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Automated tomato leaf disease recognition using deep convolutional networks

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ABSTRACT

Agriculture is essential for the entire global population. An advanced, robust, and empirically sound agriculture sector is essential for nourishing the global population. Various leaf diseases cause financial hardships for farmers and related businesses. Early identification of foliar diseases in crops would greatly help farmers, leading to a substantial increase in agricultural productivity. The tomato is a widely recognized and nourishing food that is easily accessible and highly favored by farmers. Early diagnosis of tomato leaf diseases is crucial to maximize tomato crop production. This study aims to utilize a deep learning approach to accurately detect and classify damaged leaves and disease patterns in tomato leaf images. By employing a substantial quantity of deep convolutional network models, we achieved a high level of precision in diagnosing the condition. The dataset used in our study work is a self-contained dataset obtained by direct observation of tomato fields in rural areas of Bangladesh. It consists of four classes: healthy, black mold, grey mold, and powdery mildew. In this study work, we utilized various image pre-processing techniques and applied VGG16, InceptionV3, DenseNet121, and AlexNet models. Our results showed that the DenseNet121 model attained the higher accuracy of 97%. This discovery guarantees accurate detection of tomato diseases in a rapid manner, ushering in a new agricultural revolution.

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1. INTRODUCTION

As a major contributor to both food security and economic development, tomato production is essential to the sustainability of agricultural economies worldwide. In Bangladesh, where agriculture is the main economic pillar, tomatoes are an important cash crop. Furthermore, India produces around 5,300,000 tons of goods annually on an area of about 3,50,000 hectares [1]. In many parts of the world, tomatoes constitute a major crop; an average person consumes 20 kg of tomatoes each year. Roughly 15% of all vegetables are consumed in this way [2]. Today, agricultural landscapes require continual crop and plant surveillance to prevent plant diseases [3]. However, widespread diseases threaten tomato crops, reducing productivity. Bangladeshi tomato farmers struggle with black mold, gray mold, and powdery mildew. These diseases lower tomato yield and quality and increase production costs owing to fungicide use. Understanding and treating tomato leaf diseases is essential for a strong agricultural industry in the nation. Deep learning has significantly transformed the computer vision industry by offering advanced capabilities for automatic analysis of images and recognition [4]. The existence of several minuscule objects in an image is a significant challenge for precise identification of items in the fields of computer vision and object detection research [5].

In the agricultural sector, the application of models based on deep learning for the diagnosis and detection of plant diseases has gained popularity recently. This research strives to give a comprehensive summary of multiple important publications that have advanced this quickly evolving topic, clarifying the strategies used, the datasets used, and the related accuracy levels attained by different deep learning architectures. Agarwal group: using the PlantVillage dataset, Agarwal and associates assessed the performance of deep learning models such as VGG16, InceptionV3, and MobileNet. The highest-level accuracy of 77.2% was achieved by VGG16 [6]. Chen *et al.* [7] utilizing the Hunan Vegetable Institute dataset, they conducted experiments utilizing models like AlexNet, ResNet50, ARNet, and B-ARNet. B-ARNet surpassed the others with an accuracy of 88.43%. Jiang *et al.* [8] used rectified linear units (ReLU) activations to analyze many ResNet topologies, with a focus on the AI Challenger dataset. A number of settings in their analysis showed a remarkable accuracy of up to 98.3%. Still, the dataset was not balanced. Zhou *et al.* [9] used the AI Challenger dataset to analyze deep convolutional neural network (CNN), ResNet50, DenseNet, and restructured residual dense network (RRDN) models. The RRDN model proved to be the most accurate, with a 95% accuracy rate.

Balakrishna and Rao [10] using probabilistic neural network (PNN) and k-nearest neighbor (KNN) models, they achieved a noteworthy accuracy of 91.88% when using PNN on farmland photos. Gonzalez-Huitron *et al.* [11] using the PlantVillage dataset, the researchers tested many models, including Xception, MobileNetV2, and NasNetMobile. Surprisingly, Xception obtained a flawless accuracy score of 1.00. Abbas *et al.* [12] tested DenseNet with C-GAN on PlantVillage and synthetic photos, and DenseNet performed best with an accuracy of 97.11%. Zhang *et al.* [13] ResNet under stochastic gradient descent (SGD) showed the highest accuracy of 96.51% among the photos in Zhang and colleagues' open-access image collection devoted to plant health. Hong *et al.* [14] using the PlantVillage dataset, they tested with models such as DenseNet_Xception and Xception; DenseNet_Xception achieved an accuracy of 97.10%. Kumar and Vani [15] using a subset of the PlantVillage dataset, they examined several models; VGG16 stood out with an accuracy of 99.25%. Prottasha and Reza [16] eight various state-of-the-art convolution neural network models have had their performance evaluated with an emphasis on rice plant disease diagnosis. The suggested approach accurately diagnoses diseases in rice plants and has testing and validation accuracy of 96.5% and 95.3%, respectively. Table 1 provides the summary of previous work which was described before.

Table 1. Comparative analysis with existing works

Serial no	Studies	Dataset	Models	Best accuracy
1	Agarwal *et al.* [6]	PlantVillage dataset	VGG16, InceptionV3, MobileNet	VGG 16--77.2%
2	Chen *et al.* [7]	Hunan Vegetable Institute	AlexNet, ResNet50, ARNet, B-ARNet	B-ARNet-88.43%
3	Jiang *et al.* [8]	AI Challenger	ResNet, ReLU,7×7, L-ReLU,7×7, L-ReLU,11×11	L-ReLU,11×11--98.3%,
4	Zhou *et al.* [9]	AI Challenger	Deep CNN, ResNet50, DenseNet, RRDN	RRDN--95%
5	Balakrishna and Rao [10]	Images collected from a farmland	PNN, KNN	PNN--91.88%
6	Gonzalez-Huitron *et al.* [11]	PlantVillage dataset	MobileNetV2, NasNetMobile, Xception, MobileNetV3, AlexNet, GoogLeNet, ResNet18	Xception-1.00
7	Abbas *et al.* [12]	PlantVillage, Synthetic images	CNN network, AlexNet, DenseNet, MobileNet	DenseNet, C-GAN 97.11%
8	Zhang *et al.* [13]	Open access data repo. of images that focus on plant health	AlexNet (SGD), AlexNet (Adam), GoogLeNet (SGD), ResNet (SGD), ResNet (Adam)	ResNet (SGD) 96.51%
9	Hong *et al.* [14]	PlantVillage dataset	Dense_Net_Xception, Xception, Resne_50, MobileNet, ShuffleNet	DenseNet_Xception-97.10%
10	Kumar and Vani [15]	A portion of the PlantVillage data collection	LeNet, VGG16, ResNet50, Xception	VGG16-99.11%

Despite the progress shown in these studies, there is still a lack of generalization of these models to diverse datasets and environmental conditions. Most research primarily focuses on specific datasets, which can limit the applicability of the models to real-world agricultural scenarios. In addition, there has been limited research conducted on the resilience of these models to variations in environmental factors like soil composition and lighting conditions. Resolving these issues will improve deep learning models' ability to identify plant diseases in agriculture, increasing their dependability and scope of use.

In recent time, the application of deep learning techniques in agriculture has gained traction, offering promising solutions for the early and accurate detection and management of crop diseases. Our research endeavor aims to enhance the existing knowledge in the field of deep learning and agriculture by focusing on detecting tomato leaf diseases in Bangladesh. The following is an overview of the primary contributions given to this research: i) Created a new dataset consisting of four distinct classes (black mold, gray mold, powdery mildew, healthy tomato leaves) obtained directly from actual agricultural fields of Bangladesh; ii) Applied a range of preprocessing techniques to enhance and optimize the dataset, also verify the quality of image after preprocessing; iii) We have conducted a comparative investigation of the performance of models using both preprocessed and raw datasets. Preprocessing approaches play a crucial and impactful role in determining the performance of deep learning models; and iv) This system optimizes agricultural monitoring and management procedures using advanced deep learning models, specifically VGG16, InceptionV3, DenseNet121, and AlexNet. Among them DenseNet121 got the highest accuracy of 97%. Through this research, we aspire to not only enhance the efficiency of disease detection but also to empower farmers with a valuable tool for timely intervention, ultimately mitigating the impact of tomato leaf diseases on crop yield and agricultural sustainability in Bangladesh.

2. METHOD

Bangladesh is renowned for its agricultural sector, which provides employment and sustenance for a significant portion of its population. Food crops encompass paddy, potatoes, vegetables, and various other agricultural products. Regarding veggies, tomatoes might be mentioned as one of them. According to data provided by the Bangladesh Bureau of Statistics, tomato output in fiscal year 2021–2022 amounted to 0.442 million metric tons. The decline in tomato production can be attributed to disease, with leaf disease being the most serious among them. Some of the leaf diseases include early blight, late blight, Septoria leaf spot, black mold, leaf mold, tomato yellow leaf curl virus (TYLCV), bacterial spot, bacterial mosaic virus, powdery mosaic virus, and gray leaf spot. This research aims to utilize deep learning Model with preprocessing techniques to detect various tomato leaf diseases. Figure 1 presents the overall working flowchart of our work.

A few subsections explain the methodological flowchart see Figure 1 in brief. The automated technique is being implemented by means of an idle step. We first gather raw data from actual farming areas, and then we use data preprocessing and normalization techniques. Through data labeling, we are able to apply numerous high-level models and successfully identify tomato leaf diseases. And the goal of the entire procedure is to develop an automated system.

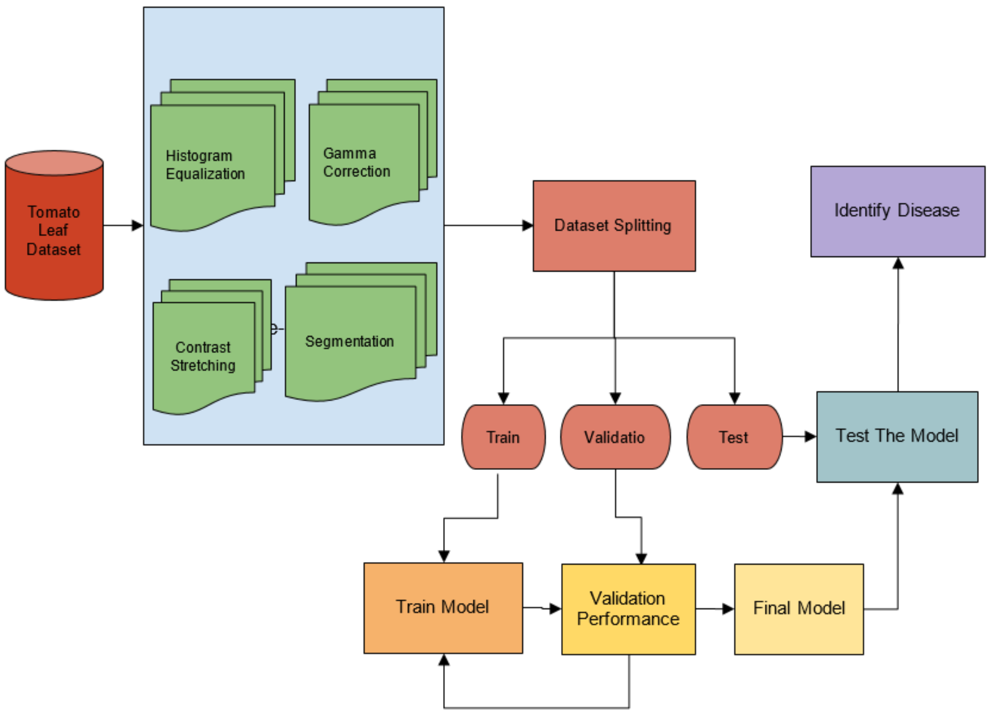

Figure 1. Methodology flow diagram

2.1. Dataset description

We are working on the tomato leaf disease dataset, which was collected from agricultural fields of Bangladesh by our research team. The dataset consists of 370 pieces of images, which hold the common disease images of black mold, gray mold, powdery mildew, and healthy as well. Here we have 133 images for the healthy class. Black mold, gray mold, and powdery mildew contain 60, 56, and 131, respectively. This dataset was validated and classified by the Sub Assistant Agricultural officer, Department of agricultural expansion, people republic of Bangladesh. Figure 2 usually represents the sample image of all classes.

Figure 2. Sample dataset of each class

2.2. Data preprocessing

To enhance the number of photos for each condition, we processed the data set using data augmentation techniques such rescaling, shifting, rotating, and horizontal flipping.

a. Resizing: Since we were collecting data from agricultural fields, the size of the images is not equal. We resize all the images into 224×224×3 pixels.
b. Histogram equalization: An image's contrast and brightness can be improved using the digital image processing technique known as histogram equalization. It works by distributing pixel intensity levels throughout the entire range of the image [17]. As a result, low-contrast areas become easier to detect, and the overall appearance of the image improves visually [17]. It can alter the appearance of the photos in our dataset by emphasizing the dark and light areas, which is advantageous for enhancing the visibility of specific details or characteristics in low-contrast images. Figure 3 shows the after and before effect of histogram equalization.
c. Gamma correction: Gamma correction is a digital image processing technique that changes the intensity values to change an image's brightness and contrast. In order to account for variations in the way monitors display light, it performs a nonlinear operation on the pixel values. It can improve the aesthetic appeal of the pictures in our collection by adjusting their brightness and contrast, and it is also frequently used to adjust pictures that seem excessively bright or dark [18]. Figure 4 shows the after and before condition of gamma correction.
d. Contrast stretching: Contrast stretching expands an image's intensity range to improve detail visibility. Linearly expanding intensity values to span the entire range is typical in 8-bit grayscale images. Contrast increases as dark areas darken and bright areas brighten. Contrast stretching can improve Our dataset photographs, especially those with low contrast due to inadequate lighting [18]. Figure 5 shows the after and before condition of contrast stretching.
e. Augmentation: In this work we have used rotation, width shifting, height shifting, shearing, zoom, horizontal flip techniques for image augmentation. Table 2 shows the number of images after augmentation.
f. Splitting: Total images are splitted into such a distribution, 80% for train purpose and 10% used for testing and other 10% for data validation.

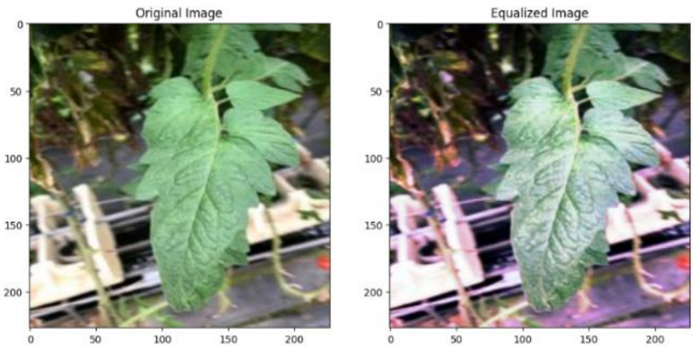

Figure 3. After histogram equalization effect

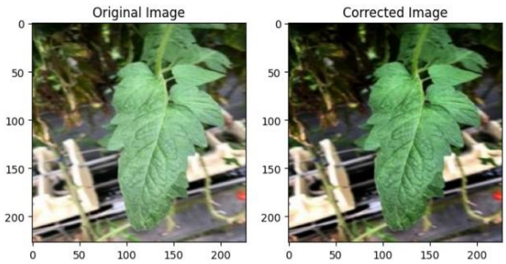

Figure 4. After Gamma correction effect

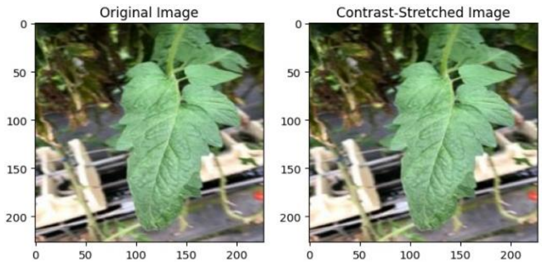

Figure 5. After contrast stretching effect

Table 2. Dataset overview according to each class

Plant Species	Class Name	Total Images	Augmented Images
Tomato	Healthy	133	1,087
	Black mold	50	410
	Gray mold	56	488
	Powdery mildew	131	1,121

2.3. Image verification techniques

Image verification methods verify an image's authenticity, integrity, or qualities. In many fields, these methods are essential for ensuring that photographs have not been manipulated or misrepresented. Image processing uses objective quality assessment extensively. Statistics including structure similarity index metric (SSIM), peak signal-to-noise ratio (PSNR), mean squared error (MSE), root mean squared error (RMSE), and parameters of frequency like spectral phase and magnitude distortions are included [19]. Table 3 shows all 10 randomly picked photographs' exceptionally happy scores. This shows how verification scores increase research quality.

Table 3. Image verification scores

Image	SSIM	PSNR	RMSE	MSE
Range	(-1 to 1)	(0 to 30)	(0 to ∞)	(0 to ∞)
Preferred Range	Close to 1	20 to 30	Close to 0	Close to 0
Image 1.	0.74	28.09	41.61	1731.81
Image 2.	0.78	28.11	34.89	1217.35
Image 3.	0.77	27.95	36.10	1303.13
Image 4.	0.82	27.98	28.58	816.64
Image 5.	0.80	27.81	31.04	963.20
Image 6.	0.84	28.21	30.65	939.12
Image 7.	0.83	27.91	33.21	1102.94
Image 8.	0.76	27.94	36.42	1326.22
Image 9.	0.75	28.23	35.86	1286.21
Image 10.	0.72	27.96	41.54	1725.87

2.4. Model implementation

In order to get an exceptional outcome, we attempt to apply multiple advanced deep learning models in this study. Our top four implemented models that are the subject of this study are presented in this post, and we go on to explain the evaluation of each model using a variety of matrices and visualizations. A synopsis of the model is provided below.

a. VGG16: Convolutional neural networks of Visual Geometry Group 16 are used for image classification. It is among the most popular techniques for extracting visual features [18]. The designation "16" alludes to the network's weight tiers. VGG16, a deep and uniform convolutional structure, excels at picture classification and recognition because to its simplicity. There are three fully linked layers and thirteen convolutional layers in the design. Max-pooling employs 2x2 filters, and convolutional layers use tiny 3×3 filters with a stride of one.
b. AlexNet: AlexNet is a revolutionary image classification CNN. It has five convolutional and three fully linked layers. AlexNet, known for using ReLU and other methods, pioneered deep learning for computer vision tasks. CNN-abstracted features offer stronger differentiation and more semantic information than artificial features, according to research using the first full connection layer of AlexNet as picture features [20].

c. InceptionV3: Google created InceptionV3 for image classification and object recognition. Transfer learning in InceptionV3, an upgraded GoogLeNet architecture, improves biomedical categorization [20]. Inception proposes a model with several convolutional filters of different sizes [21]. InceptionV3 excels at picture categorization and object detection with batch normalization, factorized convolutions, and efficiency.
d. DenseNet-121: A DenseNets convolutional neural network structure is called DenseNet-121. DenseNets' convolutional, pooling, and fully connected layers get direct input from every layer that came before them, producing highly connected feature maps [22]. Based on its 121 layers, DenseNet-121 improves training efficiency and feature reuse.

3. RESULT AND DISCUSIION

Using our core dataset, we were able to achieve highly satisfactory results in our research. It is quite well reflected in several outcome discussion dimensions. The different matrix and analytical results presented here, each with its own section, provide the proof of our achieved outcome.

3.1. Performance measurement metrics

Our evaluation considered essential metrics such as precision, recall, specificity, and F1-score [23]. These metrics provide a comprehensive assessment of the models' performance in diagnosing tomato leaf diseases, offering valuable insights for practical agricultural applications [24].

a. Accuracy

$$\text{Accuracy} = \frac{TP + TN}{TP + TN + FP + FN} \quad (1)$$

b. The Jaccard score

$$\text{Jaccard Score} = \frac{I\ A\ U\ B\ I}{I\ \ A\ U\ B\ I} \quad (2)$$

c. Precision

$$\text{Precision} = \frac{TP}{TP + FP} \quad (3)$$

d. Recall

$$\text{Recall} = \frac{TP}{TP + FN} \quad (4)$$

Here, TP, TN, FP, and FN are in full form, respectively: true positive, true negative, false positive, and false negative. False positive, false negative [25], [26].

e. The F1-score

$$\text{F1-score} = \frac{2 * Precision * Recall}{Precision + Recall} \quad (5)$$

The models we used on the tomato leaf disease dataset, considering all the measurement metrics for each model, are given next sections.

3.2. Result discussion of preprocessed dataset:

The analysis of tomato leaf disease detection algorithms reveals varying performance. InceptionV3 leads with the highest accuracy 96.63%, precision of 0.81, Recall 0.78, F1-score 0.80, Jaccard score 76.33%, and AUC 0.68. DenseNet-121 follows closely, with 96.67% accuracy and a notable AUC score of 71.73%. VGG16 performs well with 86.67% accuracy but exhibits a lower AUC score of 61.20. Surprisingly, AlexNet lags with 83.30% accuracy and the lowest precision, 0.63, and F1-score of 0.57. These results suggest InceptionV3 and DenseNet-121 as robust choices, while VGG16 and AlexNet may benefit from further optimization for this specific tomato leaf disease dataset. In Table 4 we can see the visualization of all performance measurement metrics. Table 4 displays the results of multiple measurement matrices and provides an excellent visual representation of the dataset's stability when using various models or algorithms. Issues with models' fit, such as being too tight or too loose, are almost nonexistent. The model accuracy in this preprocessed data is quite satisfying, and the other measurement issues are close to reality. Based on the comparison with the prior work, as shown in Table 1, no reliable reference can match the accuracy of our dataset and model. We use many models and validated data from expert feedback to provide an AUC value, recall, F1-score, and healthy precision.

Table 4. Image measurement methods

Models	Accuracy	Precision	Recall	F1-score	Jaccard	AUC
VGG16	86.67%	0.75	0.73	0.80	0.64	0.61
InceptionV3	96.63%	0.81	0.78	0.80	0.76	0.68
DenseNet121	96.67%	0.81	0.78	0.84	0.78	0.72
AlexNet	83.30%	0.63	0.57	0.57	0.52	0.50

3.3. Confusion matrix

It is more evident from Figure 6 that the outcome discussed in Table 4 is quite satisfactory. DenseNet121 and InceptionV3's confusion matrices provide a closer look at each class's true positive and true negative values. Figure 6 (a)-(d) represents all the applied model's confusion matrix and it provides the strong reference of our achieved results. In terms of tomato leaf identification, the under fitting and overfitting issues are extremely small and not very significant.

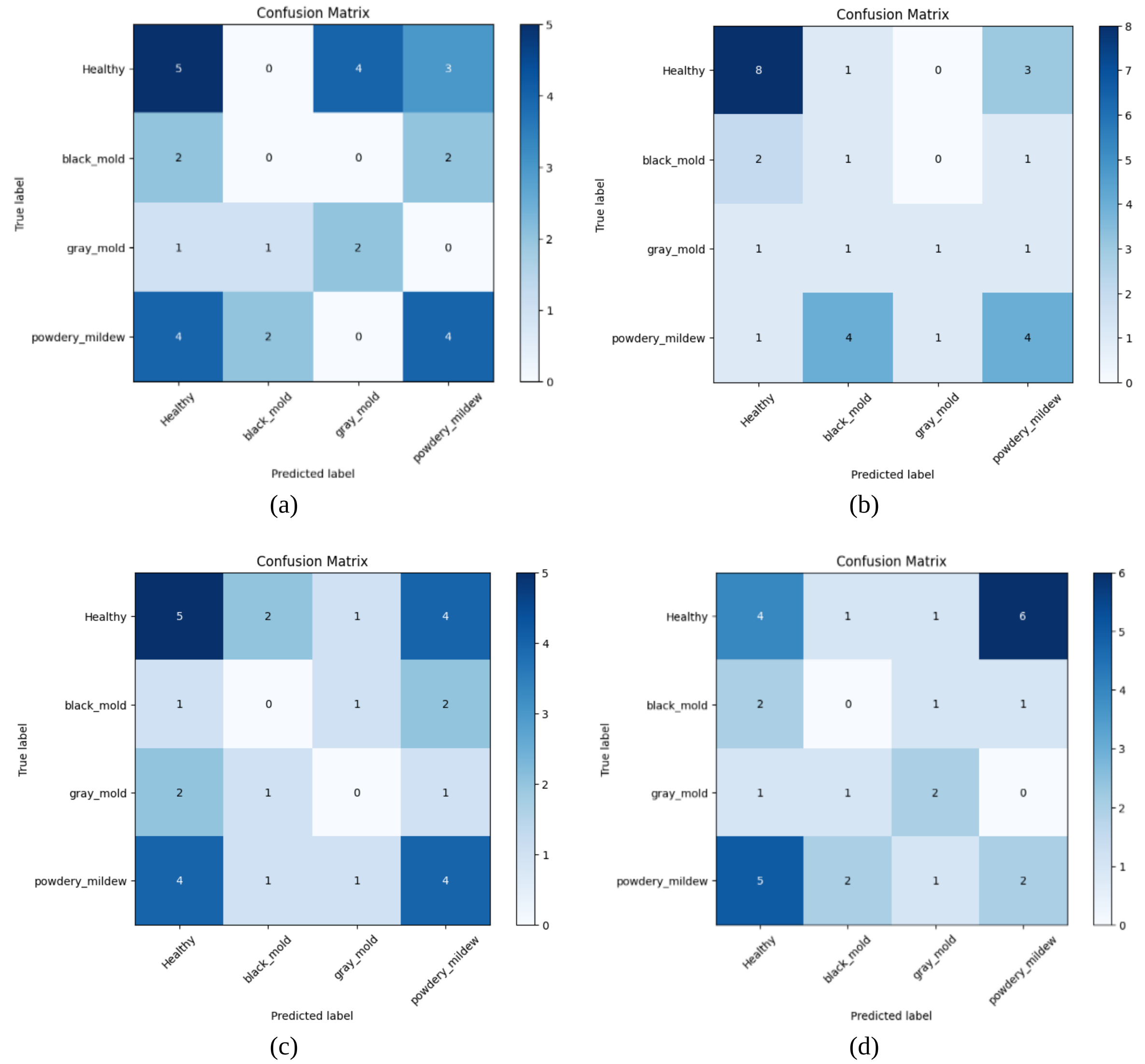

Figure 6. Confusion matrix of (a) VGG16, (b) InceptionV3, (c) DenseNet121, and (d) AlexNet

The VGG16 model's confusion matrix is shown in Figure 6(a), where the true positive value for the four classes is clearly displayed. For the black mold class, the true positive value is very low, and for the powdery mildew class, both the true negative value and the true positive value are satisfied, but the false positive rate is a little problematic. However, there is a minor issue with the Figure 6(b) InceptionV3 confusion matrix, which shows a low percentage of false positive and negative results. Finally, it is discovered that Figure 6(c) DenseNet 121, confusion matrix, is highly satisfying on TP and TN. Figure 6(d) is the AlexNet confusion matrix, which is likewise quite comparable to Figures 6(b) and 6(c), but a little bit farther away. Considering the Black_mold data in the second class is somewhat weaker than that of the others, there is a significant class variation for various models. However, compared to raw data, our preprocessing technique has very high accuracy and lowers the false-positive rate.

3.4. ROC curve

According to the true positive rate (TPR) and false positive rate (FPR), which are displayed on the ROC curve of every applied model in Figure 7, this may be achieved for the most part of the time, with the exception of instances in which the FP rate becomes excessive because of data violations and noise [27]. However, the confusion matrix scenario and high level of satisfaction in InceptionV3 are both present. Therefore, the ROC curve in Figure 7(a)-(d) provides a more significant and transparent result analysis.

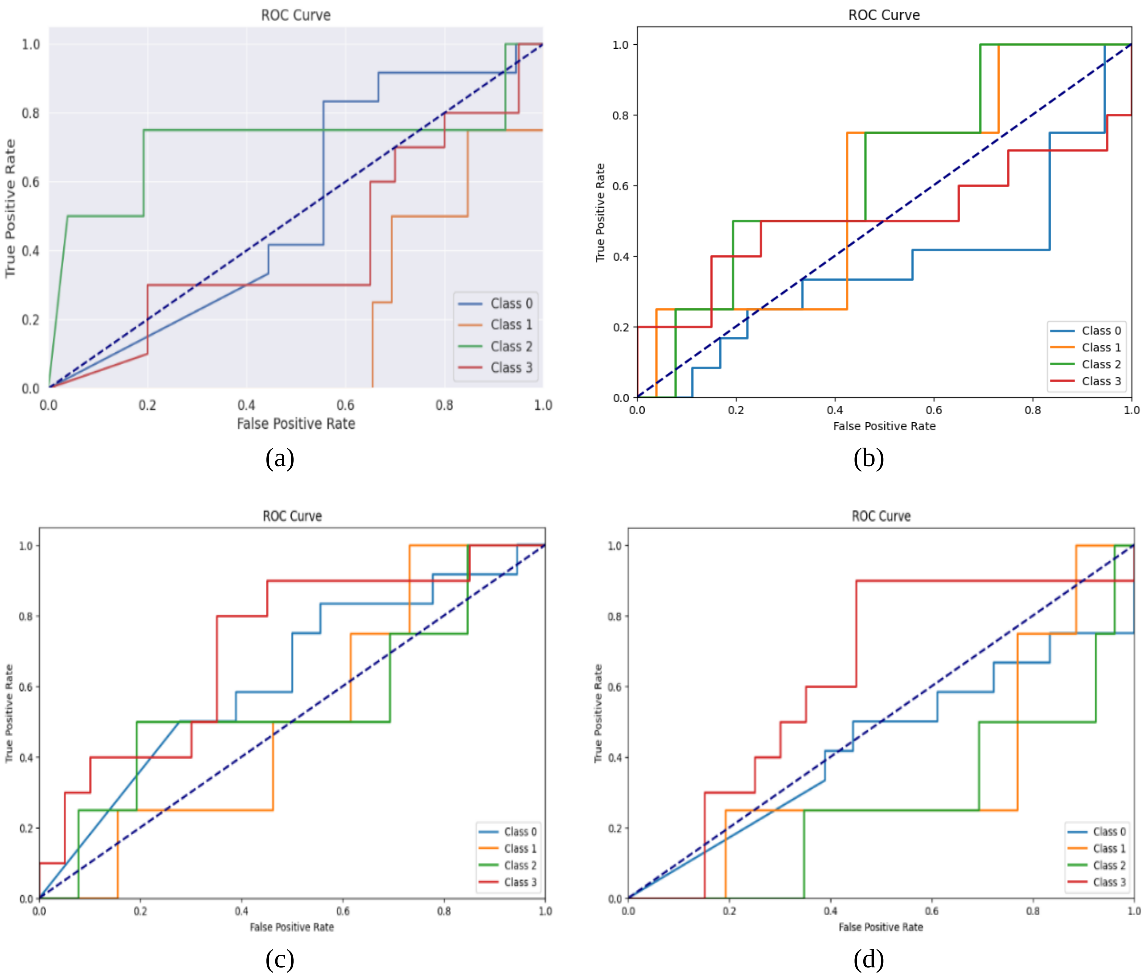

Figure 7. ROC curve of (a) VGG16, (b) InceptionV3, (c) DenseNet121, and (d) AlexNet

The ROC curve of VGG 16 is shown in Figure 7(a). From this graph, we can observe that class 1 falls under the diagonal line from the start, while other classes improve after a certain amount of time. The diagonal line in this graph actually represents no skill. In InceptionV3's ROC, Figure 7(b), we can observe that while class 0 has a few sporadic problems, other classes function admirably and receive positive evaluations from their assessments. Our best accuracy on the DenseNet 121 model is shown here, where we can observe that occasionally, particularly between 0.2 and 0.5, two classes are below the diagonal line; however, from the first to the last epoch, we consistently obtain an excellent AUC value from the curve. Figure 7(c) provides a satisfactory summary and shows the ROC of DensNet121 at the standard level for all classes. The ROC curve for the AlexNet model in Figure 7(d) is a little less accurate because the next three classes fall within the diagonal line. However, the greatest AUC value of 71.63% in DenseNet 121 is obtained by measurement, indicating a very healthy and gratifying accuracy value for the classification of tomato leaf disease.

3.5. Result discussion of raw dataset

After performing the same models on the raw dataset without any kind of preprocessing, just resizing the images in a 224*224 shape, the resultant values are given in Table 5, where InceptionV3 performed one of the best both in raw and preprocessed dataset models. However, VGG16 performed the best on raw dataset with 83.33% accuracy, whereas AlexNet and DenseNet-121 are at 63.89% and 69.88%, respectively.

The true representation of the raw data's measurement matrix is found in Table 5. The accuracy achieved after reshaping is slightly higher on the VGG16 but much lower on the other models. The other matrix, which has very low precision and AUC values, causes underfit problems in every model for every class. Thus, we may conclude that our preprocessing method is quite beneficial for this important issue.

Table 5. Image measurement methods on raw dataset

Models	Accuracy	Precision	Recall	F1-score	Jaccard	AUC
VGG16	83.33%	0.40	0.42	0.40	0.13	0.44
Inception V3	80.56%	0.43	0.39	0.35	0.16	0.57
DenseNet121	69.88%	0.35	0.33	0.28	0.20	0.62
AlexNet	63.89%	0.28	0.39	0.32	0.41	0.49

4. CONCLUSION

On the tomato leaf disease dataset, VGG16, InceptionV3, AlexNet, and DenseNet-121 were tested. DenseNet-121 and InceptionV3 performed well, whereas VGG16 and AlexNet were less accurate. Our dataset can influence this field of study, and our data pretreatment methods and raw-treated data comparison can solidify it. Automated leaf disease recognition will aid tomato farmers considerably. We try to close the research gap using previous researchers' analyses. We can detect and verify our pleased data collection. With such research and innovation, we can create advance scientific agriculture. This study can serve as the foundation for the identification of tomato leaf diseases. In a large area, more and more leaf diseases can be added to different areas that are smooth and covered. It should be noted that, owing to a lack of resources, our original data was extremely noisy and unbalanced. However, our normalization and pre-processing techniques were transformed into a healthy dataset that is useful for the agriculture sector. Identification of crop leaf diseases through automation using machine learning will be greatly enhanced, and it will be useful in the community for identifying many other crop diseases in addition to tomato leaf disease. For root-level users who are directly involved in maintaining this system, an expanded version of the program or mobile application may include a hybrid automated detection tool. We can promise that in the future, ideological problems in contemporary research will be raised by using larger datasets to discover various crop leaf diseases in a single frame.

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