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Plant Disease Detection Using Deep Learning

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Abstract: Agricultural development is a critical strategy for promoting prosperity and addressing the challenge of feeding nearly 10 billion people by 2050. Plant diseases can significantly impact food production, reducing both quantity and diversity. Therefore, early detection of plant diseases through automatic detection methods based on deep learning can improve food production quality and reduce economic losses. While previous models have been implemented for a single type of plant to ensure high accuracy, they require high-quality images for proper classification and are not effective with low-resolution images. To address these limitations, this paper proposes the use of pre-trained model based on convolutional neural networks (CNN) for plant disease detection. The focus is on fine-tuning the hyperparameters of popular pre-trained model such as EfficientNetV2S, to achieve higher accuracy in detecting plant diseases in lower resolution images, crowded and misleading backgrounds, shadows on leaves, different textures, and changes in brightness. The study utilized the Plant Diseases Dataset, which includes infected and uninfected crop leaves comprising 38 classes. In pursuit of improving the adaptability and robustness of our neural networks, we intentionally exposed them to a deliberately noisy training dataset. This strategic move followed the modification of the Plant Diseases Dataset, tailored to better suit the demands of our training process. Our objective was to enhance the network's ability to generalize effectively and perform robustly in real-world scenarios. This approach represents a critical step in our study's overarching goal of advancing plant disease detection, especially in challenging conditions, and underscores the importance of dataset optimization in deep learning applications.

Index Terms: CNN, Deep Learning, EfficientNetV2S, Classification, Plant Diseases.

1. Introduction

Agriculture is the main source of prosperity for most of the countries and their economic growth. Therefore, plant diseases and infections spread in the plant affect the quantity and quality of the plant, which makes it a threat to food security [1]. These threats have increased more than ever before due to climate changes and global trade. And that preventive treatment will not be effective in some cases of diseases. Therefore, it is necessary to pay attention to protecting plants sustain food security. Therefore, the solution is the early follow-up and correct diagnosis of the diseased plant by using advanced and automatic plant follow-up systems to reduce the percentage of crop losses and increase the amount of production [2].

The paramount research objectives center on the development of advanced and precise AI-based solutions for the early detection and management of plant diseases, an endeavor with far-reaching implications for fostering agricultural development and upholding global food security. These objectives come to the forefront amidst the burgeoning advancements in computer science and computer vision, which have unveiled novel methods for diagnosing infected plants, simplifying disease classification, and refining treatment strategies. This concerted research effort is poised to harness the synergy between technological innovation and agricultural needs, ultimately paving the way for transformative solutions that have the potential to revolutionize the safeguarding of crops on a global scale.

Existing solutions in the field of plant disease detection encompass a multifaceted approach. They begin by introducing emerging solutions such as early follow-up and precise diagnosis of diseased plants through cutting-edge automatic plant monitoring systems. Concurrently, these solutions delve into the potential of fine-tuning pre-trained models, specifically leveraging the power of pre-trained models, to enhance the accuracy of convolutional neural network (CNN)-based models in detecting plant diseases across diverse and challenging environments [3]. The utilization of general datasets during training. This pursuit of advanced and precise AI-driven solutions holds pivotal significance in propelling agricultural progress and ensuring global food security. Further contextualizing these advancements, the paragraph references the historical application of deep learning models, particularly CNNs, in plant disease detection, with a nod to prior research employing pre-trained CNNs. Challenges, such as dataset limitations, are acknowledged, and various studies are cited, encompassing transfer learning, generative networks, and data augmentation strategies to enhance disease detection accuracy [4]. Additionally, a noteworthy research endeavor examining families of detectors is highlighted, collectively offering a comprehensive overview of the existing landscape in the realm of plant disease detection.

The identification of the best solution in this study centers on the utilization of EfficientNetV2S, a pre-trained model, which emerges as a promising candidate to address the limitations encountered by previous models and attain heightened accuracy in the detection of plant diseases. Within this investigation, a suite of models was deployed for comparative analysis of classification accuracy while striving for optimal time complexity. These models were trained with a strategy involving layer freezing, thereby preserving the model's original parameters while fine-tuning them to extract essential features and allocate them to their respective categories [5]. Implemented on the Plant Disease Detection Dataset, low-resolution images were employed to bolster the model's resilience against natural environmental conditions. Remarkably, the study achieved exceptional accuracy and reduced loss in simulated real-world conditions through hyperparameter tuning of a pre-trained model, such as EfficientNet, renowned for its use of Depthwise Separable Convolution, rendering it suitable for embedded projects requiring a lightweight model. Focused on image classification tasks necessitating dimension scaling, the model underwent training and testing on an RGB dataset comprising healthy and unhealthy plants, encompassing 38 disease categories across 14 distinct plant species, with each class consistently featuring both healthy and infected specimens [6]. Notably, the model's initial pre-training on the diverse ImageNet dataset expedited the acquisition of common features, such as edges and lines, facilitating efficient learning across datasets, and was complemented by a classification head trained specifically on the plant disease dataset, thereby enabling accurate disease classification.

The main limitation encountered in this context is the inherent challenge of effectively classifying diverse plant diseases, primarily stemming from constraints imposed by limited dataset resources, thus accentuating the imperative for innovative methodologies to transform these datasets into realistic simulations of natural environmental conditions [7]. The pursuit of an accurate model capable of classifying multiple plant diseases within a unified network framework constitutes a pivotal stride towards enhancing food production quality and mitigating economic losses. Paramount to this endeavor is the model's ability to achieve exceptional accuracy under simulated natural environmental conditions while minimizing losses when processing inherently noisy images. Moreover, the imperative lies in reducing computational training time and addressing the issue of overfitting to render the model practically deployable. To attain these objectives, the utilization of pre-trained models grounded in convolutional neural networks (CNNs), coupled with meticulous hyperparameter fine-tuning, becomes essential to elevate disease detection accuracy amidst lower-resolution images, complex backgrounds, shadow-veiled leaves, varied textures, and dynamic brightness fluctuations. Ultimately, the development of such a model assumes a pivotal role in early disease detection and management, thereby making significant strides towards advancing agricultural development and addressing the pressing challenge of sustaining the burgeoning global population.

this study seeks to create a model that not only achieves high accuracy in a simulated natural environment but also addresses lower resolution images, crowded backgrounds, shadows on leaves, diverse textures, and variations in brightness. Additionally, the aim is to reduce computation time for training and overcome the problem of overfitting.

The results of an experiment evaluating the performance of the EfficientnetV2S model in handling the limitations of noisy datasets for image-based plant disease identification. The EfficientnetV2S model achieved a validation accuracy of 95.01% on the noisy dataset. The result demonstrates the effectiveness of the model in dealing with image-based plant disease identification tasks that involve noisy images, highlighting their robustness and potential for real-world applications.

The following is a summary of this paper's significant contributions:

Providing an accurate model for classifying multiple plant disease through the same network.

Getting a well-trained model that achieves a high accuracy on a simulated natural environment condition, and lower loss on noisy images.

Reduce the computation time for the training process and solving the problem of overfitting.

The rest of the paper is arranged as follows. Section 2 illustrates the related work. Presented model is applied in Section 3. Experimental in Section 4. The results and discussion are discussed in Section 5. Section 6 presents the main conclusions of this study, and the future work.

2. Related Works

Ignoring early indicators of plant diseases in the agricultural field may lead to losses in food crops and eventually lead to the collapse of the global economy [8]. This section provides a previous work in the field of plant disease detection.

Jadhav et al. proposed a model for a plant disease using CNNs [9]. In this paper, AlexNet and GoogleNet pre-trained convolutional neural networks were used to present an effective soybean disease identification technique based on transfer learning strategies. But the model slipped in Classification diversity. Many current models focus on defining a single class of plants disease instead of building a model to classify different plant diseases. This is basically due to reduction of dataset resources to train deep learning (DL) models with diverse plant species.

Table 1. Summary of CNN models that detect the plant disease

Reference	Crop Focus	Dataset	Classes	Model	Limitations	Results
[9]	Soybean leaves	Self-generated database	3	AlexNet and GoogleNet CNNs	The model slipped in Classification diversity. Many current models focus on defining a single class of plants disease instead of building a model to classify different plant diseases.	98.75% and 96.25%
[10]	Tomato	Conditional Generative Adversarial Network for generation	10	DenseNet121 model	Reliance on synthetic data may hinder model's real-world performance.	97.11%
[11]	Several	PlantVillage	38	MobileNet V3	Limited assessment of deep learning models' real-world performance on edge devices.	96.58%
[12-15]	Tomato	the Plant village and Taiwan tomato leaves,	13	CNN model	Benchmark studies lacked realism, affecting model performance in practical scenarios.	95.98%
[16]	Several	PlantVillage	39	VGG16	Solely emphasizes tomato crop disease identification, limiting broader applicability.	94.9%
[17]	Tomato plant	Self-generated database	9	Faster Region based CNN and Region based Fully Convolutional Network	Limited realism hampers model's efficacy in real-time disease recognition.	85.98%
[18]	Apple	AI-Challenger plant disease recognition	6	DenseNet-121	Insufficient exploration of apple leaf disease recognition challenges and solutions.	93.71%
[19]	Several	Public database	7	Pre-trained models	Limited analysis of deep transfer learning for plant disease identification.	91.83%
[20]	Rice	Self-generated database	4	Pre-trained CNN with SVM classifier	Focused on color features, potentially overlooking other relevant disease indicators.	94.65%

Abbas et al. [10], suggested a DL-based technique for detecting tomato diseases that creates artificial pictures of tomato plant leaves using the Conditional Generative Adversarial Network (C-GAN). then use transfer learning models to detect the disease. The development of generative networks has made previously costly, time-consuming, and Real-time data collecting or painstaking data acquisition is now feasible. Anh et al. [11], in their study, proposed the most widely used models for multi-leaf disease detection in order to determine which model is most suited for practical use. Astani et al [12], a multi-class ensemble classifier for diagnosing tomato disease. Taiwan Tomato Leaves and PlantVillage were the two datasets used to evaluate the performance of the best ensemble classifier. Based on background clutter, many leaves from the same plant, brightness fluctuations, and shadow conditions, the top ensemble classifier was able to distinguish between various illnesses. Pradeep et al. [13] presented the EfficientNet model for multi-label and multi-class classification using a convolutional neural network. The detection of diseases was improved by the CNN's hidden layer network. Yet, when tested with benchmark datasets, the model fared poorly. Enkvetchakul and Surinta [14] CNN network with a transfer learning strategy was suggested. Plant disease detection utilized two pre-trained network models: NASMobileNet and MobileNetV2. Among these, the NASMobileNet technique exhibited the highest precision in prediction results. To counter overfitting in deep learning, the data augmentation technique was applied. Our experimental setup incorporated cut-out, rotation, zoom, shift, brightness adjustments, and mix-up to effectively implement the data augmentation approach. The two types of datasets used were iCassava 2019 and datasets related to leaf disease. The examination resulted in a maximum test accuracy of 84.51%. Trivedi, et al. [15] There have been several uses of identification and classification techniques for some illnesses. To properly describe and categories tomato infections, the Convolutional Neural Network (CNN) is utilized. Agarwal et al. [16] This study condensed on CNN model with 8 hidden layers is suggested. The suggested low weight model performs better than the conventional machine learning algorithms using the publicly accessible dataset PlantVillage. Fuentes et al. [17] consider three main families of detectors: Faster Region-based Convolutional Neural Network (Faster R-CNN), Single Shot Multibox Detector (SSD), and Region-based Fully Convolutional Network (R-FCN).

The limitations that appear in most of paper that it can achieve high accuracy for only one type of plant disease and not for multiple types. Additionally, the model may not be effective when used with noisy data that represents the real environment. This is because previous models were trained on high-quality images for proper classification, making them less effective with low-resolution images or those with crowded and misleading backgrounds, shadows on leaves, different textures, and changes in brightness. Therefore, it is crucial to fine-tune the hyperparameters of pre-trained models such as EfficientNetV2S to achieve higher accuracy in detecting plant diseases in lower resolution images and noisy data.

3. Proposed

CNN models are the best for understanding, recognizing, and classifying images. Despite its ability to classify, there are obstacles faced by CNN in the process of learning on large dataset in terms of time complexity. This time-consuming process may involve traversing through various image features, even the smallest ones, leading to increased complexity. To overcome this challenge encountered by CNNs, the approach of utilizing pre-trained networks is employed. These networks leverage parameters learned from comprehensive datasets to address diverse problem scenarios effectively. In Fig. 1, the workflow of utilizing the pre-trained model the initial phase involves inputting a diverse and comprehensive dataset, such as ImageNet, which forms the foundation of the model's knowledge base. Subsequently, the pre-trained model is integrated, serving as a feature extractor with a profound understanding of generic visual patterns. Fine-tuning then takes place, adapting the model to the nuances of a specific dataset, tailored to the task at hand, such as plant disease recognition.

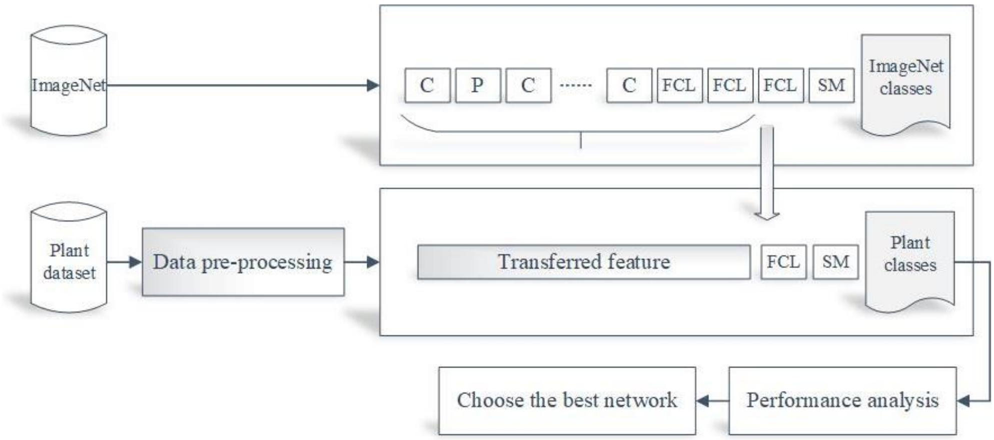


Fig.1. Illustration of the presented workflow diagram

3.1. Data Collection and Multi-class Classification

In the realm of agriculture and plant pathology, the accurate identification and classification of plant diseases are of paramount importance. To achieve this, we need a robust methodology for collecting and pre-processing data for plant disease detection models. in this section we will outline a systematic approach for data collection and pre-processing for a plant disease dataset, using corn as an example. Additionally, we will discuss the concept of multi-class categorization within this context.

The plant disease dataset consists of a collection of images of corn plants, categorized into two main groups: healthy and unhealthy. The unhealthy group encompasses various types of diseases that affect corn plants. Each image is accurately labeled with its respective category, making it a valuable resource for training and testing machine learning models.

Corn Disease Categories: For our specific example with corn plants, we have four distinct disease categories: Cercospora Leaf Spot, Northern Leaf Blight, Common Rust and Healthy. These categories represent the various conditions that corn plants can exhibit. The classification of an image into one of these categories will depend on the features and characteristics extracted from the images during the training phase.

For data collecting Firstly, we use a diverse set of images of corn plants, with a strong emphasis on capturing both healthy and diseased samples. This diversity ensures that the model encounters various disease symptoms and stages, enhancing its generalization capabilities. Secondly, to facilitate model training, we meticulously annotate each image with its corresponding disease category. Accurate labeling is pivotal to enable the model to differentiate between healthy and diseased plants and to distinguish among different disease types effectively. To further enrich the dataset and enhance the model's ability to generalize, we employ data augmentation techniques. These techniques, such as rotation, flipping, and scaling, introduce variations into the images, thereby preventing overfitting and bolstering the model's adaptability to real-world data. Lastly, we divide the dataset into training, validation, and testing subsets.

In the context of plant disease classification, multi-class categorization is essential due to the presence of multiple disease types within each class. Specifically, if there are N classes of plants (e.g., corn), and each class can exhibit M different disease categories, then each of the N classes is treated as a distinct class in the multi-class classification problem.

In summary, the methodology for data collection and pre-processing for plant disease detection involves obtaining a diverse dataset, accurately labeling it, augmenting the data, splitting it for training and testing, and applying pre-processing techniques. Furthermore, it's crucial to understand the concept of multi-class categorization, especially when dealing with plants that can exhibit multiple disease types within each category. This comprehensive approach lays the foundation for training accurate and reliable plant disease detection models.

3.2. Noisy Dataset Handling

Noisy datasets can negatively affect the performance of CNN models. In order to handle noisy datasets, there are a few techniques that used. CNN models are robust to noisy datasets and can handle them well by learning features that are invariant to noise. The first used approach is to use data augmentation techniques that artificially create noisy images during training, such as adding random noise or applying random transformations. This helps the model to learn features that are robust to different types of noise. The second approach is to use regularization techniques such as dropout, which randomly drops out units in the network during training to prevent overfitting and increase robustness to noise. Additionally, use techniques such as batch normalization, which normalizes the inputs to each layer, making the model more robust to different levels of noise and reducing the effect of outliers. Overall, by using a combination of these techniques, models can effectively handle noisy datasets without removing the noise, leading to more robust and accurate predictions.

3.3. Network Architecture Model

A. Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) represent a transformative innovation in the realm of artificial intelligence and computer vision. At their core, CNNs are specialized deep learning architectures meticulously crafted to tackle complex visual recognition tasks, making them exceptionally adept at processing images and extracting meaningful features. Unlike traditional neural networks, CNNs are designed to mimic the human visual system's ability to discern patterns and hierarchies within visual data. Their key innovation lies in the application of convolutional layers, which convolve filters over input images, enabling automatic feature extraction at different scales and levels of abstraction. This hierarchical feature extraction, combined with pooling layers that reduce spatial dimensions, creates an intricate pipeline for progressively learning and recognizing intricate patterns, textures, and structures. CNNs have found applications in diverse domains, from image classification and object detection to medical image analysis and, notably, in our context, plant disease detection. Their foundational principles underpin various advanced neural architectures, making them pivotal in shaping the landscape of modern artificial intelligence.

B. Pre-trained Model: EfficientNetV2S

To select the pre-trained network models for classifying plant diseases, we evaluated their performance in this task. A crucial aspect of feature extraction is the size of filters utilized by each network to extract features from the feature maps. Each filter convolves with the input and extracts a unique set of features, and the features extracted from the feature maps are dependent on the filter values. We tested each pre-trained network model, incorporating actual combinations of convolution layers and filter sizes.

EfficientNetV2 is a novel family of convolutional networks that outperforms earlier models in terms of training speed and parameter efficiency by using scaling and training-aware neural architecture search. The EfficientNetV2 models are searched in a space that includes new operations like Fused-MBConv. These models train up to 6.8 times faster than cutting-edge models while being smaller. The model performance can be improved by progressively increasing the image size during training, but it frequently reduces accuracy. A better approach of progressive learning is suggested to adaptively modify regularization together with image size to make up for this accuracy drop. The EfficientNetV2 model performs significantly better on the ImageNet and CIFAR/Cars/Flowers datasets than earlier models that used progressive learning [21].

The model layers of the EfficientNetV2S architecture consist of a convolutional neural network with multiple layers that perform feature extraction and classification. The include_top parameter is set to False to exclude the final classification layer, and the pooling parameter is set to avg to use global average pooling to summarize the feature maps. The Dense layer is then added on top of the extracted features with 512 units and a ReLU activation function. Finally, another Dense layer is added with 38 units and a softmax activation function to predict the 38 classes. The code sets all layers of the pre-trained model to be non-trainable and creates a new model that takes the input of the EfficientNetV2S model and produces the final output. This new model can be trained on a new dataset specific to a particular task.

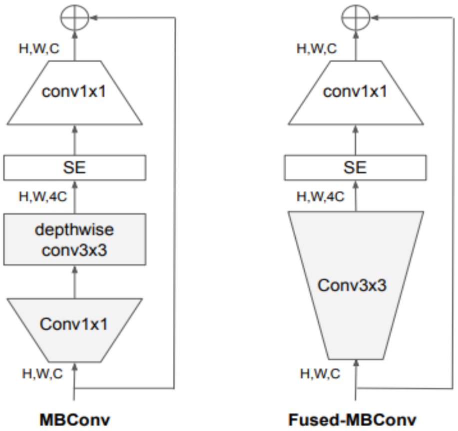


Fig.2. Structure of MBConv and Fused-MBConv [21]

Table 2. EfficientNetV2-S architecture [21]

Stage	Operator	Stride	Channels	Layers
0	Conv (3x3)	2	24	1
1	Fused-MBConv1, k (3x3)	1	24	2
2	Fused-MBConv4, k (3x3)	2	48	4
3	Fused-MBConv4, k (3x3)	2	64	4
4	MBConv4, k (3x3), SE0.25	2	128	6
5	MBConv6, k (3x3), SE0.25	1	160	9
6	MBConv6, k (3x3), SE0.25	2	256	15
7	Conv (1x1) & Pooling & FC	-	1280	1

4. Experimental

In this study, we assessed both training and testing accuracy, as well as computed model losses during these periods. The plant dataset was employed to train the model, with the intention of leveraging pre-trained models to expedite the learning process. For our investigation, we selected the EfficientNet as the pre-trained model. These models had previously undergone training using the ImageNet dataset, which comprises 1.2 million images across 1000 distinct categories.

4.1. Dataset

The new plant disease detection dataset contains many kinds of plant diseases and is openly accessible. The dataset boasts 87,000 photos, categorized into 38 different classes. To facilitate our experimental study, we divided the dataset into training, testing, and validation sets. While 20% of the dataset was used for validation and testing, the remaining 80% was allocated for training pre-existing models. The dataset comprises 87,000 samples for plant classes, of which 40 samples were used for testing, 17,572 samples for validation, and 70,295 samples for training. All 38 types of plant diseases are included and represented evenly across these sets.

4.2. Preprocessing

There is no noisy dataset so that the noise should be added manually to simulate the real world, but Adding noise to dataset it causes a problem to DL model.

- Noise can reduce the accuracy of neural networks.
- Noise led to lower generalizability while testing on real-world data.

By introducing a form of random noise to the original dataset, the neural network benefits from improved noise robustness and enhanced generalization capabilities. This technique involves incorporating random variations into the input data, effectively aiding the neural network in achieving better generalization. Moreover, this process serves to bolster the network's resilience when faced with challenging images during real-world testing, ultimately contributing to a more robust performance.

The best noise that can add to dataset it gaussian noise to represent the reality in dataset. the reason for this choice is:

The fact that the distribution itself exhibits good behaviour is a first benefit of gaussian noise. The normal distribution is so named because it has practical qualities and is so often employed in the scientific and social sciences. It is frequently employed to simulate random variables whose true distribution is uncertain. A normal distribution is what you get when you add together plenty of independent random variables. And these are only some of the numerous characteristics of this fundamental distribution. Gaussian noise is therefore previously known to most data analysts and scientists. It's handy when you disclose anonymized statistics: analysts don't need to learn too many new concepts to grasp what you're doing to secure the data.

The Gaussian distribution has attractive, thin tails, which is a second benefit. Its mean is the center of gravity for the vast bulk of its probability mass. Consider a normal distribution that has a mean of zero and a standard deviation of. A random variable taken from this distribution will, according to the 68-95-99.7 rule, be in $[-\sigma,\sigma]$ with 68% probability, $[-2\sigma,2\sigma]$ with 95% probability, and $[-3\sigma,3\sigma]$ with 99.7% probability [22].

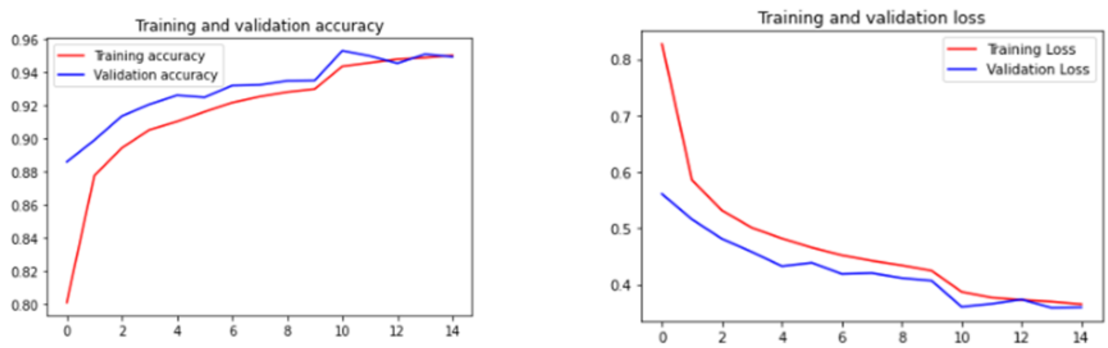
The thermal oscillation of atoms and discontinuous nature of heated object radiation are two natural factors that contribute to the Gaussian noise, also known as normal noise. values in digital photographs are typically disturbed by gaussian noise. For this reason, the PDF (Probability Density Function) or normalized histogram regarding value is the primary design and characteristic of the Gaussian noise model [23]. Adding the noise to 50% of the dataset with random distribution to create low-resolution photos, crowded, hazy backgrounds, paper shadows, various textures, and brightness adjustments.

4.3. Implementation of EfficientnetV2S Model

In this study, techniques for classifying plant diseases using CNN models based on a pre-trained architecture were explored. The models were initially pre-trained on the ImageNet dataset. Different parameters were applied to the Efficientnet model, and the output class count remained constant. Additionally, an approach involving training only the added layers was implemented, cancelling the weights and enabling the model's convolutional layers to become trainable. This allowed the model to learn from the specific dataset pertaining to the problem, leveraging the information contained within its hidden layers.

When using a modified dataset to detect diseases of the new plant and adding noise during training to match reality, because a pure picture like this cannot be obtained in reality. These images were separated into groups representing 80% used for training and use 20% for validation to train a pre-trained Efficientnet model that ran for 20 epochs with different learning rate for each 10 epochs that start with 0.001 learning rate.

In the experiment, to evaluated the performance of the efficientnetv2 model using a modified dataset and enhance its performance, we added some layers and trained the model on 80% of the modified dataset, while 20% was used for testing and validation. Fig. 3a, indicates that the efficientnetv2 model achieved a validation accuracy of 95.01% and a training accuracy of 95.08% on the noisy dataset. As shown in Fig. 3b, the loss of the training and validation models was found to be 0.362% and 0.36%, respectively



(a) (b)

Fig.3. (a)Training and validation accuracy of Efficientnet model – (b) training and validation loss of Efficientnet model.

Early detection of crop diseases is crucial for ensuring high agricultural yields. Leveraging advanced technology can aid in the timely identification of plant diseases, leading to the maintenance of optimal agricultural output. In this research study, deep learning (DL) models were employed to replace traditional image classification techniques, which often necessitate large datasets and intricate training processes. The pre-trained EfficientNet model was evaluated for its effectiveness in categorizing various plant diseases. Performance assessment employed specificity, sensitivity, and F1-score values for the pre-trained model. Validation accuracy was calculated using precision, F1-score, and recall. The validation accuracy of the pre-trained EfficientNet model, demonstrating its superior performance. Generally, a model's performance improves as it approaches a value of 1, with precision, recall, and F1-score values ranging between 0 and 1. The experiment yielded a validation accuracy of 0.9501 for EfficientNet.

The confusion matrix is a tabular representation that shows the counts of true positive, false positive, true negative, and false negative predictions made by the model. These values represent different scenarios of correctly and incorrectly classified samples. To gain a comprehensive understanding of the model's performance, various statistical measures are calculated using the confusion matrix.

The following performance metrics are commonly used:

Accuracy: It measures the overall correctness of the model's predictions. It is calculated as

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

Recall (Sensitivity or True Positive Rate): It measures the ability of the model to correctly identify positive samples (infected plants). It is calculated as

$$Sensitivity\ or\ Recall = \frac{TP}{TP + FN} \tag{2}$$

Precision: It measures the proportion of correctly classified positive samples out of all samples predicted as positive. It is calculated as

$$Precision = \frac{TP}{TP + FP} \tag{3}$$

F1-score: It is the harmonic mean of precision and recall, providing a balanced measure of the model's performance. It is calculated as

$$F1\_Score = \frac{2*(Precision*Recall)}{Precision + Recall} \tag{4}$$

The results are summarized in Table 3., which show the performance of EfficientNet model for different plant diseases. It is noteworthy that the transferred parameters from the EfficientNet architecture achieved the accuracy, recall and F1-score of 0.95, 0.95 and 0.95, respectively.

The performance evaluation of the EfficientNetV2 model as it shows in Fig. 4, its remarkable capability in plant disease classification. With consistently high precision, recall, and F1-score values across various disease categories, the model demonstrates exceptional accuracy and reliability. The precision values, hovering around the mid-to-high 90s, indicate the model's proficiency in correctly classifying positive cases while minimizing false positives. Likewise, recall values in the same range signify the model's effectiveness in capturing most of the true positive instances. The harmonious balance between precision and recall is reflected in the F1-scores, consistently achieving values in the high 90s. This suggests that the EfficientNetV2 model is not only accurate but also robust in distinguishing between healthy and diseased plants, even in the presence of noise or variations in the dataset. Overall, these results underscore the model's suitability for the critical task of plant disease detection, offering a promising solution for enhancing agricultural practices and crop management.

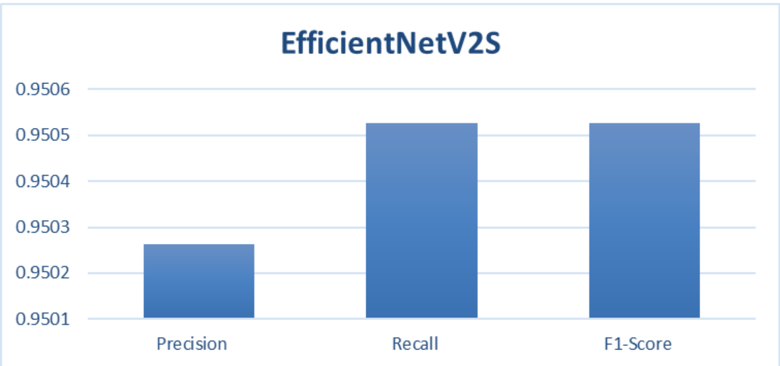


Fig.4. Evaluation metrics F1-Score, recall and precision

Table 3. The classification accuracy of EffifientNet-V2 CNN

Class name	precision	recall	f1-score	support
'Apple _ scab'	0.95	0.95	0.95	983
'Apple _ Black _ rot'	0.97	0.96	0.97	969
'Apple _ Cedar _ apple _ rust'	0.96	0.95	0.96	837
'Apple _ healthy'	0.94	0.96	0.95	1022
'Blueberry _ healthy'	0.97	0.97	0.97	910
'Cherry_ (including _ sour _ Powdery _ mildew'	0.97	0.97	0.97	803
'Cherry_ (including _ sour) _healthy'	0.98	0.99	0.99	913
'Corn_ Cercospora _ leaf _ spot Gray _ leaf _ spot'	0.98	0.96	0.97	861
'Corn_(maize) _ Common _ rust_'	1.00	1.00	1.00	938
'Corn_(maize)_Northern _ Leaf _ Blight'	0.97	0.98	0.99	975
'Corn_(maize) _ healthy'	0.99	0.99	0.99	944
'Grape _ Black _ rot'	0.93	0.95	0.94	935
'Grape _ Esca_ (Black _ Measles)'	0.96	0.96	0.96	946
'Grape _ Leaf _ blight _(Isariopsis _ Leaf _Spot) '	0.98	0.97	0.97	854
'Grape_ healthy'	0.99	0.99	0.99	843
'Orange _ Haunglongbing _ (Citrus _greening)'	0.98	0.98	0.98	1008
'Peach _ Bacterial _ spot'	0.97	0.97	0.97	916
'Peach _ healthy'	0.98	0.99	0.99	836
'Pepper _ bell _Bacterial _spot'	0.97	0.96	0.96	979
'Pepper _bell _healthy'	0.96	0.95	0.96	1007
'Potato _ Early _blight'	0.97	0.99	0.98	1006
'Potato _Late _blight'	0.94	0.94	0.94	931
'Potato _healthy'	0.96	0.97	0.96	901
'Raspberry _healthy'	0.96	0.97	0.97	867
'Soybean _healthy'	0.98	0.97	0.97	1027
'Squash _Powdery _mildew'	0.97	0.98	0.98	908
'Strawberry _Leaf _scorch'	0.98	0.98	0.98	858
'Strawberry _healthy'	0.96	0.98	0.97	917
'Tomato _Bacterial _spot'	0.93	0.94	0.93	855
'Tomato _ Early _blight'	0.93	0.89	0.91	950
'Tomato _Late _ blight'	0.95	0.93	0.94	921
'Tomato _ Leaf _ Mold'	0.94	0.96	0.95	943
'Tomato _ Septoria _ leaf _spot'	0.92	0.90	0.91	915
'Tomato _Spider _mites Two-spotted _ spider _mite'	0.91	0.91	0.91	905
'Tomato _ Target _Spot'	0.89	0.90	0.90	936
'Tomato _Yellow _Leaf _Curl _Virus'	0.97	0.96	0.96	1014
'Tomato _mosaic _virus'	0.96	0.97	0.96	913
'Tomato _healthy'	0.97	0.96	0.97	954

The results of our experiment demonstrated the effectiveness of the EfficientNet model in handling the limitations posed by noisy datasets. Despite the presence of noise in the dataset, our model was able to achieve a high validation accuracy of 95% and a loss of 0.36%. This highlights the robustness of the model in dealing with image-based plant disease identification tasks that involve noisy images. Furthermore, we compared our results with those of two previous studies. When comparing the results of previous studies, it becomes evident that different approaches have been employed to tackle specific agricultural classification tasks. For instance, in [18], a DenseNet-121 model achieved an accuracy of 93.71% in identifying only apple plants. In [19], multiple plant species were considered, and pre-trained models achieved a combined accuracy of 91.83%. However, this approach experienced a decrease in accuracy by 5.17% due to the inclusion of diverse plant categories. Another study [20] focused solely on rice crops and utilized a pre-trained CNN with an SVM classifier, reaching an accuracy of 94.65%. In comparison, our proposed model, employing EfficientNetV2S, surpasses these achievements with an impressive accuracy of 95.01%. These findings underscore the potency of our approach in enhancing the precision of plant classification tasks.

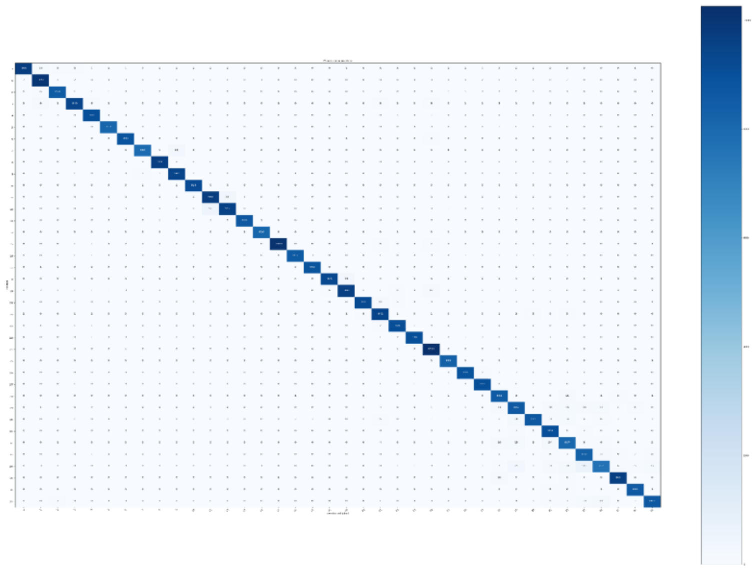


Fig.5. A Confusion Matrix of EfficientNet model validation accuracy

In the case of the EfficientNet model used in the previous result, the confusion matrix was shown the number of true positives, true negatives, false positives, and false negatives for each class in the dataset. This given a more detailed view of the performance of the model, beyond just the overall accuracy as shown in Fig. 5. the matrix was shown that the model performs well in predicting certain classes but struggles with others because the noise affects in a spot of the paper. Additionally, the confusion matrix used to calculate additional metrics, such as precision, recall, and F1-score, which provide further insights into the performance of the model as it happens in the experimental section. Overall, the confusion matrix is a useful tool for evaluating the effectiveness of a classification model and can help identify areas for improvement.

5. Results and Discussion

The results obtained from our experiment underscore the efficiency of the EfficientNet model in addressing the challenges associated with noisy datasets. Despite the presence of significant noise within our dataset, our model exhibited exceptional performance, achieving a validation accuracy of 95% and a minimal loss of 0.36%. This noteworthy outcome underscores the model's robustness in the context of image-based plant disease identification tasks, particularly when confronted with noisy image inputs.

The evaluation of the EfficientNetV2 model's performance reveals its exceptional capabilities in plant disease classification. Across various disease categories, the model consistently demonstrates high precision, recall, and F1-score values, signifying remarkable accuracy and reliability. Precision values consistently in the mid-to-high 90s indicate the model's proficiency in correctly identifying positive cases while minimizing false positives. Similarly, recall values within the same range highlight the model's effectiveness in capturing most true positive instances. The harmonious balance between precision and recall, reflected in consistently high F1-scores in the high 90s, underscores the model's accuracy and robustness in distinguishing between healthy and diseased plants, even in the presence of dataset noise or variations. In summary, these results underscore the model's suitability for the critical task of plant disease detection, offering a promising solution to enhance agricultural practices and crop management.

To gain a comprehensive perspective, we compared our results with those from prior studies as in the Table 4., in terms of the crop focus, dataset, and models used. While some papers focused on a single crop such as tomato or rice, our experiment covered several crops. Additionally, we used a modified dataset with 38 classes, which is larger than some other studies that used datasets with fewer classes. And the datasets modified by add noise to simulate the real environment not to improve the resolution of the images. Our experiment also utilized EfficientNetV2S model, while other studies used different models such as DenseNet121, VGG16, and pre-trained CNNs with SVM classifiers. In terms of results, our EfficientNetV2 model achieved 95.01% accuracy, which is competitive with or better than the results reported in other studies. For example, our experiment also differed in the sense that we considered multiple crops and used a modified dataset with more classes. And some of the other studies achieved lower accuracy rates than our experiment, such as the studies on Apple disease recognition and rice disease detection, which reported 93.71% and 94.65% accuracy, respectively [20,23]. Overall, our experiment provides a more comprehensive and effective solution for multi-crop disease detection using deep learning models.

Table 4. Comparison between our experiment and another papers

Reference	Crop Focus	Classes	Model	Results	Differences
our Experiment	Several	38	EfficientNetV2	95.01%	-
[10]	Tomato	10	DenseNet121 model	97.11%	Only use the single plant tomato diseases and that the same dataset for train and test
[11]	Several	38	MobileNet V3	96.58%	Datasets used not fully capture the range of variations and disease manifestations seen in real-world scenarios, potentially leading to biased or incomplete training.
[17]	Tomato plant	9	Faster Region based CNN and Region based Fully Convolutional Network	85.98%	Limited realism hampers model's efficacy in real-time disease recognition.
[12-15]	Tomato	13	CNN model	95.98%	Use only tomato crop and This limitation has the potential to introduce biases or result in incomplete training.
[16]	Several	39	VGG16	94.9%	Models not perform well on new datasets due to their reliance on specific datasets for training and testing.
[18]	Apple	6	DenseNet-121	93.71%	Using only apple crop not multi plant diseases detection
[19]	Several	7	Pre-trained models	91.83%	Limited analysis of deep transfer learning for plant disease identification.
[20]	Rice	4	Pre-trained CNN with SVM classifier	94.65%	Using only Rice crop not multi plant diseases detection and focused on color features, potentially overlooking other relevant disease indicators

6. Conclusions

Our research makes significant strides in advancing the current state of knowledge in the field of plant disease detection using deep learning models. We have systematically evaluated various convolutional neural network architectures, with a particular focus on the efficientnet model, to classify a diverse range of 38 plant diseases. The outcomes of our study demonstrate the superior performance of efficientnet in terms of classification accuracy, sensitivity, and the F1 score, highlighting its potential to revolutionize the domain of agricultural disease management.

From a scientific perspective, our work offers valuable insights into the efficacy of deep learning models for robust and accurate plant disease identification, even in the presence of noisy and varied datasets. The utilization of efficientnet, with its streamlined parameter count and reduced computational complexity, represents a novel and efficient approach to tackle the challenges associated with plant disease detection.

Looking forward, the implications of our findings extend to various practical applications, such as precision agriculture and crop management. The development of a multi-object deep learning model for plant disease detection, as part of our future work, promises to further enhance the field's capabilities, enabling the identification of diseases across clusters of leaves rather than isolated instances. This innovative approach has the potential to improve disease monitoring in agricultural settings and contribute to more sustainable and resilient crop production. our research not only elevates the current understanding of plant disease detection but also provides a scientifically justified framework for the adoption of efficientnet-based models in agricultural practices. The work serves as a stepping stone for future endeavors in the field, offering the promise of enhanced disease management and crop protection.

In our future research endeavors, we intend to address challenges related to real-time data collection and further advance our efforts by developing a multi-object deep learning model capable of detecting plant diseases from a cluster of leaves rather than focusing solely on individual leaves.

References

[1] Prodeep, A.R.; Hoque, A.M.; Kabir, M.M.; Rahman, M.S.; Mridha, M.F. Plant Disease Identification from Leaf Images using Deep CNN’s EfficientNet. In Proceedings of the 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand, 23–25 March 2022; pp. 523–527.

[2] Li, L.; Zhang, S.; Wang, B. Plant Disease Detection and Classification by Deep Learning—A Review. IEEE Access 2021, 9, 56683–56698.

[3] Scientist, D.; Bengaluru, T.M.; Nadu, T. Rice Plant Disease Identification Using Artificial Intelligence. Int. J. Electr. Eng. Technol. 2020, 11, 392–402.

[4] classification of citrus diseases through machine learning. Data Brief 2019, 26, 104340.

[5] Panigrahi, K.P.; Das, H.; Sahoo, A.K.; Moharana, S.C. Maize leaf disease detection and classification using machine learning algorithms. In Progress in Computing, Analytics and Networking; Springer: Singapore, 2020.

[6] Mohsin Kabir, M.; Quwsar Ohi, A.; Mridha, M.F. A Multi-plant disease diagnosis method using convolutional neural network. arXiv 2020, arXiv:2011.05151.

[7] Aldhyani, T.H.; Alkahtani, H.; Eunice, R.J.; Hemanth, D.J. Leaf Pathology Detection in Potato and Pepper Bell Plant using Convolutional Neural Networks. In Proceedings of the 2022 7th International Conference on Communication and Electronics Systems (ICCES), Coimbatore, India, 22–24 June 2022; pp. 1289–1294.

[8] Prodeep, A.R.; Hoque, A.M.; Kabir, M.M.; Rahman, M.S.; Mridha, M.F. Plant Disease Identification from Leaf Images using Deep CNN's EfficientNet. In Proceedings of the 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand, 23–25 March 2022; pp. 523–527.

[9] Jadhav, S.B.; Udupi, V.R.; Patil, S.B. Identification of plant diseases using convolutional neural networks. Int. J. Inf. Technol. 2021, 13, 2461–2470.

[10] Abbas, A.; Jain, S.; Gour, M.; Vankudothu, S. Tomato plant disease detection using transfer learning with C-GAN synthetic images. Comput. Electron. Agric. 2021, 187, 106279.

[11] Anh, P.T.; Duc, H.T.M. A Benchmark of Deep Learning Models for Multi-leaf Diseases for Edge Devices. In Proceedings of the 2021 International Conference on Advanced Technologies for Communications (ATC), Ho Chi Minh City, Vietnam, 14–16 October 2021; pp. 318–323.

[12] Astani, M.; Hasheminejad, M.; Vaghefi, M. A diverse ensemble classifier for tomato disease recognition. Comput. Electron. Agric. 2022, 198, 107054.

[13] Prodeep, A.R.; Hoque, A.M.; Kabir, M.M.; Rahman, M.S.; Mridha, M.F. Plant Disease Identification from Leaf Images using Deep CNN's EfficientNet. In Proceedings of the 2022 International Conference on Decision Aid Sciences and Applications (DASA), Chiangrai, Thailand, 23–25 March 2022; pp. 523–527.

[14] Enkvetchakul, P.; Surinta, O. Effective Data Augmentation and Training Techniques for Improving Deep Learning in Plant Leaf Disease Recognition. Appl. Sci. Eng. Prog. 2022, 15, 3810.

[15] Trivedi, N.K.; Gautam, V.; Anand, A.; Aljahdali, H.M.; Villar, S.G.; Anand, D.; Goyal, N.; Kadry, S. Early Detection and Classification of Tomato Leaf Disease Using High-Performance Deep Neural Network. Sensors 2021, 21, 7987.

[16] Agarwal, M.; Gupta, S.K.; Biswas, K.K. Development of Efficient CNN model for Tomato crop disease identification. Sustain. Comput. Inform. Syst. 2020, 28, 100407.

[17] Fuentes, A.; Yoon, S.; Kim, S.C.; Park, D.S. A Robust Deep-Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition. Sensors 2017, 17, 2022.

[18] Zhong, Y.; Zhao, M. Research on deep learning in apple leaf disease recognition. Comput. Electron. Agric. 2020, 168, 105146.

[19] Chen, J.; Chen, J.; Zhang, D.; Sun, Y.; Nanehkaran, Y. Using deep transfer learning for image-based plant disease identification. Comput. Electron. Agric. 2020, 173, 105393.

[20] Shrivastava, V.K.; Pradhan, M.K. Rice plant disease classification using color features: A machine learning paradigm. J. Plant Pathol. 2021, 103, 17–26.

[21] Tan, M., & Le, Q. (2021, July 1). EFFICIENTNETV2: Smaller models and faster training. PMLR. Retrieved March 19, 2023, 139.

[22] Abd Al-salam Selami, Ameen & Fadhil, Ahmed. (2016). A Study of the Effects of Gaussian Noise on Image Features. Kirkuk University Journal / Scientific Studies (1992-0849). 11. 152 - 169. 10.32894/kujss.2016.124648

[23] A. Boyat and B. Joshi, "A Review Paper: Noise Models in Digital Image Processing" Signal & Image Processing: An International Journal (SIPIJ) Vol.6, No.2, April 2015.

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