% until there was no improvement in the model training accuracy. From Figure 8B it can be seen that the training accuracy rate of VGG16 started at 35% from the first iteration and continued to improve until iteration 22. From iteration 22 model has been performing well in terms of training accuracy and has reached the optimal accuracy. Whereas when it comes to the validation accuracy, it can be seen that model has performed identically to training accuracy. When it comes to the training loss and validation loss, it can be depicted from the Figure that at initial iterations the model isn't doing well due to the high number of losses. But gradually it can be seen that when the model started to learn and remember more about the data, it performed well, and the training and validation loss decreased. By the 20th iteration, it can be seen that model accuracy reached to maximum value. From Figure 8B it can be seen that VGG16 has achieved 96.5% accuracy. When it comes to InceptionV3, it has performed similarly to VGG16 in terms of training and validation. However, the accuracy rate of VGG16 is better than InceptionV3. It may be due to many factors such as architectural design, parameter efficiency, computational efficiency, dimensional reduction, and auxiliary classifiers.

Figure 8D,E present the training accuracy, validation accuracy, training loss, and validation loss of MobileNetV3 and EfficientNetB3. From Figure 8D,E, it can be seen that both models are performing better than AlexNet, VGG16, and InceptionV3 in terms of training accuracy. The model validation accuracy of MobileNetV3 and EfficientNetB3 started from 55% and 70% respectively. From Figure 8D it is evident that the MobileNetV3 model has reached optimal accuracy before reaching 35 iterations whereas EfficientNetB3 has reached optimal accuracy within the first 10 iterations. As far as training and validation loss is concerned both models are performing well. During the training accuracy, validation accuracy, training loss, and validation loss, it can be concluded that EfficientNetB3 has outperformed state-of-art models.

Figure 9 shows the confusion matrixes of sunflower leaf and bloom classification results of all models. where it is seen that most of the images were assigned to the correct classes. According to Figure 9E, the EfficientNetB3 model has the fewest misclassifications. EfficientNetB3 predicted 3 items in the Leaf Scars class as the Downy Mildew class and 4 items in the Downy Mildew class as the Leaf Scars class. Figure 9A shows that 39 out of 286 images were misclassified by AlexNet, which is the highest misclassifica-

tion score. According to Figure 9B,D, several misclassifications made by VGG16 (10) and MobileNetV3 (9). However, all models showed perfect recognition of healthy leaves and gray mold disease, where no misclassifications were observed, except AlexNet. It can be also observed that AlexNet did not perform well and had the highest number of misclassifications in all the classes.

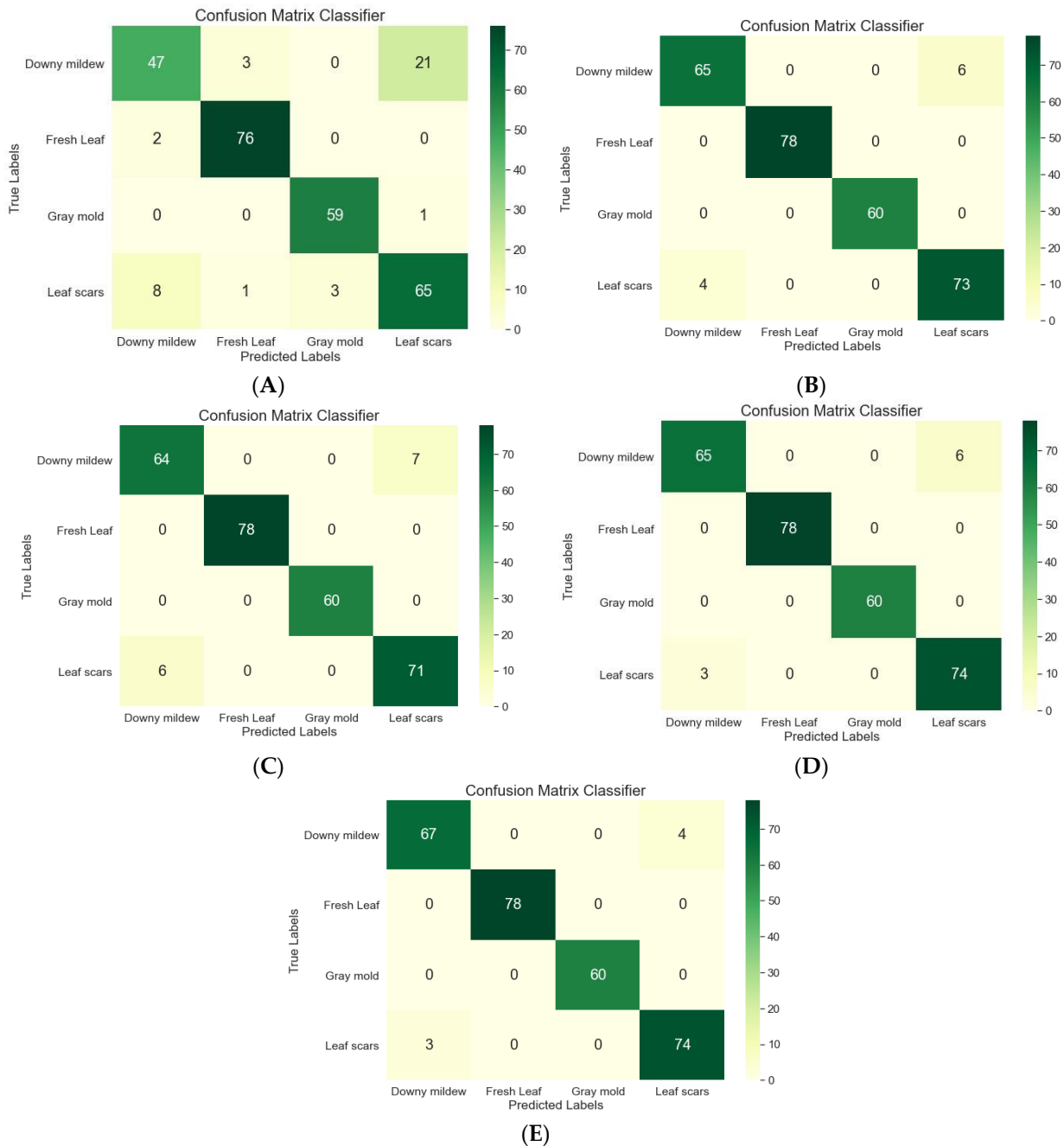


Figure 9. Confusion Matrix of Models. (A) AlexNet, (B) VGG16, (C) InceptionV3, (D) MobileNetV3, (E) EfficientNetB3.

Table 2 shows the evaluation metric in terms of precision, recall, F1-score, and accuracy of all the models used in this study. According to the results given in Table 2 performance of the models in the discrimination of healthy leaves from infected items is very high, where the classification accuracy is 100%. The classification accuracy for the detection of Gray Mold disease was also 100% (except AlexNet), whereas classification accuracies for the detection of Downy Mildew and Leaf Scars disease were comparatively lower

for all models. Downy Mildew and Leaf Scars classes were classified by InceptionV3 with accuracies of 91.4% and 91.0%, respectively. whereas for VGG16, it got 94.2% and 92.4% for Downy Mildew and Leaf Scars classes respectively. The lowest performance in the detection of Downy Mildew and Leaf Scars disease was obtained by AlexNet, with classification accuracies of 82.4% and 74.7%, respectively. The highest performance in detection of sunflower diseases is obtained by EfficientNetB3, with a classification accuracy for Downy Mildew and Leaf Scars is 95.7% and 94.9%, respectively.

Table 2. Evaluation Metrics for the Performance of Models.

Model	Class	Precision	Recall	F1-Score	Accuracy
AlexNet	Downy Mildew	0.824	0.662	0.734	0.662
	Fresh Leaf	0.950	0.974	0.962	0.974
	Gray Mold	0.952	0.983	0.967	0.983
	Leaf Scars	0.747	0.844	0.793	0.844
VGG16	Downy Mildew	0.942	0.915	0.929	0.915
	Fresh Leaf	1.000	1.000	1.000	1.000
	Gray Mold	1.000	1.000	1.000	1.000
	Leaf Scars	0.924	0.948	0.936	0.948
InceptionV3	Downy Mildew	0.914	0.901	0.908	0.901
	Fresh Leaf	1.000	1.000	1.000	1.000
	Gray Mold	1.000	1.000	1.000	1.000
	Leaf Scars	0.910	0.922	0.916	0.922
MobilNetV3	Downy Mildew	0.956	0.915	0.935	0.915
	Fresh Leaf	1.000	1.000	1.000	1.000
	Gray Mold	1.000	1.000	1.000	1.000
	Leaf Scars	0.925	0.961	0.943	0.961
EfficientNetB3	Downy Mildew	0.957	0.944	0.950	0.944
	Fresh Leaf	1.000	1.000	1.000	1.000
	Gray Mold	1.000	1.000	1.000	1.000
	Leaf Scars	0.949	0.961	0.955	0.961

The overall performance of the models before and after incorporating transfer learning is given in Table 3. From the table it can be seen that incorporating transfer learning the precision, recall, F1-score, and accuracy has changed by a lot in all the models. Before transfer learning the model the accuracy of AlexNet, VGG16, InceptionV3, MobileNetV3, EfficientNetB3 are 83.5%, 93.4%, 93.2%, 83.2% and 88.5% respectively. However, after incorporating transfer learning EfficientNetB3 model has achieved the highest accuracy, 97.6% in just 89 epochs among all the models. MobilenetV3 achieved an accuracy of 96.9% in 126 epochs, whereas the AlexNet model achieved the lowest classification accuracy (86.4%) in 117, the second worst accuracy obtained by a model is InceptionV3 with 95.4% accuracy within 201 epochs, which has the highest number of epochs compared to other models.

Table 3. Overall performance of models before and after transfer learning.

Models	Models	Precision	Recall	F1-Score	Accuracy	Epochs
Before Transfer Learning	AlexNet	0.835	0.831	0.832	0.835	300
	VGG16	0.934	0.936	0.935	0.934	300
	InceptionV3	0.932	0.933	0.932	0.932	300
	MobilenetV3	0.832	0.835	0.838	0.832	300
	EfficientNetB3	0.902	0.890	0.889	0.885	300
After Transfer Learning	AlexNet	0.865	0.866	0.861	0.864	117
	VGG16	0.965	0.965	0.965	0.965	76
	InceptionV3	0.954	0.954	0.954	0.954	201
	MobilenetV3	0.969	0.969	0.969	0.969	126
	EfficientNetB3	0.976	0.976	0.976	0.976	89

To evaluate the skill of the used models and check dependency to dataset K-fold cross-validation technique was applied. In this study entire data set was divided into 5 subsets. One subset was used for testing and the remaining 4 subset were used in training in loop, where different subsets were assigned as validation set. The results of applied method are given in Table 4.

Table 4. K-fold cross-validation results.

Models	Loop1 Acc	Loop2 Acc	Loop3 Acc	Loop4 Acc	Mean Acc
AlexNet	0.846	0.857	0.854	0.846	0.851
VGG16	0.960	0.960	0.981	0.957	0.965
InceptionV3	0.936	0.955	0.955	0.981	0.957
MobilenetV3	0.959	0.955	0.960	0.955	0.957
EfficientNetB3	0.984	0.970	0.976	0.989	0.980

According to the results given in Table 4 EfficientNetB3 model has achieved the highest mean accuracy of 98.0% among all the models. AlexNet model achieved the lowest classification accuracy of 85.1%. The second-best accuracy was obtained by VGG16 model (96.5%). InceptionV3 and MobilenetV3 achieved the same mean accuracy of 95.7%.

Inference time performance results of these models are given in Table 5. The trained models are used in real-time systems, different batch sizes and inference times are calculated for each model in order to obtain test performance results. A total of 1000 test data were used as test data in order to calculate the inference times precisely, and thus more normalized values were obtained. For example, for AlexNet architecture the Batch Size = 1 as shown in Table 5, the calculated time is 4.4 ms. This value is calculated as follows: 1000 images are given as test data and Batch size = 1 is chosen. The total test time is 4447 ms, during which 1000 images were classified. In other words, it took $4447/1000 = 4.4$ ms to classify 1 image. Similarly, Batch Size is set to 16 for AlexNet model, the total test time of 1000 images were calculated as 1832 ms. In other words, it took $1832/1000 = 1.8$ ms to classify 1 image. These operations were performed for all models and batch sizes in the table, and the results are obtained as mentioned in Table 5.

Table 5. Inference time performance.

Model Name	Batch Size = 1 (ms)	Batch Size = 16 (ms)	Batch Size = 32 (ms)
AlexNet	4.4	1.8	1.7
VGG16	9.9	4.1	4.0
InceptionV3	18.3	3.8	3.3
MobileNetV3	11.1	2.2	1.9
EfficientNetB3	25.7	9.4	5.7

Based on these results, when such a classification is desired to be used in real-time applications, the EfficientNetB3 model can be used to achieve high accuracy, if there is no shortage of time. If such an application will be used on mobile devices and in case of hardware capacity shortage, it would be more accurate to use the MobileNetv3 model in terms of both accuracy and low inference time.

4. Discussion and Conclusions

In this comparative study, we investigated the classification of sunflower diseases using deep learning models and incorporated transfer learning techniques. The models evaluated in this study included AlexNet, VGG16, InceptionV3, MobileNetV3, and EfficientNet. By leveraging pre-trained models, we aimed to enhance the accuracy and efficiency of sunflower disease classification.

Our findings indicate that deep learning models are highly effective in accurately identifying and classifying various sunflower diseases. Through a thorough analysis of the results, we observed that all the models achieved considerable accuracy rates, highlighting their potential for disease detection in sunflower crops. However, some models demonstrated superior performance compared to others, providing valuable insights into their capabilities for this specific task.

Among the models evaluated, EfficientNetB3 consistently outperformed the other architectures in terms of accuracy, precision, recall, and F1-score metrics. It may be due to many characteristics that make it stand out compared to the other models:

- **Compound Scaling:** EfficientNetB3 includes a technique known as compound scaling, which systematically grows the model's depth, width, and resolution all at once. This method enables EfficientNetB3 to perform better across a wide variety of computational resources and dataset sizes. EfficientNetB3 achieves improved accuracy while keeping efficiency by scaling the model in a balanced manner.
- **Depth and Width:** When compared to MobileNetV3 and InceptionV3, EfficientNetB3 is deeper and wider. Because of the enhanced depth, it can capture more complicated features and hierarchies in the data. The increased width, which refers to the number of channels in each layer, improves the model's representational capacity and allows for more fine-grained detail to be captured.
- **Resolution:** When compared to AlexNet, MobileNetV3, InceptionV3, and VGG16, EfficientNetB3 has higher-resolution input images. The higher the input resolution, the more visual information the model can learn from, which is very useful when working with detailed or high-quality photos.
- **Efficient Architecture:** Despite its depth and breadth, EfficientNetB3 retains computational efficiency. It accomplishes this by employing efficient network design ideas such as inverted residual blocks and squeeze-and-excite modules. When compared to VGG16 and InceptionV3, these design choices lower the number of parameters and operations, resulting in faster training and inference times.
- **State-of-the-Art Performance:** EfficientNetB3 has regularly achieved top performance in a variety of computer vision tasks, including picture classification and object recognition, in many benchmark datasets, including ImageNet. The balanced scalability and efficient architecture contribute to its high performance, making it a suitable solution for many real-world applications.

The utilization of transfer learning in sunflower disease classification showcases its potential as a valuable technique for agricultural applications. By leveraging pre-trained models, we were able to benefit from the learned features and representations of general images, adapting them to the specific task of sunflower disease classification. This approach circumvents the need for training models from scratch, which can be computationally expensive and resource intensive.

As with any scientific study, there are opportunities for future work to build upon the findings of this research. One avenue for future research includes expanding the dataset used for training and evaluation. While our study utilized a comprehensive dataset, incorporating additional samples from diverse geographical locations and under different environmental conditions would further enhance the generalization capability of the models. This would enable the models to accurately classify diseases in various regions and environments, ensuring robustness and reliability. Exploring the interpretability of the deep learning models could be also a potential improvement. Interpretability is a crucial aspect, especially in agricultural applications, where understanding the decision-making process is vital for the acceptance and adoption of these models. While deep learning models are often regarded as black boxes due to their complex architectures, efforts have been made to interpret and visualize the learned features and decision boundaries. Such interpretability techniques can provide valuable insights into the factors contributing to disease classification, ultimately aiding farmers and agricultural experts in decision-making processes.

Furthermore, exploring model optimization techniques specific to sunflower disease classification could potentially improve the performance of the deep learning models. Techniques such as neural architecture search (NAS) can be employed to automatically discover optimal architectures for this task, considering the unique characteristics of sunflower diseases.

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