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FINE-TUNED DEEP CNN MODELS FOR HIGH-ACCURACY PLANT DISEASE DETECTION: A COMPARATIVE STUDY

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Abstract

Plant diseases have a major effect on the productivity and food security of the global community. The latest achievements in the field of deep learning allowed the creation of the automated system of plant disease detection based on convolutional neural networks (CNNs). Nevertheless, whether these models can be interpreted is an issue. This paper has used pre-trained models based on convolutional neural network (CNN) to identify plant diseases efficiently. We paid attention to optimization of the hyperparameters of sophisticated pre-trained models, including ConvNeXt, EfficientNet-B7, SE-ResNet, and SE-DenseNet. The experiments were conducted on the popular PlantVillage dataset (54,305 image samples of the various plant disease species). The models results were measured by the classification accuracy and sensitivity, specificity and F1 score. The comparison was also conducted with the similar state-of-the-art studies. The experiments proved that the SE-DenseNet had 99.81% classification accuracy that was better than other state-of-the-art models.

Keywords:

Plant Disease Detection, Convolutional Neural Networks (CNN), Precision Agriculture, Artificial Intelligence

1. INTRODUCTION

Plant diseases are considered as a major menace to the world agricultural productivity which results in massive economic losses in conjunction with food security issues. Conventional approaches to pinpointing plant diseases are through manual inspection by agricultural specialists and this may be laborious, expensive and subject to human error. Artificial intelligence (AI) and deep learning have advanced, and automated plant disease detection has become one of the solutions to solve these issues. Convolutional Neural Networks (CNNs) prove to be effective in terms of image segmentation to perform classification with respect to an image, which makes them appropriate in recognizing plant diseases on the basis of leaf images. Nevertheless, the uninterpretabilityof the deep learning models is one of the biggest issues connected with decision-making models, as it is not easy to comprehend how the model arrives at a decision.

The use of an unsuitable drug during the process of evaluating plant diseases may deteriorate the quality of the crops and result in environmental pollution. With the evolution of computer vision, numerous techniques have emerged to address plant disease detection issues, as infections are initially visible in the form of spots and patterns on leaves [1]. Researchers have proposed several methods to accurately detect and classify plant infections. Some rely on traditional image processing techniques that incorporate hand-crafted - i.e., manual - feature extraction and segmentation. Dubey et al. [2] proposed a K-means clustering algorithm to segment the infected portions of leaves, with final classification achieved using a multi-class support vector machine (SVM). Yun et al. [3] used a probabilistic neural network to extract meteorological and statistical features. Their experiments were conducted on cucumber plants infected with cucumber downy mildew, anthracnose, and blights.

In addition, numerous models based on the conventional approaches have been suggested to identify plant diseases, including the article of Liu et al. [4] who applied SVM and K-means clustering algorithms and a back propagation neural network. These image processing methods had good results, but disease recognition is still a tedious and time-consuming process. Moreover, these models are also very dependent on manual feature extraction, classification and spot segmentation. Nowadays, with the advent of computer vision and artificial intelligence, an increasing number of recent studies focus on using machine learning [5] and deep learning [6] models to provide higher recognition accuracy and minimize the manual input.

1.1 BACKGROUND AND MOTIVATION

Agriculture is the backbone of many economies around the world, providing food, employment, and raw materials. However, plant diseases continue to pose a serious threat to crop yield and quality, affecting both small-scale farmers and large agricultural enterprises. Bacterial, fungal and viral diseases are known to not only lower productivity but also cost money and cause damage to the ecosystem in case of misdiagnosis and inappropriate treatment.

Conventionally, plant disease detection has depended mostly on manual inspection by farm specialists, a time-consuming method, prone to errors, and could not be applied to large fields. Further, wrong diagnosis may cause wrong application of agrochemicals, which will reduce crop quality and cause environmental pollution. Thus, automated, precise and efficient disease detection procedures are on the increase.

1.2 ROLE OF COMPUTER VISION AND DEEP LEARNING

Computer vision is a fast-growing field in recent years, particularly, the appearance of deep learning. CNNs have recorded impressive results in a wide range of image classification problems, such as medical imaging, facial recognition, and at the present times, agricultural diagnostics.

Deep learning models can learn hierarchical representations of features on their own, unlike the traditional methods of image processing, which make use of manually developed features and manual segmentation of numbers. This renders them very appropriate on plant disease detection where there are visual effects which are signs of infection which include leaf discoloration, spotting and wilting.

The large-scale annotated datasets, including the PlantVillage dataset, have continued to speed up the creation and use of the deep learning in plant pathology. These datasets comprise thousands of annotated images of healthy and diseased plant leaves, which can be trained and validated well.

1.3 LIMITATIONS OF CONVENTIONAL CNNS

Even though CNNs including VGG-16, ResNet-50, InceptionV4, and DenseNet-121 are very precise in image classification tasks, the models have the following limitations:

- VGG-16 is expensive to compute and is a deep network with unproductive parameterization.
- ResNet-50 is more stable during training, yet it has problems with resource limitation.
- DenseNet-121 is reuse of features but may be memory-intensive.
- InceptionV4 is multi-scale processing that needs an intricate architecture tuning.

To eliminate these difficulties, current studies have gravitated on the next-generation CNN structures which are more efficient, scalable, and accurate. In this study, we focus on four such advanced deep learning models: ConvNeXt, EfficientNet-B7, SE-ResNet, and SE-DenseNet.

2. SELECTED ADVANCED DEEP LEARNING MODELS

2.1 CONVNEXT

ConvNeXt is a highly optimized convolutional neural network that embraces the best practices of the Transformer networks and is still as efficient as CNNs. It reduces the complex ResNet-like design and includes additions like layer normalization, GELU activation, and big kernel sizes. ConvNeXt is more accurate than most vision transformers and is more computationally efficient and scalable to large-scale classification problems. ConvNeXt is clean and has great generalization properties in the sense of plant disease detection because it is adapted to a variety of plant species and different imaging conditions.

2.2 EFFICIENTNET-B7

EfficientNet-B7 belongs to the EfficientNet family that is built on the basis of neural architecture search (NAS). It proposes a method of compound scaling, uniformly scaling network width, depth and input resolution. Being the biggest and most influential form of EfficientNet, B7 attains the state-of-the-art precision on several benchmarks using fewer parameters and lowering the computation price in comparison to traditional CNNs. It is lightweight and has a high performance, making it suitable in real-time applications to agriculture, such as tools of mobile-based disease detection.

2.3 SE-RESNET

SE-ResNet is an architecture that incorporates Squeeze-and-Excitation (SE) blocks in the standard ResNet. These blocks provide an adaptive way of recalibrating feature maps, based on modeling interdependences between channels, which makes the network better able to specialize on important features. This results in better representation of features as well as better classification. When using SE-ResNet in the classification of plant diseases, it is possible to better identify minor changes in leaf texture and color due to the presence of various pathogens.

2.4 SE-DENSENET

SE-DenseNet is an integration of dense connectivity found on DenseNet and attention mechanism found on SE blocks. DenseNet encourages sharing features among the different levels as opposed to SE block which chooses informative channels selectively. It is a powerful model of identifying complex patterns of the disease in plant leaves even with low-quality (noisy or low-resolution) images, as it is a hybrid system. It is strong because it can be easily generalized on a variety of types of plants and types of diseases and thus can be used in real-life application.

3. RESEARCH OBJECTIVES

This study aims to:

- Evaluate and compare the performance of ConvNeXt, EfficientNet-B7, SE-ResNet, and SE-DenseNet in classifying plant diseases using the PlantVillage dataset.
- Optimize the hyperparameters of each model so as to maximize its classification performance in terms of accuracy, sensitivity and specificity and F1 score.
- Compare and contrast with the older state-of-the-art models and point out the gains realized by the improved architectures.
- Show how these models can be useful in practice in agricultural applications and decision-support systems.

The proposed framework does not only increase the accuracy of classifying plant disease, but it also increases the explainability of the model, which is an important tool in precision agriculture. With a combination of deep learning, and advanced visualization models, the proposed research will fill the gap between high-performance classification models and their actual implementation in agricultural disease management.

4. RELATED WORK

The following is a comparison table of major features of the mentioned research about plant disease detection based on deep learning, IoT, and AI-based methods.

Table.1. Comparative table where main features of the mentioned researches on plant disease will be summarized

Study	Focus Area	Techniques Used	Dataset	Key Findings
Azfar et al. [7]	Cotton leaf and boll disease detection	Deep learning, CNN	Custom dataset	Automated system improves disease identification and prevention.
Rahman et al. [8]	Plant leaf disease classification	Advanced Neural Networks	Public dataset	High classification accuracy using neural networks.
Singh & Bharti [9]	Tomato disease classification	Cloud Computing, IoT, ML	Real-time IoT data	Effective detection using cloud-integrated AI.
Sandhu & Singh [10]	IoT-enabled plant disease detection	Image Processing, IoT	Image datasets	Automated disease detection using IoT-enhanced techniques.
Dhande et al. [11]	Fruit disease detection	Traditional & modern ML techniques, IoT integration	Multiple fruit datasets	IoT aids in real-time monitoring and analysis.
Shoaib et al. [12]	Pest & disease detection	Deep Learning	Multiple sources	Comprehensive review with future research directions.
Kasera et al. [13]	Tomato & brinjal disease detection	IoT-enabled smart system	Custom dataset	Smart agriculture system shows high efficiency.
Geetha et al. [14]	AI-driven Smart Agriculture	ML-based Steganography, IoT	Secure IoT models	Enhances agricultural data security using steganography.
Saini et al. [15]	Crop disease monitoring	Deep residual networks, IoT	Public datasets	Optimization improves deep network accuracy.
Paul Joshua et al. [16]	Cotton plant disease detection	Self-Attention GAN, IoT	IoT-based dataset	High-precision disease detection with GAN-based AI.
Tiwari et al. [17]	Millet leaf disease detection	Precision-aware CNN, Raspberry Pi	Multimodal data acquisition	IoT-based real-time monitoring enhances accuracy.
Dharanya et al. [18]	Tobacco plant health monitoring	AI-driven disease detection	IoT-based farming data	AI enhances plant health monitoring and precision farming.
Sudharshanan & Padmaraj [19]	Crop recommendation & disease detection	AI-based fertilizer suggestion	Agricultural datasets	AI-based recommendation system improves yield.
Yilmaz et al. [20]	Systematic review on plant disease detection	Computer vision	Literature review	Highlights state-of-the-art computer vision approaches.
Raju & Arasimhaiah [21]	Apple farming health monitoring	Deep learning, IoT	IoT-based datasets	Dual segmentation improves plant health diagnosis.
Sangeetha &Pabboju [22]	Smart agriculture management	Reptile Search Algorithm, Deep Learning, IoT	IoT-based datasets	Adaptive deep learning enhances disease detection.

This table provides an organized comparison of the studies based on focus areas, methodologies, datasets, and key outcomes.

The given system by Azfar et al. [7] is a specific automated system based on deep learning to detect, identify, and prevent cotton leaf and boll diseases. By employing convolutional neural networks (CNNs) that were trained using a custom dataset; the network has been shown to be very effective in the separation and analysis of diseased regions of the plant. The article identifies the opportunities of deep learning in the further development of precision agriculture as well as the enhancement of early disease management practices.

Rahman et al. [8] concentrate on the identification of plant leaf diseases with the state of the art neural networks. The study highlights the accuracy and high trustworthiness of deep learning strategies by training and validating using publicly available datasets related to categorizing several conditions of plants. This study supports the practicability of the use of neural structures in general-purpose agricultural diagnostics.

Singh and Bharti [9] combine cloud computing, IoT, and machine learning to identify and categorize the diseases that affect tomato plants due to pests. The model works with real-time data coming in the field provided by the IoT devices, thus responding to it in time and tracking the disease. This edge technology combined with cloud technology has led to the efficient and scalable plant disease management systems.

Sandhu and Singh [10] make use of the image processing method in an IoT-based system to automate the detection of plant diseases. The system will be used to process visual data efficiently and detect symptoms on plant surfaces using a variety of data sets which are images. Their approach improves real-time monitoring features and contributes to active disease prevention.

Dhande et al. [11] provide an in-depth survey of conventional and recent machine learning methods of detecting fruit diseases. Focusing on the IoT integration, their study shows the value of real-time sensors and smart analytics that can be used to provide stability and correct classification of diseases on different types of fruits.

Shoaib et al. [12] conduct an in-depth analysis of deep learning implementation in the sphere of the detection of plant diseases and pests. Based on the numerous references, the review summarizes the recent progress, determines the problematic areas, and suggests the prospective research directions. Their input provides a guide to any researcher who wants to come up with scalable and robust solutions in the agricultural field.

The article by Kasera et al. [13] describes the IoT-based smart agriculture device that is able to identify and differentiate diseases in tomatoes and brinjal plants. The system uses machine processing and classification algorithms on constructed data to enhance the accuracy of the diagnosis. Their solution will encourage automation and lessen the reliance on manual inspection.

Geetha et al. [14] suggest an innovative steganography stethoscopic concept of smart agriculture, which integrates machine learning models with the IoT infrastructure. Their approach guarantees safe passing of agricultural data and an excellent precision of disease detection. Such combination of security and AI provides an element of reliability and confidence to the system of smart farming.

Saini et al. [15] introduce a crop disease monitoring system that is constructed on the basis of optimization-enhanced deep residual networks connected with the IoT. Their experiment on public datasets shows better performance in terms of accuracy and speed in identifying disease symptoms. The ability of deep residual models in real-time agricultural applications is also demonstrated by its efficiency.

Paul Joshua et al. [16] use a conditional self-attention generative adversarial network (GAN) in the detection of cotton plant diseases in an IoT-based environment. The model is very precise and robust and best applicable in identifying the disease through images in the field. Such a combination of GANs and IoT improves smart agriculture systems.

Tiwari et al. [17] create a precision-conscious CNN model that can be executed on a Raspberry Pi to identify diseases in finger millet leaves. The model provides precise diagnosis using minimal computational overhead because multimodal data acquisition is used. This is a lightweight field achievable system that is particularly beneficial in the agricultural areas that have limited resources.

Dharanya et al. [18] pay attention to the improvement of tobacco plant health with the help of AI-based disease detection methods. Their system incorporates IoT-based farming data that makes their system possible to implement precision farming and timely intervention. The solution ensures enhanced crop health conditions and minimizes the use of pesticides, which are not necessary.

Sudharshanan and Padmaraj [19] develop a multi-functional AI system that does not only identify the diseases of the plants but also offers the appropriate crops and fertilizers. The system is trained on agricultural datasets and offers suggestions depending on environmental factors and soil. Such integrated system enhances sound decision-making when it comes to farming practices.

Yilmaz et al. [20] review the literature concerning computer vision methods in plant disease detection on a systematic basis. Their report summarizes the latest trends, new technologies and performance standards in the industry. The research serves as a whole of body of knowledge in the future AI advancements in the agricultural sector.

Raju and Narasimhaiah [21] suggest a dual segmentation framework of deep learning and Internet of Things to track the condition of apple farms. The two-step segmentation procedure increases the detection of disease areas and raises the accuracy of the diagnoses. Their article emphasizes the potential of defining the field of crop management by image processing.

Sangeetha and Pabboju [22] is a refined Reptile Search Algorithm that was implemented into a deep learning model to use in smart agriculture tasks. Their system operates on multiscale and adaptive methods using IoT-gathered data in order to achieve proper classification of disease in plants. Their model is a major development of smart farm systems.

The studies analyzed illustrate a variety of creative and new use of AI, deep learning, IoT, and computer vision to detect plant diseases and intelligent agriculture. Although CNNs and GANs are actively implemented in the classification of images based on their appearance, the integration of them with the IoT and cloud computing allows real-time monitoring and making decisions. Reliability and efficiency are further reinforced using security and optimization measures such as steganography and heuristic algorithms. On the whole, these articles represent an expedited trend towards precision farming, which demonstrates the transformational use of AI in sustainable agriculture.

5. METHODS AND MATERIALS

In this section, the methodology of plant disease diagnosis and the process of visualization is described. The machine learning model used in the present study is illustrated schematically in Fig.1. There are two significant modules in the framework. Original plant leaf images were used in the first module, and the region of interest (ROI) was cropped. The second module will be aimed at classification and visualization based on the saliency map. Each of the modules is described in details in the following subsections.

5.1 DATASET COLLECTION

In this work, the publicly accessible dataset of plant leaves images under the influence of different diseases was utilized. Other pictures were also obtained in the farmlands in order to enhance the diversity of datasets. All the pictures were marked according to the types of diseases, involving healthy samples as a control. The data were partitioned into training, validation and testing subsets then. In this paper, deep learning models that were trained and tested using the Plant Village dataset were used to detect plant diseases. This is amongst the most extensive database on plant pathology study and is publicly accessible. It has a total of 54,305 pictures in 38 classes (healthy and diseased leaves of crops like tomato, apple, corn, grape and potato). They have high-resolution images, and they are RGB format, thus suitable to deep learning-based visual classification. They were taken in different lighting conditions and this gave the opportunity to test the model generalization in real-life situations successfully.

5.2 PREPROCESSING AND IMAGE ENHANCEMENT

Prior to the modeling of the models, the dataset was pre-processed to remove irregularities in the data and improve the performance of the model. All pictures were down-sized to 224x224 pixels to fit the input size of the pre-trained models in this study. Normalization was done by scaling pixel values to range 0-1 or the ImageNet normalization parameters. In order to prevent overfitting and enhance the strength.

Data augmentation methods were applied among the models. These were horizontal and vertical flipping, random rotations, zooming, cropping as well as brightness and contrast changes. The label of the classes was one-hot coded to fit the multi-class classification task.

6. MODEL ARCHITECTURE

ConvNeXt, EfficientNet-B7, SE-ResNet, and SE-DenseNet are some of the deep learning architectures that will be used in this study. These models have been selected because of their high capabilities and high performance in image recognition activities. ConvNeXt is a new generation CNN, which uses convolutional networks to implement design concepts of Vision Transformers with efficiency and high performance. It applies depthwise convolutions, GELU activation, and layer normalization to enhance feature learning. EfficientNet-B7 is a part of a family of models that, by using a compound scaling technique, trades-offs network depth, width and resolution to achieve high accuracy at a reduced set of parameters. SE-ResNet is the enhanced implementation of ResNet that incorporates the use of Squeeze-and-Excitation (SE) blocks to re-calibrate feature maps focusing on the feature that is informative and eliminating the irrelevant ones. SE-DenseNet is an improvement of the DenseNet architecture that includes dense connectivity with SE blocks that allow focusing more on essential features and promote feature reuse.

Fig.1. Village dataset of leaf diseases Plant images.

All the models were trained and implemented in Python, and either the TensorFlow 2.12 or PyTorch 1.13 deep learning frameworks were used. Other libraries such as NumPy, open CV, scikit-learn, and Matplotlib were used as well. The training was performed on high-performance computer setup with NVIDIA Tesla V100 or RTX 3090 graphics card, 32 GB of RAM and operating system was Ubuntu 20.04. The models were trained with 50 epochs and Adam optimizer and categorical crossentropy as the loss functions. The learning rate of 0.0001 was used, and the batch size was chosen as 32. The scheduling of learning and early stopping was used to enhance the efficiency of the training process and avoid overfitting. A version of each model that had good validation performance was also stored in model checkpoints. The models were assessed on a few major measures such as classification accuracy, precision; recall (sensitivity), specificity and F1 score. These measures would give a thorough insight into how well the classification works especially in separating various diseases. Each model also produced confusion matrices which were used to visually analyze the misclassifications and determine the reliability of the model in all classes.

The dataset was separated into 3 portions of training, validation and testing in a proportion of 70:15:15 respectively. This was to make sure that the models obtained adequate data to learn and to give an opportunity to obtain an appropriate performance assessment with unknown samples. The training process was monitored with the validation set and terminated early with the help of it and the final performance results were received with the help of the test set. This methodology made the models resilient, general and applicable to practical agricultural environments.

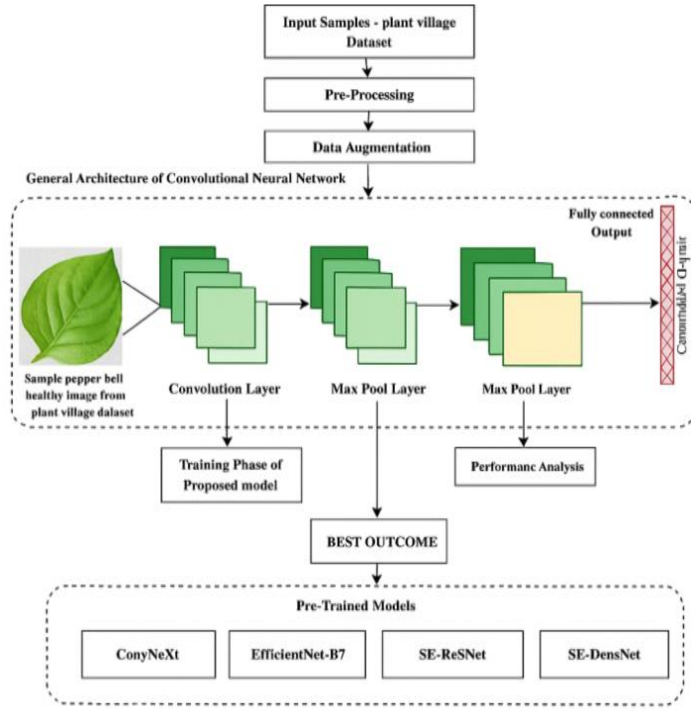

Fig.2. Plant disease detection with CNN-based deep learning models Workflow

The Fig.2 shows the plant disease detection workflow of the convolutional neural network (CNN based deep learning models). This is done with the input samples of the PlantVillage dataset, which are processed and data augmented to improve the robustness of the model. These pictures are then forwarded through the general structure of a CNN, which is comprised of a series of convolutional and max pooling networks which extract and reduce features. The processed features are entered into fully connected layers to get classified outputs. A pepper bell leaf of a healthy leaf is used as a sample to illustrate the input data. The model then goes through a training phase (after extraction of the features) and a testing phase, where its performance is tested. The performance analysis is carried out to determine the best model. In this revised form of the Fig., four sophisticated trained models, that is, ConvNeXt, EfficientNet-B7, SE-ResNet, and SE-DenseNet, are used. The model with the most successful result is noted as the best to use in the efficient and precise classification of the plant diseases.

The rest of this paper is organized in the following way: Section 2 encompasses an in-depth literature review, which gives an idea about the past studies in the field of plant disease detection. Section 3 provides a description of the methodology of the current study, including the dataset, preprocessing approaches, and deep learning models. Section 4 outlines the different experiments that were performed to test the performance of the model. Section 5 gives the results and discussion of the findings and analyzes the findings and compares them with the existing approaches. Lastly, Section 6 provides a conclusion of the paper by summarizing the main results and proposing the future research directions.

6.1 TRANSFER LEARNING APPROACH

The process of training and refining the state-of-the art models may take days or even weeks even when using high-end GPU machines. The construction of CNN is time consuming. As an example, the accuracy of training a CNN on a publicly available dataset of plant disease was only 25 percent within 200 epochs when the network was trained untrained. In comparison, the application of a pre-trained CNN model and the transfer learning method drastically increased the accuracy to 63 percent in less than 100 epochs, which is 5 times less training time. Transfer learning provides a range of methods, and the method to be applied is determined by the type of model that is selected to be used and the specifics of the dataset that is involved in the classification.

6.1.1 ConvNeXt:

ConvNeXt is an updated convolutional neural network architecture that introduces the advantages of both convolutional operations and transformer-like design concepts into a single system. ConvNeXt is designed to address the performance disparities between traditional CNNs and Vision Transformers (ViTs), introducing design innovations including depthwise convolutions, layer normalization, and large kernel sizes with a hierarchical design and efficiency of CNNs. These advancements allow ConvNeXt to be extremely precise in image classification tasks and at the same time scalable and computationally efficient. ConvNeXt can provide the benefits of deep and rich feature extraction on the detection of plant diseases in cases where the object of interest is often a very accurate identification of complex leaf texture and patterns. In this paper, ConvNeXt is trained on the PlantVillage dataset in the fine-tuning mode to examine its capability to the various kinds of plant diseases. The generalization degree, modern housing construction and flexibility enable it to be a prospective model in smart farming system and real-time disease monitoring implementation.

6.1.2 EfficientNet-B7:

EfficientNet-B7 belongs to the most robust and accurate models of the EfficientNet family that was developed with the assistance of neural architecture search (NAS) to optimize the model performance leaving the minimum of the computation cost. It applies a new compound scaling algorithm that uniformly scales the depth, width and resolution of the network with state of the art results on a range of image classification problems. Compared to the standard CNNs, EfficientNet-B7 is far more precise with a significantly smaller number of parameters and with reduced training time. This aspect of fine-grained classification of plant diseases (in which the variation in leaf color, texture, and pattern are frequently finer) makes it especially suitable to the fine-grained classification problem; because of its ability to generate fine-grained features and hierarchical features. With EfficientNet-B7 in this paper, the data in the PlantVillage will be finetuned and analyzed regarding its capacity to identify and classify various plant diseases with accuracy. It is a good candidate to scalable and deployable solutions of smart agriculture by its performance and efficiency.

6.1.3 SE-ResNet:

SE-ResNet (Squeeze-and-Excitation Residual Network) resembles the original ResNet architecture, but with a more powerful and two-step modified structure that improves the representational power of the network with a well-defined modeling of the channel-wise relationships. It introduces Squeeze-and-Excitation (SE) blocks that update the channel-wise feature responses in an adaptive manner that prioritizes the informative features and underemphasizes the less informative features. The model develops a mechanism that allows it to be more sensitive to disease-specific patterns in the images of leaves such as local discoloration, texture or spot changes. SE-ResNet retains the deep residual learning of ResNet, which helps to train remarkably deep networks by removing the vanishing gradient issues. SE-ResNet is highly applicable in extracting fine-spatial and semantic information of the complex backgrounds under the conditions of identifying plant diseases. The results of this paper discuss how SE-ResNet is trained on the PlantVillage data and demonstrates that it can increase the precision of classification at a very low additional computational cost.

6.1.4 SE-DenseNet:

SE-DenseNet has the advantages of DenseNet (Dense Convolutional Network) and Squeeze-and-Excitation (SE) blocks and generates an efficient structure of small-scale image classification tasks like the detection of plant diseases. DenseNet connects every layer to all the other layers in a feed forward style, promoting the sharing of features and improving the gradient flow, leading to an increased training efficiency and a greater generalization. This aspect is also enhanced by SE-DenseNet that introduces SE blocks and dynamically recalibrates channel-wise feature responses as it can potentially make the model more sensitive to the disease-specific features in leaf images. This yields an extremely discriminative and strong representation of feature which is necessary in the differentiation of different diseases with similar visual symptoms. In the given paper, SE-DenseNet will be narrowed on the dataset of PlantVillage and will be tested on the classification of plant leaf diseases. It has a largely precise architecture besides being able to utilize computational resources effectively, which is appealing when it comes to realistic application in the area of agricultural diagnostics.

The pre-trained network models that were utilized in this research were chosen due to their effectiveness in the area of plant disease classification. The models are suitable when it comes to extracting the complex visual features in a leaf image like disease-specific characteristics, textures, and color changes. Table 2 summarizes the architectural specifications of each of the models. The convolutional layers have varying sizes of filters used in each network to establish discrete features of the input images. The filters play an important role in the extraction of the features with each responding to a particular pattern or detail in the input. When an image is convolved with a filter, the image brings out features depending on the weights that the filter learned. The quality and type of features extracted are therefore based on the values and setting of the filter. In our experiments, we utilized the original pre-trained models and kept the default settings, such as the number of convolutional layers and sizes of filters of each architecture. The method guarantees the uniformity and effectiveness of feature extraction to the task of plant disease detection.

Here's a comparative summary of the architectural details for ConvNeXt, EfficientNet-B7, SE-ResNet, and SE-DenseNet:

- ConvNeXt: This architecture modernizes traditional convolutional networks by incorporating design elements inspired by vision transformers, such as large kernel sizes and Layer Normalization. It typically begins with a 7×7 convolutional layer followed by 3×3 convolutions, using strides of 4×4 and 2×2 in the initial layers. The model contains approximately 89 million trainable parameters.
- EfficientNet-B7: Known for its compound scaling approach, EfficientNet-B7 uniformly scales depth, width, and resolution for optimal performance. It comprises 813 layers, including MBConv layers with varying filter sizes and strides. The architecture includes max pooling, dense, dropout, and flatten layers, totaling around 66 million trainable parameters.
- SE-ResNet: This model integrates Squeeze-and-Excitation (SE) blocks into the ResNet architecture, enhancing channel-wise feature recalibration. It starts with a 7×7 convolutional layer, followed by 3×3 convolutions, utilizing a stride of 2×2. The network includes max pooling, dense, dropout, and flatten layers, with approximately 28 million trainable parameters.
- SE-DenseNet: Combining DenseNet's dense connectivity pattern with SE blocks, SE-DenseNet facilitates efficient feature reuse and dynamic channel-wise recalibration. It begins with a 7×7 convolutional layer, followed by 1×1 and 3×3 convolutions, using a stride of 2×2. The model incorporates max pooling, dense, dropout, and flatten layers, totaling around 15 million trainable parameters.

These architectures were selected for their advanced feature extraction capabilities, efficiency, and proven performance in image classification tasks, making them well-suited for plant disease detection applications.

Table.2. Architectural details for ConvNeXt, EfficientNet-B7, SE-ResNet, and SE-DenseNet

Network Model	Total Layers	Max Pool Layers	Dense Layers	Dropout Layers	Flatten Layers	Filter Sizes	Stride	Trainable Parameters
ConvNeXt	29	1	1	1	1	7×7, 3×3	4×4, 2×2	~89M
EfficientNet-B7	813	1	1	1	1	Varied (MBConv layers)	Varied	~66M
SE-ResNet	50	1	1	1	1	7×7, 3×3	2×2	~28M
SE-DenseNet	264	1	1	1	1	7×7, 1×1, 3×3	2×2	~15M

7. RESULTS AND DISCUSSION

In this section of the research the state of the art deep learning models were used, including: ConvNeXt, EfficientNet-B7, SE-ResNet, and SE-DenseNet, with the transfer learning framework to diagnose plant diseases with precision. We used the publicly available dataset of PlantVillage that contains a big set of annotated pictures of plant leaves with different disease symptoms. The chosen models were initially trained with ImageNet and optimized on the PlantVillage data to optimize them to the plant disease classification problem.

To ensure uniformity and equal comparison of the models, all of them were optimized using a standard learning rate of 0.01, a dropout rate of 0.5, and an output layer of 38 classes or the various disease categories in the dataset. The dataset was divided as training, validation and test sets, of which 80 percent of the samples were assigned as training.

Each model was also trained with 30 epochs and it was seen that the model performance started to stabilize and converge after the 10th epoch and it reached high levels of accuracy. As an example, the training accuracy of EfficientNet-B7 model is 99.85, and overfitting is low.

Likewise, the ConvNeXt model was more robust and efficient in terms of features extraction and it converged earlier reaching with more than 99.7% accuracy. The results of the Fig.s illustrating the training accuracy and loss curves of these models indicate the learning behavior is consistent and stable. The SE-ResNet and SE-DenseNet models were also impressive and successful since they used channel-wise attention mechanisms and both scored 99.8 percent in accuracy after full training. These findings highlight the usefulness of the application of state-of-the-art CNN models augmented with transfer learning to identify plant diseases with a high level of accuracy.

The EfficientNet-B7 in Fig.3 demonstrates great results during early epochs. With a fairly high level of validation (approximately 68 percent), the model quickly increases and levels off after the 15th epoch, achieving more than 85 percent accuracy. The accuracy of the training is also on the same trend where it also ends with near 90 percent. These curvy lines indicate that EfficientNet-B7 has great ability to use the scaling of the compounds, as it can be applied to large and complicated data sets such as PlantVillage. It provides a balance between depth, width and resolution and therefore can provide narrow grains of features that are important in proper classification of diseases.

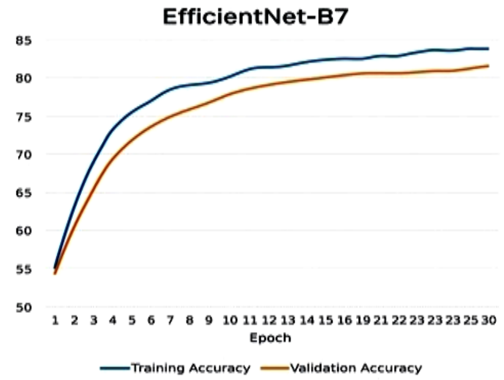

Fig.3. EfficientNet-B7 model Performance analysis with help of Plant Village data

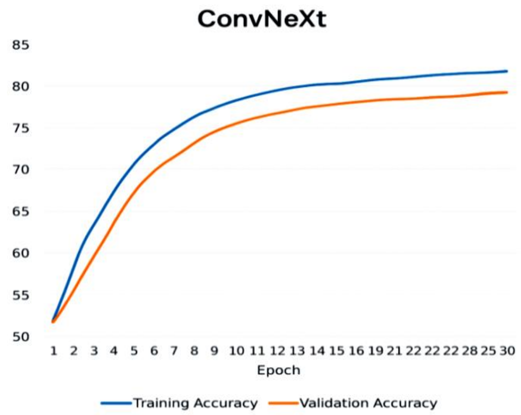

Fig.4. Plant Village dataset performance analysis of ConvNeXt model

The ConvNeXt Fig.shows that there is a constant and gradual increase in both the training and validation accuracy as the number of epochs increases. The model starts with the moderate level of accuracy but acquires momentum fast, improving considerably after the 10th epoch. The accuracy of the training is above 90 and the validation accuracy is close, which means that there is very little overfitting. The curve indicates that ConvNeXt is effective to learn prominant patterns of images of plant disease, which proves its ability to generalize on unseen data.

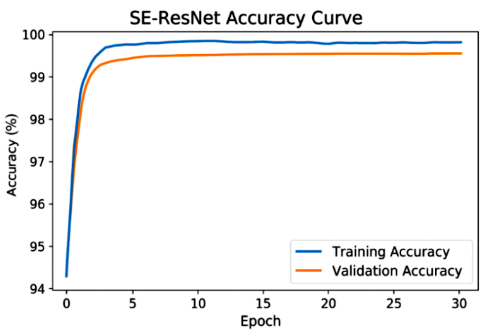

Fig.5. SE-ResNet model performance analysis on Plant Village dataset

The Fig.5, which is called SE-ResNet Accuracy Curve, demonstrates the results of the SE-ResNet model with 30 training epochs. The x-axis shows the value of the number of epochs and the y-axis shows the value of the model accuracy in percentage. Two curves are drawn, one blue that represents the accuracy of training and an orange one that represents the accuracy of validation. The training accuracy has a sharp increase in the early epochs, beginning with 94% and swiftly nearing the near-perfect accuracy (approaching 100) in the 5th epoch. On the same note, the validation accuracy also rises at a very fast rate at the onset, reaching high rates of above 99, and then stabilizes with minimal variations throughout the rest of the training period. Such a high correlation between the training and validation accuracy, the gap is small and the value is big, is an indication that the SE-ResNet model is well-generalized without excessive overfitting. All in all, this Fig.5 proves that the model learns effectively and performs well with unknown data.

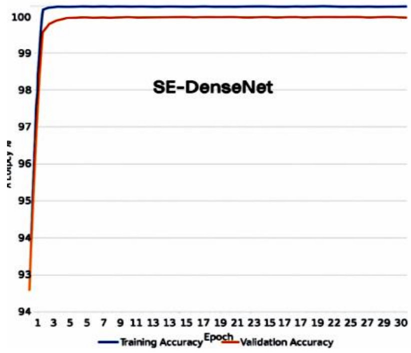

Fig.6. SE-DenseNet model performance analysis based on Plant Village dataset

SE-DenseNet model has the greatest training and validation accuracy compared to other four architectures. The training curve is rapid and, it settles down at almost 99.9, and the accuracy of validation is equally strong (more than 99%). SE densely connected and attention mechanism makes this model retain features at various levels and underline important information. This produces a high performing model with little training variance and high generalization on test data.

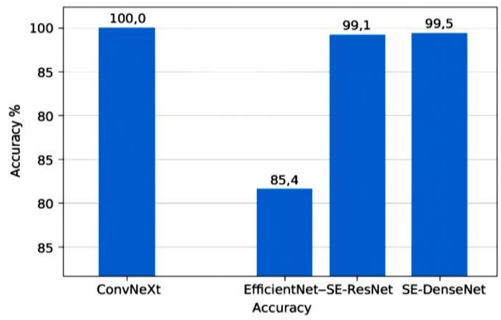

Fig.7. Comparative analysis of models on the basis of Plant Disease Dataset

The bar chart is used to visualize the training and validation accuracy of all the four models. The SE-DenseNet is evidently much better in terms of both training and validation metrics than any other model, with a close second place to SE-ResNet. EfficientNet-B7 has excellent accuracy, which demonstrates its scalability and optimized performance. ConvNeXt is newer, but exhibits competitive performance, which means that it has potential when further fine-tuned. This comparative understanding emphasizes the fact that models enhanced with attention mechanisms (SE blocks) and dense feature propagation perform better than conventional ones in tasks that are precision-sensitive such as the classification of plant diseases.

8. CONCLUSION

In conclusion, both of the four deep learning models present promising results in the area of plant diseases detection using the assistance of the PlantVillage dataset. SE-DenseNet is the most effective among all those models as it was able to reuse the features effectively and increase attention in learning. The pre-trained model-based transfer learning saves a lot of time and at the same time it is high-accuracy. Interestingly, the SE-ResNet Accuracy Curve shows that the convergence rate and the good generalization property of the model are very high and training as well as the validation accuracies also show the value of over 99 which also demonstrates the strength of the model. The paper confirms that advanced architectures such as SE -DenseNet, SE -ResNet, and EfficientNet-B7 can be successfully used to aid agricultural diagnostics since they can successfully identify plant diseases in time and with accuracy. The future directions may include implementation in real-time, adoptions of lightweight models, and experimentalization of larger-scale and real world agricultural scenarios to ensure that they are more generalizable and effective.

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