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Analyzing performance of deep learning models under the presence of distortions in identifying plant leaf disease

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ABSTRACT

Convolutional neural networks (CNN) trained using deep learning (DL) have advanced dramatically in recent years. Researchers from a variety of fields have been motivated by the success of CNNs in computer vision to develop better CNN models for use in other visually-rich settings. Successes in image classification and research have been achieved in a wide variety of domains throughout the past year. Among the many popularized image classification techniques, the detection of plant leaf diseases has received extensive research. As a result of the nature of the procedure, image quality is often degraded and distortions are introduced during the capturing of the image. In this study, we look into how various CNN models are affected by distortions. Corn-maze leaf photos from the 4,188-image corn or maize leaf Dataset (split into four categories) are under consideration. To evaluate how well they handle noise and blur, researchers have deployed pre-trained deep CNN models like visual geometry group (VGG), InceptionV3, ResNet50, and EfficientNetB0. Classification accuracy and metrics like as recall and f1-score are used to evaluate CNN performance.

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1. INTRODUCTION

Agriculture is the mainstay for both the economy and survival. Currently, the growth rate of agriculture production has been decreasing due to various diseases in plants because of weather conditions, global warming, and pollution. Plant diseases mainly affect the quality and it is indeed a challenging task. With farmers making rough measurements manually, results may not be efficient and are time-consuming. Digital agriculture is the concept to use new and advanced technologies, consolidated in one system that enables farmers to improve the quality and production of food [1]. Digital process accumulate data periodically and accurately, usually combined with a few external sources like weather information. The resulting data is examined and depicted so the farmer can make decisions with high accuracy. To get accurate output, new automatic approaches are introduced such as sensors, unmanned aviation systems (UAS), robotics, artificial intelligence (AI), and other computational approaches. These approaches enable the farmers to reduce cost and time. Thus, moving for rapid, economical, precise, and computerized methods to identify diseases in plants is very crucial. Computer vision has developed thoroughly in the agriculture industry with the capability to process multimedia information in the form of images [2].

The detection can be done by machine learning (ML) approach or deep learning (DL). The ML system is made up of two parts: a feature extraction module that pulls out relevant details like edges and textures, and a classification module that assigns labels to those details. The fundamental drawback of ML is that it cannot extract discriminating characteristics from the training set of data, which is necessary for separation. Fortunately, this shortcoming is corrected by utilizing DL. A subfield of ML, DL uses its own special kind of computation to learn. As an alternative to the haphazard way in which humans make judgments, a DL model is provided to consistently deconstruct information with a uniform structure [3]. To do this, DL employs an artificial neural system expressed as a layered structure comprising many algorithms artificial neural network (ANN) [4]. The human brain's biological neural network is used as a model to simulate an ANN's design. Because of this, DL has proven to be more effective than other types of ML. Therefore, in this work, DL was utilized for the aim of detection.

Image acquisition, preprocessing, segmentation, feature extraction, and classification are the several phases involved in the process of detecting plant diseases. The process of classifying plant diseases requires making educated guesses about the category or label. The first step in the classification process involves placing photos into one of several predetermined categories. Because image processing is one of the most quickly developing technologies, the process of image capture is frequently accompanied by a number of different types of distortions throughout the process of image acquisition [5]. For instance, when we process image acquisition, there is a possibility that it will add some form of blur or distortion to the image. In the course of this line of research, we are attempting to determine the impact that image distortions have on convolutional neural network (CNN)-based image classifiers. Image blurring, image noise (also known as independent noise or spike noise), Poisson noise (also known as shot noise), and numerous types of image blurring include the following: motion blur, average blur, Gaussian blur, out-of-focus blur, and atmospheric turbulence blur [6], [7].

Numerous earlier study papers have been published to review agricultural research, including the detection of plant diseases using DL or ML [8], [9] but they lacked some of the most recent developments in visualization methods for plant disease diagnosis. To the best of the author's knowledge, distortions that happen during classification have not been considered by any researchers, despite the fact that these distortions may cause variations in the results. As a result, the motivation behind the proposed work is to find out how well CNN models perform when distortions are present. In this study, two different kinds of picture distortions, namely Gaussian blur and salt and pepper noise, have been investigated to determine the impact that each type of distortion has on CNN-based image classifiers. The performance of pre-trained CNNs is evaluated using a dataset of plant diseases and is compared to how well they function when subjected to the influence of Gaussian blur and salt and pepper noise, respectively. Thus, the main objective of this study is to find the robustness of various CNN’s model against distortions.

The remainder of the paper is divided into the following sections: in section 2, the findings of previous studies are summarized. Section 3 provides a method for the proposed work. In section 4, the results and evaluation are discussed. The conclusions from the study are summarized in section 5.

2. RELATED WORK

The literature presented in this section covers extensive research and provides an idea of the work accomplished through deep models. In the wake of Table 1, bring to a close the investigation of the history of work concerning the categorization and identification of plant diseases. CNNs model was used to classify diseases in rice plants with a dataset of nearly 500 naturally collected images of both healthy and unhealthy rice leaves and was compared with support vector machine (SVM), back propagation, and particle swarm optimization algorithm [10]. The dataset included images of both healthy and unhealthy rice leaves. An algorithm for the diagnosis of diseases was developed and implemented by [11]. Image processing and artificial neural algorithms were utilized by the author in order to determine whether or not the brinjal leaf was infected. The k-means approach was used for the segmentation of the images, and then neural networks were used for the classification. Maeda-Gutiérrez *et al*. [12] focused on a comparative study of various CNN models (AlexNet, GoogleNet, Inception V3, ResNet 18, and ResNet 50) using the PlantVillage dataset consisting of nine classes to analyze tomato leaves. The tomato disease detection method, which was developed by Wang *et al.* [13] and was based on a deep CNN and an object detection model, was successfully implemented. Both faster region-based CNN (R-CNN) and mask R-CNN were utilized in this process. In order to determine which model is best suited for the detection of tomato disease, the author conducted an analysis that combined two different object detection models with four distinct deep CNN.

Image recognition of apple diseases was accomplished by Chuanlei *et al.* [14] using region growing algorithm (RGA), genetic algorithm and correlation-based feature selection (GA-CFS), and SVM. The image recognition was based on the colour, shape, and texture features that were extracted from the affected leaf images. The apple leaves that are afflicted with diseases are the primary topic of investigation in this study. The author took into consideration a total of 38 image features, including 14 colour features, 4 shape features, and 20 texture features. These image features are extracted from each segmented spot image, and they are then normalized, respectively. Research by Ferentinos [15] used CNN models AlexNet, AlexNetOWTBn, GoogLeNet, and visual geometry group (VGG) on a publicly accessible database of 25 different plant species. They were able to achieve an accuracy of 99.53% success rate through the use of these models. Research by Mahajan *et al*. [16] proposed a DL model called DL-based haze perceptual quality evaluator (DLHPQE) for predicting image quality in hazy conditions. This model is used to estimate the effect of an environmental factor known as haze on image quality. Research by Rahman *et al*. [17] has contributed large-scale architectures such as InceptionV3 and VGG16 for the purpose of detecting and identifying rice diseases. These have been compared with two-stage small CNN architectures such as MobileNet, SqueezeNet, and NasNet mobile. Data was collected in a real-world setting from paddy fields at the Bangladesh rice research institute (BRRI), which comprises eight distinct classes. On the UC Merced land use aerial dataset, the performance of the AlexNet and GoogleNet architectures was analyzed and compared in [18], taking into account the influence of Gaussian blur. Results that have been compiled investigated the resistance of CNN's model towards blur. As a result of GoogleNet's greater adaptability to a wide range of Gaussian blurring levels than AlexNet's, the research presented in the literature demonstrated the applicability of CNNs to a wide variety of domains and scenarios. The purpose of this paper is to conduct an analysis of how CNNs actually work in practice with regard to image distortions. The dataset is improved by including some salt-and-pepper noise as well as some Gaussian blurring. This paper makes a contribution by demonstrating the impact of the blurring effect and noise effect on the classification performance of CNNs.

Table 1. Summarized review of plant disease detection based on DL

Year	Authors	Method	Application area
2018	Chouhan *et al*. [2]	Bacterial foraging optimization	Plant leaf classification and identification
2017	Yang Lu *et al*. [10]	Deep CNN	Recognition of rice diseases
2017	Zhang *et al*. [3]	K-Mean clustering and sparse representation	Cucumber leaf disease recognition
2020	Rahman *et al*. [17]	CNN	Identification of diseases in rice and pests
2017	Zhou *et al*. [19]	Deep CNN	Classification of distorted images
2020	Mishra *et al*. [20]	CNN	Corn plant disease recognition based on real-time
2020	Sharma *et al*. [21]	CNN models	Analyzing the performance of CNN models for plant disease identification
2017	Megha *et al*. [22]	FCM-clustering technique	Image processing system for plant disease identification
2017	Prakash *et al*. [23]	K-Mean clustering, GLCM and SVM	Detection of citrus leaf diseases and classification
2019	Jaisakthi *et al*. [24]	Genetic algorithm	Classification of fungal disease in grapes leaves
2020	Kumar *et al*. [25]	ResNet model	Classification of plant leaf diseases
2020	Rao and Kulkarni [26]	GLCM and neuro-fuzzy logic	Hybrid approach for plant leaf disease recognition

3. METHOD

The DL is currently generating a revolution in a wide range of industries, from robots to medicine and everything in between [20]. CNN are among the DL models that can automatically learn spatial feature hierarchies. These networks are able to handle grid pattern data in a similar manner to how a photo is handled. We will look into the suggested technique for our study in this part. The basic method for using CNN models to identify the presence of plant leaf diseases is shown in Figure 1.

The PlantVillage dataset's secondary data were first gathered as a preliminary step. Following that, the data was subjected to distortions like blur and noise so that it could be investigated to determine how they influenced the detection of plant leaf diseases. Although there are many different types of noise and blur distortions, this study has used salt-and-pepper noise and randomly generated Gaussian noise. Some other distortions that are already present may be taken into account by researchers in the future. The blurring is done by applying the gaussian function, which is given by the equation in the equation box below. It accomplishes this by averaging the values of the pixels that are directly surrounding the one in question [19]. The equation that requires solving is as (1):

$$G(x,y) = \frac{1}{2\pi\sigma^2}\, e^{-(x^2+y^2)/2\sigma^2} \tag{1}$$

here σ represents blur factor, e represents euler number, and (x, y) represents horizontal and vertical distance with respect to center pixel. Similarly, noise is introduced into dataset by applying salt and pepper noise expressed as (2):

$$n(s) = \begin{cases} N_a, & s = a \\ N_b, & s = b \\ 0, & otherwise \end{cases} \quad (2)$$

where s represents the pixel's intensity values in a noisy image. Also, a and b represent noise impulses; for $b > a$, intensity b appears to be a light point, while a pitch appears as a dark point on the image [27].

The following data pre-processing is done to change the photos' shape and scale them to 150×150×3. In accordance with this, the data is enhanced by shearing and zooming with a value of 0.2. CNN models are then fed the augmented data (both with and without distortions). The ResNet50, VGG16, VGG19, InceptionV3, and EfficientNetB0 pre-trained CNN models are used [15]. These are pre-trained CNN models that were trained using the more than 20,000 classes and over 14 million images in the ImageNet dataset. Microsoft's ResNet50 [20] model accepts more than a million 224×224-pixel pictures as input. VGG models accept photos with 3 channels and 224×224-pixel input sizes. The input size for InceptionV3 is 299×299 pixels, and it contains 48 deep layers [21]. EfficientNet [22], a different pre-trained model, has eight alternative implementations (B0 to B7). With 5.3 million parameters, EfficientNetB0 is the most basic and performs best in terms of top-1 accuracy. These models are summarised in Table 2.

The models include a variety of layers, including fully linked, pooling, and convolutional layers. The convolutional layer uses image pixels from the plant leaf database to perform convolution operations and produce convolution maps. The convolved map is subjected to the activation function, similar to rectified linear unit (ReLU), to create a rectified feature map. For the purpose of identifying the prominent characteristics, the image is processed using different convolutions and ReLU layers.

To identify certain areas of an image, distinct pooling layers with various filters are used. In order to classify the type of plant leaf disease, the output of the pooling layer is flattened and provided as input to a fully connected layer. As CNNs are implicitly present during the feature extraction process, the features are extracted layer by layer. The many filters of an individual DL model's activation maps are shown in Figure 2, which visualises the activation maps from various convolution layers, activating various elements of an image, such as the background, edges, and outer border. As a result, more features are abstracted from an image as it moves through deeper layers, which helps with correct classification.

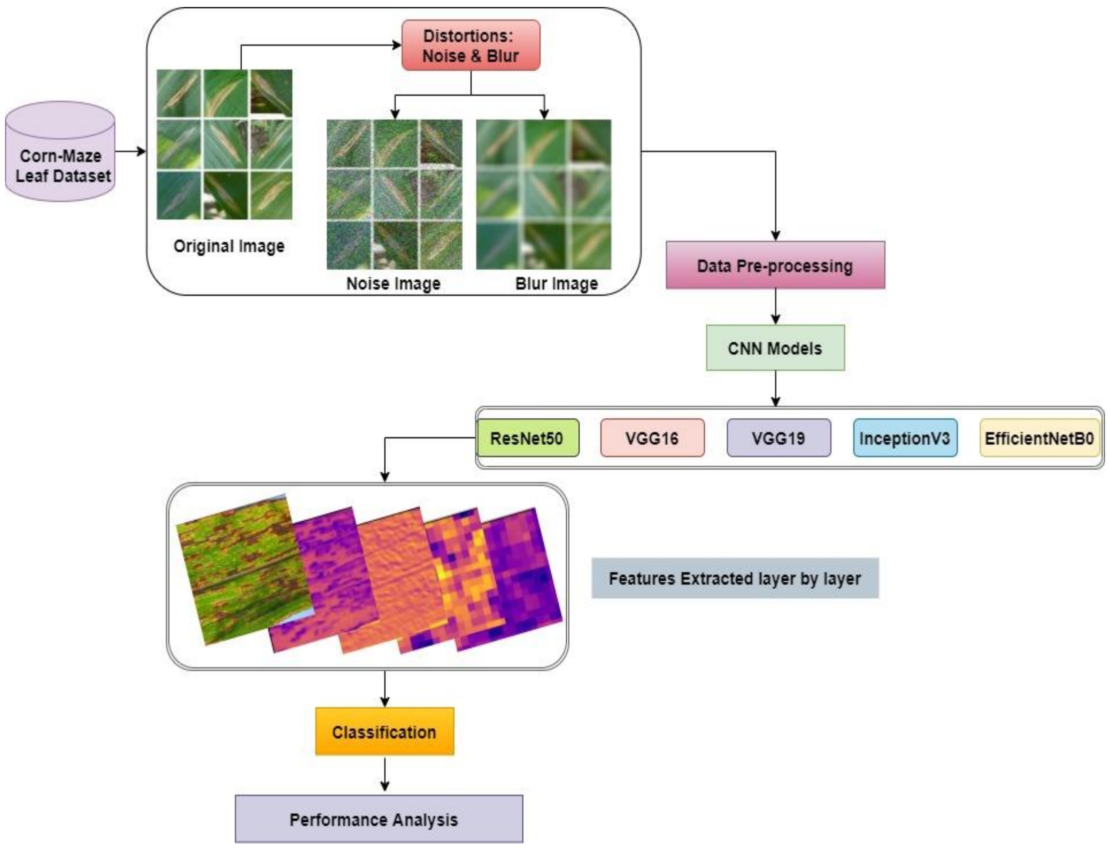


Figure 1. Proposed method for classification of plant disease using CNN models

Table 2. Salient features of CNN models implemented in proposed work

Models	Years	Layers	Total parameters	Top-1 accuracy	Top-5 accuracy
ResNet50 [28]	2012	48 convolutional layers, 1 max pool layer, 1 average pool layer	25,636,712	0.749	0.921
VGG16 [29]	2014	16 layers with learnable weights (13 convolutional layers and 3 fully connected layers)	138,357,544	0.713	0.901
VGG19 [29]	2014	19 layers with learnable weights (16 convolutional layers and 3 fully connected layers)	143,667,240	0.713	0.9
InceptionV3 [29]	2015	48 layers deep	2,385,178,4	0.779	0.937
EfficientNetB0 [30]	2019	237 layers deep	4.049.564	0.771	0.933

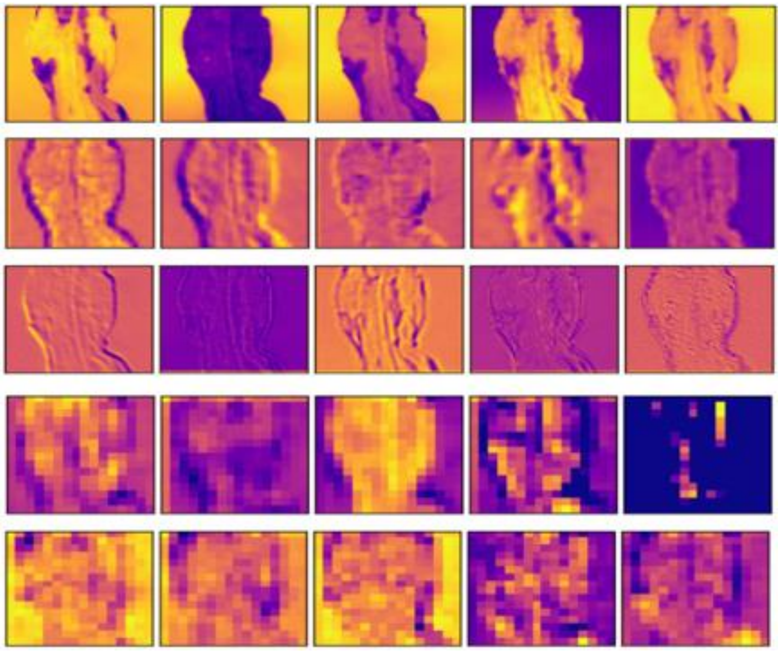


Figure 2. Visualization of the activation maps of various CNN layers

4. RESULTS AND DISCUSSION

The experiment being conducted has been analyzed, and the output has been generalized. The primary goal of the experiment is to discuss the impact of these distortion-relevant issues, such as the impact of the number of classes used while training the network. The experiment is running on an 11^{th} generation Intel(R) Core (TM) i3-1115G4 processor running at 3.00 GHz with 4 GB of RAM. The platform used to implement CNNs is Python on Windows 10. Results have been analysed by calculating various performance metrics: precision, recall, and f1-score, which are given below for true positive (TP), true negative (TN), false positive (FP), and false negative (FN), respectively. Precision is the ratio of true predicted positive observations to the total predicted positive observations.

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

Recall also called as sensitivity, measured as the ratio of truly predicted positive observations to the all observations belongs to actual class.

$$Recall = \frac{TP}{TP+ FN} \tag{4}$$

F1 score is the weighted average of precision and sensitivity. It takes both FP and FN.

$$F1\ score = \frac{2*Precision*Recall}{Precision+ Recall} \tag{5}$$

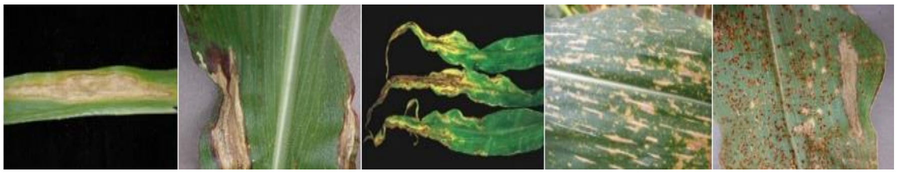
4.1. Dataset description

Fungal, viral, and bacterial are the three main categories of plant diseases, which also include blight, leaf spot, mildew, rot, curly top, mosaic, late blight, scab, rust, and many others [31]. The proposed research has focused on three distinct maize leaf diseases. These include the typical grey leaf spots, common rust, and blight. The corn or maize leaf dataset [32], which comprises corn or maize leaf, was used to collect the data for this study. Table 3 lists the number of classes and the images that are included in each class. The input images have been resized with 150 as the height and width before being used for classification. Figure 3 depicts an example of a diseased corn or maize leaf, with Figure 3(a) showing corn leaves affected by blight, Figure 3(b) showing leaves affected by grey leaf spot, and Figure 3(c) showing leaves affected by common rust.

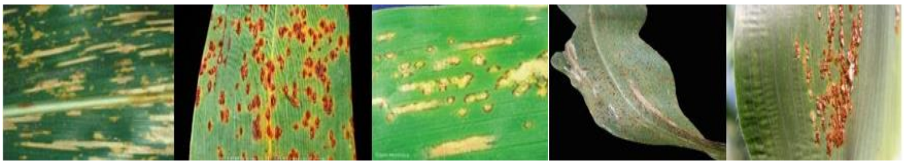
The 80% of image data was used for training, while the remaining 20% was used for testing. To measure the consequences of these distortions, we blurred and distorted clear images using Gaussian and salt-and-pepper noise, respectively. The sample of original photos and distorted images is shown in Figure 4, where Figure 4(a) depicts original images, or images without distortions, Figure 4(b) depicts leaf images with salt-and-pepper noise, and Figure 4(c) depicts leaf images with Gaussian blur.

Table 3. Dataset for corn-maze leaf disease classification

Class	Blight	Gray leaf spot	Common rust	Healthy
Train images	916	1,044	458	929
Test images	230	262	115	233
Total no. of images	1,146	1,306	573	1,162



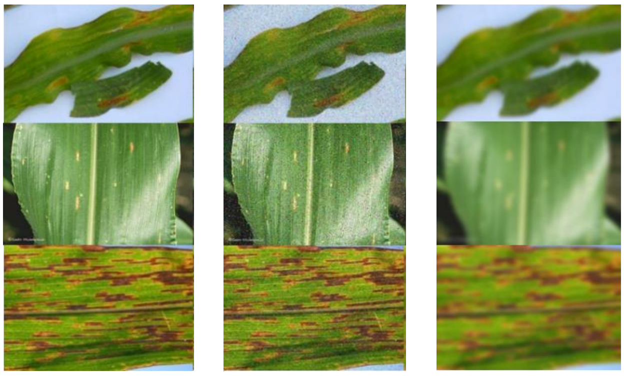
(a)



(b)

(c)

Figure 3. Samples of diseased corn leaf where (a) depicts blighted corn leaves, (b) depicts leaves with grey leaf spot disease, and (c) depicts leaves with common rust disease



(a) (b) (c)

Figure 4. Samples of both original and distorted images where (a) original images, (b) noise-distorted images, and (c) blur-distorted images

4.2. Observations

To attain the highest accuracy, 100 epochs of both distorted and undistorted data were used to implement all of the aforementioned models. Different training-validation plot curves were generated for each model, and EfficientNetB0, which has a validation accuracy of over 90%, is the most accurate model. The training and validation accuracy of the implemented EfficientNetB0 model are presented in Figure 5, both without distortions (in Figure 5(a)) and with distortions (in Figures 5(b) and 5(c)). Similarly, all of the aforementioned CNN models have been used and vary in accuracy from 70 to 95%. Table 4 provides a summary of the changes in validation accuracy based on image distortions. According to this result, the performance of CNN's model varies in response to distortions. The graphs shown in Figure 6 help to visualize comparisons between implemented CNN pre-trained models on the basis of accuracy. Figure 6(a) shows the model's accuracy on the original data, whereas Figure 6(b) shows its accuracy on distorted data.

According to the performance of CNN models, the predicted values i.e., class labels are validated and confusion matrices were generated giving us count of TP, TN, FP, and FN, respectively. Figure 7 shows the generated confusion matrix, describing the performance of pre-trained implemented CNN architecture for VGG19 as an example, where Figure 7(a) representing the generated confusion matrix of original data, Figures 7(b) and (c) depicting the confusion matrix of noise-distorted and blur-distorted data. The values conjured by the confusion matrices were then used to calculate the performance parameters: precision, recall, and f1-score. Following Table 5 summarises the performance parameters of the implemented CNN architectures for identification of plant leaf disease and reflect the effect of distortions in identifying as well.

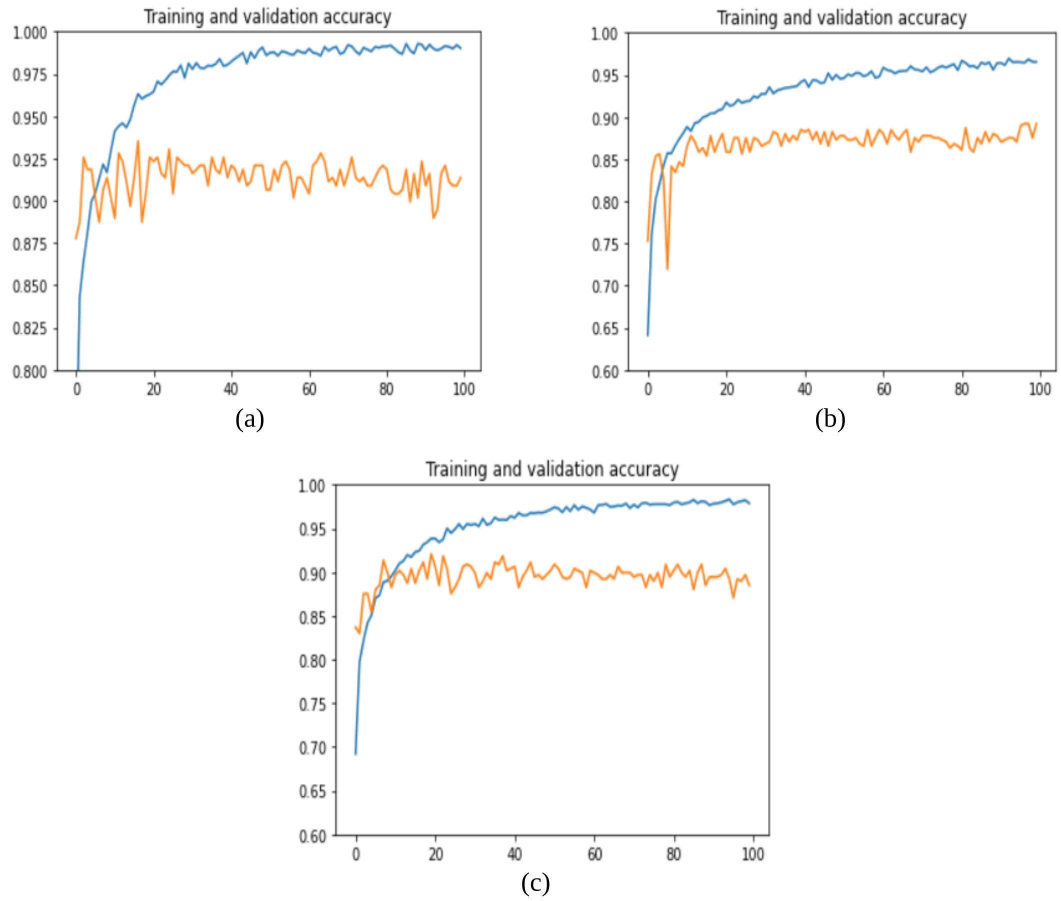
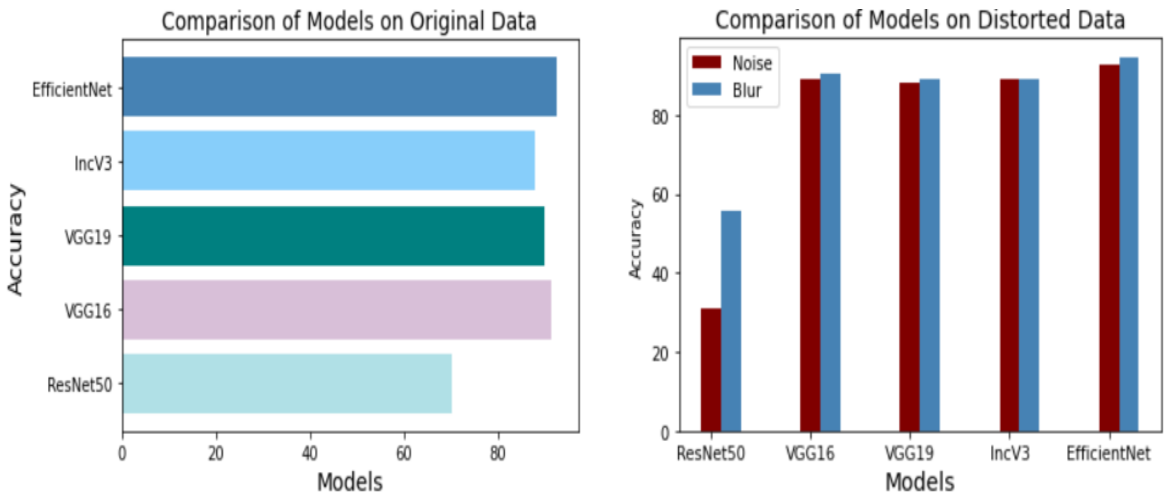


Figure 5. Plot history of training and validation accuracy of EfficientNetB0 model on (a) original, (b) noise, and (c) blur images respectively

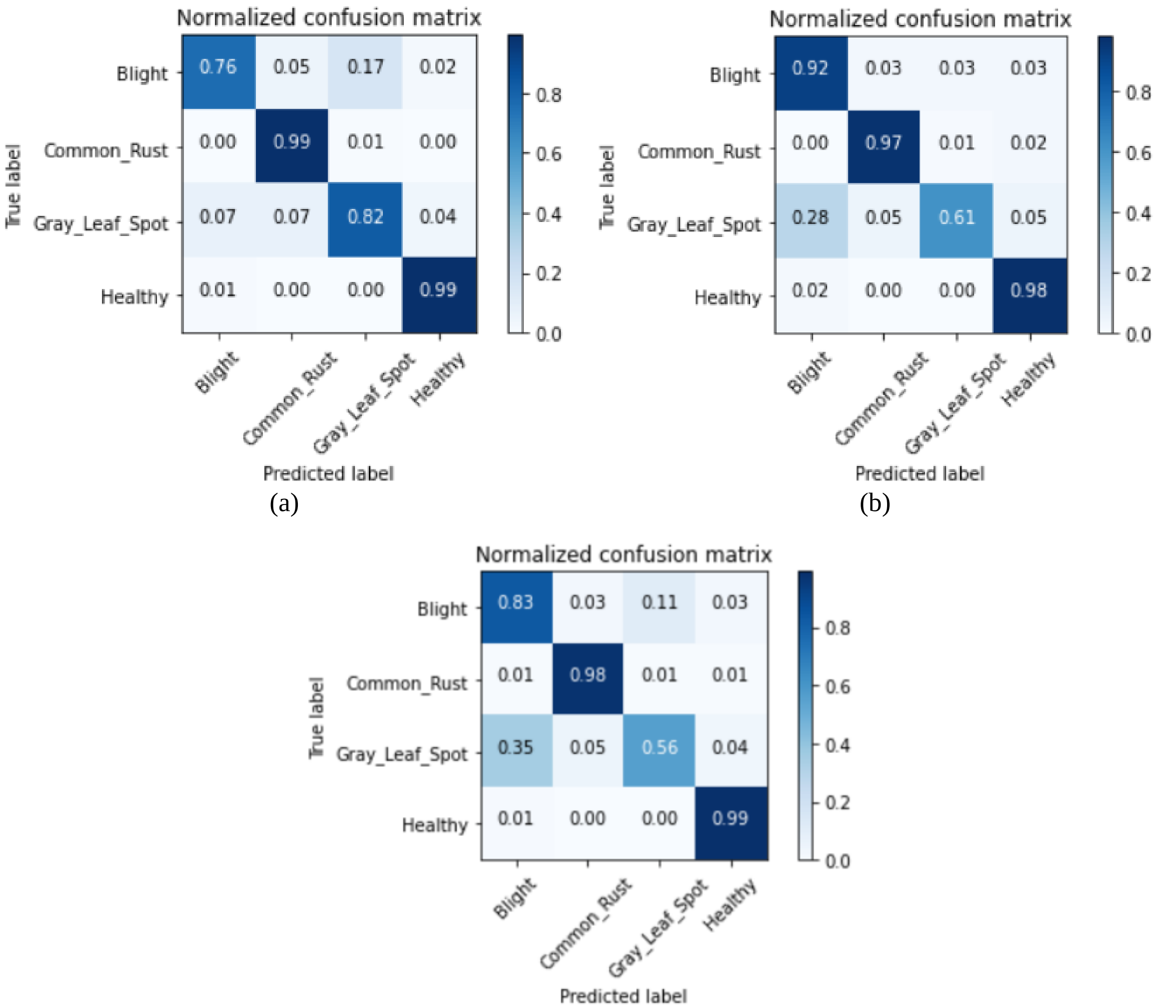
Table 4. Average accuracy of images with/without distortions

CNN models	Original image	Noise image	Blur image
ResNet50	70.02	55.64	31.18
VGG16	91.37	90.41	89.21
VGG19	89.69	89.21	88.01
InceptionV3	87.77	89.21	88.97
EfficientNetB0	92.33	94.72	92.57



(a) (b)

Figure 6. Graphical represenation of CNN models based on validation accuracy for (a) original and (b) distorted images, respectively



(a) (b)

(c)

Figure 7. Confusion matrix generated by VGG19 model (a) representing the original data classification, (b) representing the classification based on noise-distorted data, and (c) depicting classification based on blur distorted data

Table 5. Performance metrics of different CNN architectures

Models	Original images			Blur images			Noise images		
	Precision	Recall	F1_score	Precision	Recall	F1_score	Precision	Recall	F1_score
ResNet50	78.19	62.12	60.11	77.93	25.00	11.88	34.20	45.00	35.83
VGG16	91.08	88.82	89.66	90.87	89.72	90.20	88.02	87.64	87.81
VGG19	88.53	89.28	88.51	85.32	84.07	84.50	90.81	87.17	88.27
InceptionV3	89.95	89.53	89.72	88.89	89.10	88.93	87.13	87.37	87.18
EfficientNetB0	92.91	90.35	91.27	87.49	86.65	86.99	91.47	89.50	90.26

Receiver operating characteristics (ROC) The curve is a graphical plot of the false positive rate (FPR) against the true positive rate (TPR) for a number of classification models with threshold values between 0.0 and 1.0. It gives a probability curve that assesses the performance of classification models. A higher ROC indicates the superiority of the classification model [30]. Figures 8(a)-(c) and 9(a)-(c) show the best and the worst ROC curves given by the CNN models, respectively. InceptionV3 performed admirably, with area under the curve (AUC) values of 0.97, 0.96, and 0.96 for original, noisy, and blurred images, respectively. ResNet50, on the other hand, deprived low values, i.e., 0.75, 0.5, and 0.5 for original, noisy, and blurred images, respectively. For models with an AUC value between 0.5 and 1, there is a high possibility that the classifier will actually want to recognize the positive class values from the negative class values.

Through various graphs and performance metrics, we could infer ResNet50 underperforms with an accuracy of 70.02% and low classification metrics compared to others. Further, ResNet50 does not classify distorted images accurately, whereas the EfficientNetB0 and InceptionV3 models achieved much better accuracy with fewer parameters compared to ResNet. Parallelly, it classified distorted images with better performance metrics, meaning the influence of distortions does not affect the classification process. Other models, such as VGG16 and VGG19, also demonstrated comparable performance. We compared our approach to other comparable case studies involving different types of leave, as shown in Table 6, and concluded that it performed better, with an accuracy rate of 92%.

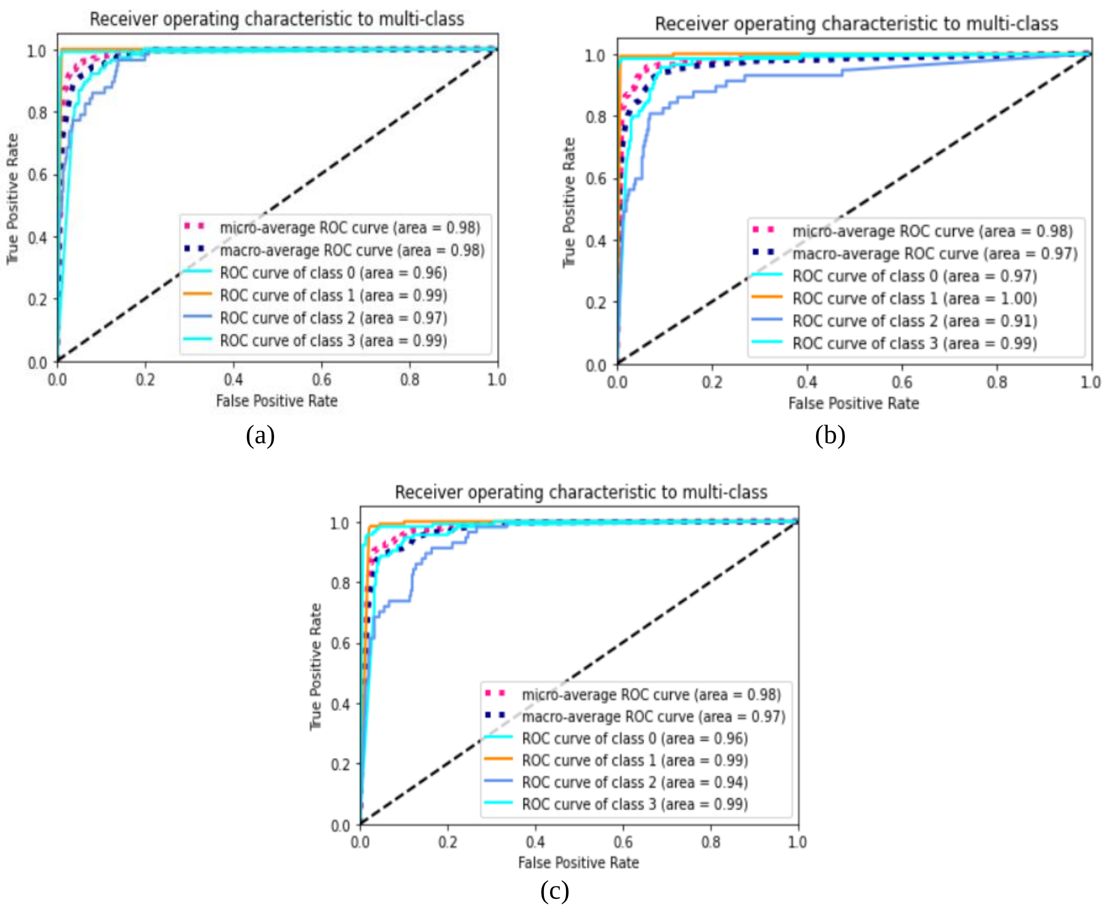
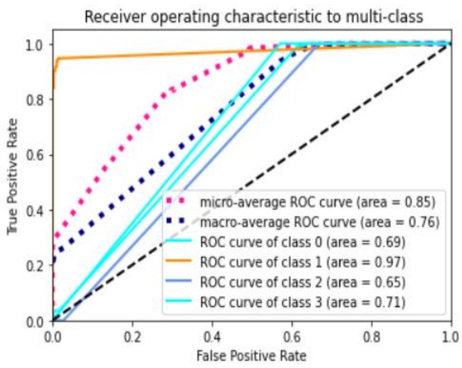
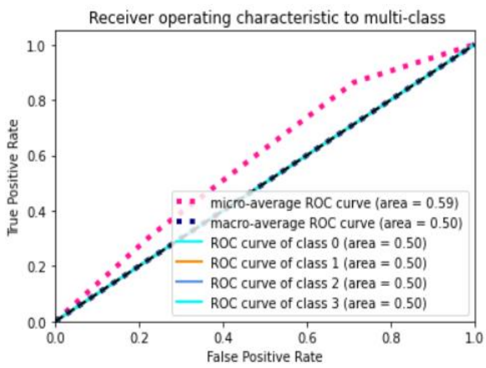


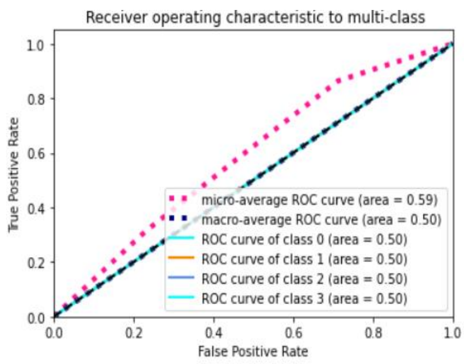
Figure 8. ROC curve for best performed model InceptionV3 on (a) original, (b) noise, and (c) blur images



(a)



(b)



(c)

Figure 9. ROC curve for worst performed model ResNet50 on (a) original, (b) noise, and (c) blur images

Table 6. Comparative analysis of proposed approach with other existing approaches

Reference	Plant category	Techniques	Accuracy (%)
2020 [33]	Tomato leaf	VGG16	77.2
		MobileNet	63.75
		Inception	63.4
2022 [34]	Apple leaf	MobileNet	73.50
		InceptionV3	75.59
		ResNet152	77.65
Ours	Corn-maize	ResNet50	70.02
		VGG16	91.37
		VGG19	89.69
		InceptionV3	87.77
		EfficientNetB0	92.33

5. CONCLUSION

In this work, pretrained DL models were implemented for plant leaf disease detection and compared various CNN architectures with the original images and distorted images to determine the influence of distortions like blur and noise. Particularly, the ResNet50, VGG16, VGG19, InceptionV3, and EfficientNetB0 models were trained on the corn-maize leaf dataset, which consists of 4188 total images with four classes. In comparison, the ResNet50 model performed poorly due to the effects of distortions. In terms of model accuracy, however, EfficientNetB0 outperforms the implemented CNN models, both with and without distortions. InceptionV3 has also performed significantly better in terms of its capacity to recognise positive and negative classes compared to others.

REFERENCES

[1] V. Singh and A. K. Misra, “Detection of plant leaf diseases using image segmentation and soft computing techniques,” *Information Processing in Agriculture*, vol. 4, no. 1, pp. 41–49, Mar. 2017, doi: 10.1016/j.inpa.2016.10.005.
[2] S. S. Chouhan, A. Kaul, U. P. Singh, and S. Jain, “Bacterial foraging optimization based radial basis function neural network (BRBFNN) for identification and classification of plant leaf diseases: an automatic approach towards plant pathology,” *IEEE*

Access, vol. 6, pp. 8852–8863, 2018, doi: 10.1109/ACCESS.2018.2800685.
[3] S. Zhang, X. Wu, Z. You, and L. Zhang, "Leaf image based cucumber disease recognition using sparse representation classification," *Computers and Electronics in Agriculture*, vol. 134, pp. 135–141, Mar. 2017, doi: 10.1016/j.compag.2017.01.014.
[4] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, Jun. 2016, pp. 770–778, doi: 10.1109/CVPR.2016.90.
[5] E. Kurimo, L. Lepistö, J. Nikkanen, J. Grén, I. Kunttu, and J. Laaksonen, "The effect of motion blur and signal noise on image quality in low light imaging," in *Scandinavian Conference on Image Analysis*, 2009, pp. 81–90, doi: 10.1007/978-3-642-02230-2_9.
[6] K. Ahmad, J. Khan, and M. S. U. D. Iqbal, "A comparative study of different denoising techniques in digital image processing," in *2019 8th International Conference on Modeling Simulation and Applied Optimization (ICMSAO)*, Apr. 2019, pp. 1–6, doi: 10.1109/ICMSAO.2019.8880389.
[7] T. Hafsia, H. Tlijani, and K. Nouri, "Comparative study of methods of restoring blurred and noisy images," in *2020 4th International Conference on Advanced Systems and Emergent Technologies (IC_ASET)*, Dec. 2020, pp. 367–370, doi: 10.1109/IC_ASET49463.2020.9318267.
[8] A. K. Singh, B. Ganapathysubramanian, S. Sarkar, and A. Singh, "Deep learning for plant stress phenotyping: trends and future perspectives," *Trends in Plant Science*, vol. 23, no. 10, pp. 883–898, Oct. 2018, doi: 10.1016/j.tplants.2018.07.004.
[9] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.
[10] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, "Identification of rice diseases using deep convolutional neural networks," *Neurocomputing*, vol. 267, pp. 378–384, Dec. 2017, doi: 10.1016/j.neucom.2017.06.023.
[11] R. Anand, S. Veni, and J. Aravinth, "An application of image processing techniques for detection of diseases on brinjal leaves using k-means clustering method," in *2016 International Conference on Recent Trends in Information Technology (ICRTIT)*, Apr. 2016, pp. 1–6, doi: 10.1109/ICRTIT.2016.7569531.
[12] V. Maeda-Gutiérrez *et al.*, "Comparison of convolutional neural network architectures for classification of tomato plant diseases," *Applied Sciences (Switzerland)*, vol. 10, no. 4, pp. 1–15, Feb. 2020, doi: 10.3390/app10041245.
[13] Q. Wang, F. Qi, M. Sun, J. Qu, and J. Xue, "Identification of tomato disease types and detection of infected areas based on deep convolutional neural networks and object detection techniques," *Computational Intelligence and Neuroscience*, pp. 1–15, Dec. 2019, doi: 10.1155/2019/9142753.
[14] Z. Chuanlei, Z. Shanwen, Y. Jucheng, S. Yancui, and C. Jia, "Apple leaf disease identification using genetic algorithm and correlation based feature selection method," *International Journal of Agricultural and Biological Engineering*, vol. 10, no. 2, pp. 74–83, 2017, doi: 10.3965/j.ijabe.20171002.2166.
[15] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311–318, Feb. 2018, doi: 10.1016/j.compag.2018.01.009.
[16] P. Mahajan, V. Jakhetiya, P. Abrol, P. K. Lehana, B. N. Subudhi, and S. C. Guntuku, "Perceptual quality evaluation of hazy natural images," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 12, pp. 8046–8056, Dec. 2021, doi: 10.1109/TII.2021.3065439.
[17] C. R. Rahman *et al.*, "Identification and recognition of rice diseases and pests using convolutional neural networks," *Biosystems Engineering*, vol. 194, pp. 112–120, Jun. 2020, doi: 10.1016/j.biosystemseng.2020.03.020.
[18] P. Mahajan, P. Abrol, and P. K. Lehana, "Effect of blurring on identification of aerial images using convolution neural networks," in *Proceedings of ICRIC 2019*, 2020, pp. 469–484, doi: 10.1007/978-3-030-29407-6_34.
[19] Y. Zhou, S. Song, and N.-M. Cheung, "On classification of distorted images with deep convolutional neural networks," in *2017 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Mar. 2017, pp. 1213–1217, doi: 10.1109/ICASSP.2017.7952349.
[20] S. Mishra, R. Sachan, and D. Rajpal, "Deep convolutional neural network based detection system for real-time corn plant disease recognition," *Procedia Computer Science*, vol. 167, pp. 2003–2010, 2020, doi: 10.1016/j.procs.2020.03.236.
[21] P. Sharma, Y. P. S. Berwal, and W. Ghai, "Performance analysis of deep learning CNN models for disease detection in plants using image segmentation," *Information Processing in Agriculture*, vol. 7, no. 4, pp. 566–574, Dec. 2020, doi: 10.1016/j.inpa.2019.11.001.
[22] S. Megha, R. Niveditha, N. Sowmyashree, and K. Vidhya, "Image processing system for plant disease identification by using FCM clustering technique," *International Journal of Advance Research, Ideas and Innovations in Technology*, vol. 3, no. 2, pp. 445–449, 2017.
[23] R. M. Prakash, G. P. Saraswathy, G. Ramalakshmi, K. H. Mangaleswari, and T. Kaviya, "Detection of leaf diseases and classification using digital image processing," in *2017 International Conference on Innovations in Information, Embedded and Communication Systems (ICIIECS)*, Mar. 2017, pp. 1–4, doi: 10.1109/ICIIECS.2017.8275915.
[24] S. M. Jaisakthi, P. Mirunalini, D. Thenmozhi, and Vatsala, "Grape leaf disease identification using machine learning techniques," in *2019 International Conference on Computational Intelligence in Data Science (ICCIDS)*, Feb. 2019, pp. 1–6, doi: 10.1109/ICCIDS.2019.8862084.
[25] V. Kumar, H. Arora, Harsh, and J. Sisodia, "Resnet-based approach for detection and classification of plant leaf diseases," in *2020 International Conference on Electronics and Sustainable Communication Systems (ICESC)*, Jul. 2020, pp. 495–502, doi: 10.1109/ICESC48915.2020.9155585.
[26] A. Rao and S. B. Kulkarni, "A hybrid approach for plant leaf disease detection and classification using digital image processing methods," *The International Journal of Electrical Engineering & Education*, pp. 1–19, Oct. 2020, doi: 10.1177/0020720920953126.
[27] A. K. Boyat and B. K. Joshi, "A review paper: noise models in digital image processing," *Signal & Image Processing : An International Journal*, vol. 6, no. 2, pp. 63–75, Apr. 2015, doi: 10.5121/sipij.2015.6206.
[28] A. Brodzicki, J. Jaworek-Korjakowska, P. Kleczek, M. Garland, and M. Bogyo, "Pre-trained deep convolutional neural network for clostridioides difficile bacteria cytotoxicity classification based on fluorescence images," *Sensors*, vol. 20, no. 23, pp. 1–17, Nov. 2020, doi: 10.3390/s20236713.
[29] M. Türkoğlu and D. Hanbay, "Plant disease and pest detection using deep learning-based features," *Turkish Journal of Electrical Engineering and Computer Sciences*, vol. 27, no. 3, pp. 1636–1651, May 2019, doi: 10.3906/elk-1809-181.
[30] M. Tan and Q. V. Le, "EfficientNet: rethinking model scaling for convolutional neural networks," in *36th International Conference on Machine Learning, ICML 2019*, 2019, pp. 6105–6114.
[31] J. Liu and X. Wang, "Plant diseases and pests detection based on deep learning: a review," *Plant Methods*, vol. 17, no. 1, pp. 1–18, Dec. 2021, doi: 10.1186/s13007-021-00722-9.
[32] S. Ghose, "Corn or maize leaf disease dataset," *Kaggle.Com*, 2020. https://www.kaggle.com/datasets/smaranjitghose/corn-or-

maize-leaf-disease-dataset (accessed Dec. 20, 2022).
[33] M. Agarwal, A. Singh, S. Arjaria, A. Sinha, and S. Gupta, "ToLeD: tomato leaf disease detection using convolution neural network," *Procedia Computer Science*, vol. 167, pp. 293–301, 2020, doi: 10.1016/j.procs.2020.03.225.
[34] C. Bi, J. Wang, Y. Duan, B. Fu, J.-R. Kang, and Y. Shi, "MobileNet based apple leaf diseases identification," *Mobile Networks and Applications*, vol. 27, no. 1, pp. 172–180, Feb. 2022, doi: 10.1007/s11036-020-01640-1.

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