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(Review Article)

A novel approach for detecting Pomegranate leaf pathologies using deep learning

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Abstract

Pomegranate cultivation is essential for ensuring global food security, yet it faces significant threats from diseases. This has resulted in significant losses of yield. Integrated disease management strategies are therefore crucial for addressing this problem and include cultural practices, disease resistant varieties and timely application of fungicides. Artificial intelligence (AI), primarily deep learning, has recently made great strides that can help change the landscape on how agricultural diseases are diagnosed. In this study, therefore, we will develop a highly accurate and efficient system for early detection of diseases in pomegranate crops using deep learning algorithms. Using convolutional neural networks (CNNs) along with transfer learning coupled with data augmentation techniques such as rotation, flipping and scaling automate the identification and classification of disorders related to leaves growing on pomegranate plants. Rigorous experimentation and evaluation using performance metrics like accuracy, precision, recall, and F1 score demonstrate the efficacy of the CNN models. The underlying theory behind this is that AI technologies would be able to successfully detect all BLB diseases associated with pomegranates at an accuracy rate of 96.33 percent using Inception v3 CNN model. These results point out that AI technology changes everything about dealing with crop diseases in agriculture while also emphasizing its importance towards global food security efforts. This study not only presents a novel approach to disease detection but also provides practical solutions for farmers to mitigate crop losses and improve yield quality, promoting more sustainable and resilient farming.

Keywords: Pomegranate disease detection; Convolutional neural networks (CNN); Deep learning; BLB; Machine learning

1. Introduction

Pomegranate farming is crucial to ensure food security across the globe, but it is confronted with significant challenges from diseases like Bacterial Leaf Blight (BLB) that lead to a substantial reduction in yield. Integrated disease management approaches are important and should encompass cultural practices, use of resistant cultivars and pests and diseases control through a mix of biological, cultural and chemical methods. These include strategic watering and good crop hygiene. A robust disease control plan is needed which includes appropriate seed and soil treatment measures to prevent diseases while maintaining pomegranate quality. In storage management, there are post-harvest options such as optimal temperature regulation, maintenance of airflow and application of fungicides that help in controlling diseases effectively [1].

In summary, preventative measures such as seed treatments, soil treatments, integrated pest management (IPM), and proper storage management are vital in combating pomegranate diseases threatening production and promoting sustainable farming. There are promising paths that may aid in revolutionizing disease recognition in agriculture using artificial intelligence (AI) technologies with deep learning being the most mentioned one. In this regard, automating the identification and classification of plant diseases has been achieved through convolutional neural networks (CNNs) developed by researchers from visual symptoms [1]. With these developments speeding up diagnosis process, it will be

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easier to detect diseases early enough when their infestation can lead to huge losses on crop productivity. A major contribution to more efficient control of agricultural diseases is thus made by them.

This study seeks to contribute in the ongoing improvement of agricultural practices by using AI and deep learning techniques. We aim to develop a highly precise, effective system that can detect plant diseases early which will reduce their detrimental impacts on pomegranate crop yield by employing deep learning, transfer learning and data augmentation methods. These findings demonstrate the potential of AI based approaches for providing farmers with proactive disease management tools which in turn can improve food security and make sustainable development in pomegranate production worldwide[19].

Integrating AI technology is very promising for addressing plant diseases challenges in agriculture. Researchers and stakeholders in agriculture can create better systems for detecting diseases through the use of deep learning processes. This would eventually save crop yields while ensuring food security remains intact." Employing advanced NN architectures as well as optimization procedures is known to significantly boost accuracy and reliability associated with disease identification process [19]. Ongoing research and innovation are needed to fine tune these AI-driven solutions so they can be accepted widely thereby benefiting farmers as well as global foods systems.

2. Methodology

1 The methodology for developing the CNN model involves outlining its architecture, training process, experimental setup, and dataset preparation. Additionally, the process of adding augmented photos to the training set is explained, using methods with defined parameters including rotation, flipping, zooming, and rescaling[3]. The dataset is split into an 80:20 train-test ratio, with further details provided in table: 1 of the proposed dataset. To categorize illnesses in pomegranate leaves, automated feature extraction using deep CNNs and preprocessing of collected images are employed. Dataset images are selected from public databases like Plant Village, Kaggle, and Mendeley based on intensity color changes and differences in leaf form and size[8]. Transfer learning with pre-trained models like VGG16, VGG19, Inception v3, and MobileNet is utilized. A generalized overview depicted in fig:work flow illustrates the classification of pomegranate plant leaf disease using transfer learning with a dataset from a public database. Challenges in the literature, such as incorrect identification and variation in diseases, are addressed by the multi-level deep learning model, utilizing YOLOv5 image segmentation and a novel pomegranate leaf disease detection convolutional neural network for accurate detection of BLB diseases[10].

3. Dataset collection

The dataset used in this study is made up of high-resolution photos from Kaggle that show pomegranate leaves afflicted with BLB illness as well as images of healthy leaves. The dataset contains a total of 549 images. BLB disease symptoms include small, dark spots on leaves, whereas healthy instances show no abnormalities. Each image underwent thorough examination, with only those devoid of deformities considered healthy[3]. Selection criteria included visible BLB symptoms for diseased cases and a normal appearance for healthy leaves. These images were annotated to denote the presence or absence of pomegranate BLB disease, categorized as diseased or healthy, respectively. Additionally, 549 pomegranate leaf images from the Plant Village dataset, comprising three categories, were analyzed. The dataset was divided into training and testing sets in an 80:20 ratio for training and validation, respectively[2]. Image dimensions were resized to 256 x 256 x 3 pixels to ensure compatibility with the CNN model and enable computationally feasible training.

4. Data pre-processing

In this study, the dataset utilized comprises highresolution images of pomegranate leaves affected by BLB disease ,additionally images of healthy pomegranate leaves, sourced from Kaggle. These dataset contains a total of 549 images. BLB disease symptoms include small, dark spots on leaves, whereas healthy instances show no abnormalities. Each image underwent thorough examination, with only those devoid of deformities considered healthy. Selection criteria included visible BLB symptoms for diseased cases and a normal appearance for healthy leaves[14]. These images were annotated to denote the presence or absence of pomegranate BLB disease, categorized as diseased or healthy, respectively. Additionally, 549 pomegranate leaf images from the Plant Village dataset, comprising three categories, were analyzed. The dataset was divided into training and testing sets in an 80:20 ratio for training and validation, respectively. Image dimensions were resized to 256 x 256 x 3 pixels to ensure compatibility with the CNN model and enable computationally feasible training.

In addressing the presence of noise in contaminated plant leaf images, various image pre-processing methods are employed to enhance training accuracy performance. One such technique involves image clipping, where the leaf image is cropped to isolate the area of interest, thus removing extraneous elements such as leaf sand or dust. Additionally, smoothing filters are applied to achieve image smoothing, further refining the visual clarity of the leaf image. In image processing, techniques like ZCA whitening, standardized rotation, and translation are utilized for data augmentation, aiding in the augmentation of the dataset and improving the model's ability to generalize patterns effectively. These preprocessing methods collectively contribute to optimizing the quality and usability of the dataset for training deep learning models, ultimately enhancing the accuracy and reliability of disease detection algorithms applied to plant leaves.

5. Image segmentation

Image segmentation is a fundamental technique for classifying each pixel in an image into specific classes. Given the diverse sizes of pomegranate plant leaves, effectively locating and segmenting the image is crucial for improving the identification of pomegranate diseases by reducing background interference and focusing on the regions of interest for feature extraction by models such as Inception v3. This segmentation technique is achieved based on various intensity discontinuities and similarities among pixels[2]. Image segmentation involves partitioning the image into various parts, converting RGB images to the HIS model to segment out the desired regions of interest. This segmentation approach aids in enhancing the accuracy of disease detection by isolating relevant features within the pomegranate leaf images. Accurate segmentation of these regions facilitates improved identification and classification of pomegranate leaf diseases, ultimately contributing to more precise disease detection and diagnosis[19].

6. Classification

In the classification phase, Convolutional Neural Networks are employed to categorize images into different categories. The CNN model architecture includes convolutional layers followed by pooling layers, which extract features from images through a hierarchical process[9]. The model's convolutional layers learn various features, while the pooling layers reduce the spatial dimensions and retain important information. The final classification is achieved through fully connected layers that aggregate the extracted features and perform the categorization based on learned patterns. By applying CNNs, complex patterns in the image data are detected and classified. The model's ability to recognize and distinguish between different classes, such as diseased and healthy pomegranate leaves, is enhanced through the training process[8]. CNNs are well-suited for detection of plant disease due to their capacity to learn and generalize from diverse input data, making them effective for tasks involving image classification in agriculture.

Table 1 Details of the proposed dataset

Dataset	BLB	Healthy	Total
Train	210	230	440
Test	52	57	109

7. Feature extraction using the proposed CNN model

Feature extraction plays a important role in object recognition and classification, particularly in digital image analysis. It involves extracting pertinent features from images crucial for distinguishing between different classes of objects while maintaining consistency within the similar class. This process serves as a vital dimensionality reduction step, essential for efficient pattern recognition and machine learning. In the specific domain of identifying pomegranate leaf diseases, deep learning techniques, notably Convolutional Neural Networks, are utilized for feature extraction from acquired images[17]. By automatically extracting deep characteristics from these images, CNNs facilitate the classification of the images into predefined classes such diseased (BLB) and healthy leaves. CNNs, inspired by biological models of human vision, operate through multiple layers that mimic the human visual system's processing hierarchy, capturing spatial and temporal dependencies within images by applying filters across different layers. Feature extraction with CNNs condenses the image representation, requiring fewer computations while preserving essential features for accurate prediction. The CNN architecture comprises several layers, including convolutional layers, ReLU layers, pooling layers, dropout layers, and fully connected layers. In this study, a hierarchical structure of feature maps is constructed by consecutively applying learnable filters to the input image[17]. The initial convolutional layer captures lowlevel features such as edges, corners, texture, and lines, while subsequent layers extract higher-level features based on more complex characteristics, aiding in the identification of objects and structures within the image. To optimize the CNN model for feature extraction, three convolutional layers were employed to ensure the capture of both low-level and high-level features relevant to pomegranate leaf disease classification, ultimately leading to the highest accuracy in the experiment. Additionally, before feature extraction, pre-processing techniques such as standardization, thresholding, and binarization were applied to digital images. These techniques help enhance the standard of the images and improve the extraction of meaningful patterns. The extracted patterns are then utilized to form feature vectors, which aid in the recognition and categorization of objects during the classification process. In this study, feature extraction was specifically performed using the inception-v3 model, a widely used architecture known for its effectiveness in image classification tasks. Leveraging the inception-v3 model further enhances the efficacy of the classification process, enabling the accurate identification of pomegranate leaf diseases based on the extracted features[17].

8. Model training

After the CNN network architecture was utilized to extract the features from input images, the CNN model underwent training using a set of labeled training images. Subsequently, the classification process categorized the data into the desired categories using the retrieved features[13].

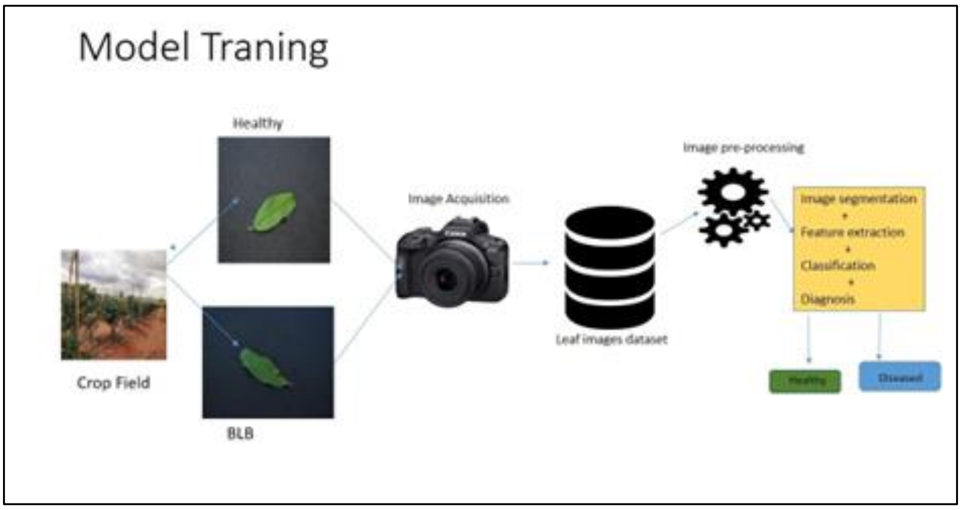

Figure 1 Architecture used in the Study

8.1. Softmax

The Softmax classifier is utilized to determine the probability distribution of an image belonging to a specific class. The Softmax function outputs values between 0 and 1, representing the likelihood of each class. In this study, the Softmax classifier is used to categorize pomegranate leaf images into either diseased or healthy classes. The CNN model's output is processed throughthe Softmax functionality to generate class probabilities, with the highest performance indicatingThe expected class. The model is initialized with pre-trained weights from the Inception v3 model and optimized using the Adam algorithm to improve its classification performance.

9. Optimization algorithms

The Adam optimization technique is employed to optimize the model by minimizing the error rate. Adam calculates adaptive learning rates for each parameter by combining the benefits of both the AdaGrad and RMSProp algorithms. This technique adjusts the learning rates dynamically based on the gradients' moments, enhancing the model's convergence and performance[15]. Adam's adaptive learning rate approach allows for more efficient training and better generalization of the CNN model. By utilizing Adam optimization, the model's weight updates are improved, leading to a more precise and reliable classification of pomegranate leaf diseases.

10. Learning rate (LR)

A learning rate of 0.001 was chosen for the optimization process based on experimental evaluations. Although a lower learning rate results in longer training times, it yields improved performance and accuracy. The selected LR of 0.001 ensures effective weight updates and enhances the model's ability to generalize from the practice data. By optimizing the learning rate, the model achieves better performance in classifying pomegranate leaf diseases and accurately detecting BLB disease in plant images.

11. Model evaluation

Evaluated the trained model from the testing set to assess its performance. Evaluation metrics such as precision, accuracy,f1 score and recall to calculate the model's effectiveness in detecting BEL disease were estimated. Confusion matrix was generated to analyse the model's performance in terms of true positives, true negatives, false positives, and false negatives.

Accuracy is the ratio of correctly classified samples to the total number of samples, providing an overall measure of classification performance. It is suitable when observations for each class are balanced. Mathematically, accuracy (per cent) is measured as:

$$Accuracy(\%) = \frac{TP + TN}{TP + FP + TN + FN} \times 100$$

Precision measures the quantity of true positives among Every sample was considered positive, offering insights into the classifier's ability to correctly determine each class. Precision (per cent) is computed as:

$$Precision(\%) = \frac{TP}{TP + FP} \times 100$$

Recall indicates the ability to identify all similar instances in dataset and avoid false negatives. It evaluates the classifier's performance in representing all positive instances. Recall (per cent) is expressed as:

$$Recall(\%) = \frac{TP}{TP + FN} \times 100$$

The F1 Score is a statistic that evaluates the classifier’s overall performance by taking the harmonic mean of precision and recall. It is often applied to jobs involving binary categorisation but can be extended to multi-class scenarios. F1 Score (per cent) is measured as:

$$F1Score(\%) = \frac{2 \times (Precision \times Recall)}{Precision + Recall} \times 100$$

Where
· True Positive : Number of samples correctly identified as Healthy.
· False Positive : Number of samples incorrectly identified as Healthy.
· True Negative : Number of samples correctly identified as diseased.
· False Negative : Number of samples incorrectly identified as diseased.

Table 2 Summary of hyperparameters used for model training

Parameter	**Values**
Epoch	100
Batch Size	32
Activation Function	SoftMax
Loss Function	Categorical Cross-Entropy
Optimization Algorithm	Adam
Learning Rate	0.001

12. Results and discussion

Results and Discussion All of the details of the experiment including the outcomes of each experiment and the discussions of these results are described in this section. The experimental results are presented in the form of figures and tables.

Figure 2 Prediction accuracy of the model

13. Experimental setting

In the classification of pomegranate BLB, the experimental setup involved utilizing Python as the programming language and Anaconda Jupyter notebook as the primary tool for code development. The model has been trained with specific hyperparameters: the loss function was defined as categorical crossentropy, and the Adam optimizer was employed in a learning rate set of 0.001.There were 32 batches and 100 epochs in the training procedure. The experimentation was conducted on a system integrated with HLBS Technologies for Future and utilising an x64-based processor and 64-bit Windows 10 operating system. The system utilized a 12th Gen Intel(R) Core (TM) i3-12700 processor operating at 2.10 GHz, with 8 GB RAM.

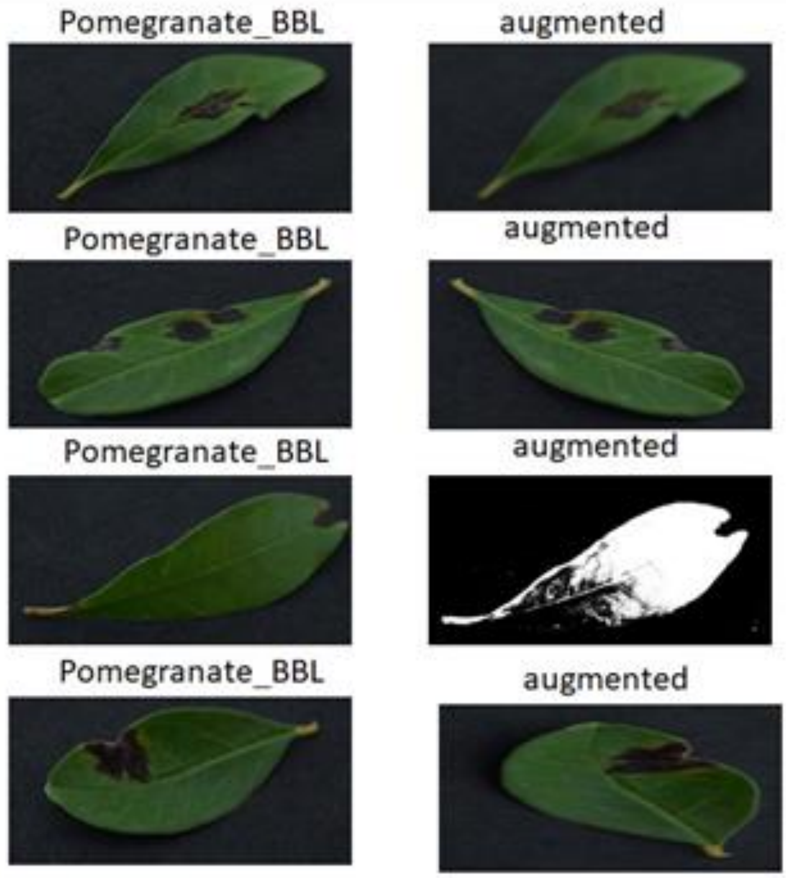

Figure 3 Prediction accuracy of the model

14. Experimental results

In this learn, our objective was to examine the accuracy of a Convolutional Neural Network classifier in distinguishing pomegranate BLB disease from images. The dataset consisted of sample images illustrating distinct symptoms of BLB. BLB symptoms included, dark spots on leaves. On the other way, ultimately resulting in BBL disease. Healthy instances displayed no visible abnormalities. To bolster the model's robustness, various techniques of data augmentation such as flipping, rotation, and zooming were implemented to the sample images from the dataset.

During CNN model training, several hyperparameters were fine-tuned, including 100 epochs,an activation function for SoftMax with a batch size of 32, Categorical Cross-Entropy loss function, Adam optimization algorithm, and at 0.001 the learning rate is set .illustrates the iterative reduction in both training and validation set losses as the model undergoes training. This reduction indicates the effective learning process of the model, gradually converging towards the global minima. By the 40th epoch, both validation and training losses had reached their minimum values, subsequently stabilizing around 0.2 by the 100th epoch.

We observe an upward trend in accuracy for both validation and the training sets over successive iterations. The peak accuracy was attained around the 40th epoch. However, beyond this point, a noticeable discrepancy in accuracy between validation and training curves emerged. While the training curve reached a peak accuracy of 90.00 percent by the 100th epoch, the validation curve peaked at the 50th epoch, consistently maintaining an accuracy exceeding 90.00 percent in subsequent iterations. Notably, our models demonstrated an accuracy 96.33 percent, correctly predicting BLB disease and identifying healthy pomegranate plants. This high level of accuracy underscores the efficiency of the CNN classifier in accurately diagnosing BLB disease from images, highlighting its potential as a valuable tool in managing agricultural diseases. By offering a graphical representation of the model's performance, confusion matrix is a particular table that makes it easier to evaluate if the model incorrectly labels one class as another. illustrates the CM comparing the true class against the predicted class in the split test group of images for pomegranate BLB disease. The calculated values describe the classification rate for individual classes, with higher color density signifying higher accuracy for the individual classes. The proposed dataset comprises a total of 549 pomegranate plant images, categorized into two classes: pomegranate BLB, pomegranate Healthy. In the training set, there are 210 images for pomegranate BLB, while pomegranate Healthy comprises 230 images. The set of test consists of 52 images for pomegranate BLB, while 57 images for pomegranate Healthy. This dataset ensures a balanced distribution of samples across the different classes, facilitating effective evaluation and training of ML models for the pomegranate disease classification task. Evaluation metrics such as recall, accuracy, precision, and F1 score of the developed model on the recognition of BLB disease were determined using the confusion matrix.The evaluation measures are shown in Table 3 for the developed BLB disease detection using CNN. It is evident from Table 3 that the developed model shows an Accuracy of 96.33 percent, Precision of 96.33 percent, Recall of 96.33 percent, and F1 Score of 96.33 percent.These measurements show the efficiency and dependability of the developed CNN model in accurately detecting and classifying pomegranate BLB disease.

Table 3 Model evaluation

Evaluation Metrics	Percent
Accuracy	96.33
Precision	96.33
Recall	96.33
F1 Score	96.33

Table 4 Performance comparison of different models for prediction of pomegranate BLB diseases

SL. NO	Model Name	Accuracy	Precision	Recall	F1 Score
1	VGG16	52.29	52.29	52.29	52.29
2	MobileNet	94.49	94.49	94.49	94.49
3	Inception V3	96.33	96.33	96.33	96.33
4	VGG19	52.29	52.29	52.29	52.29

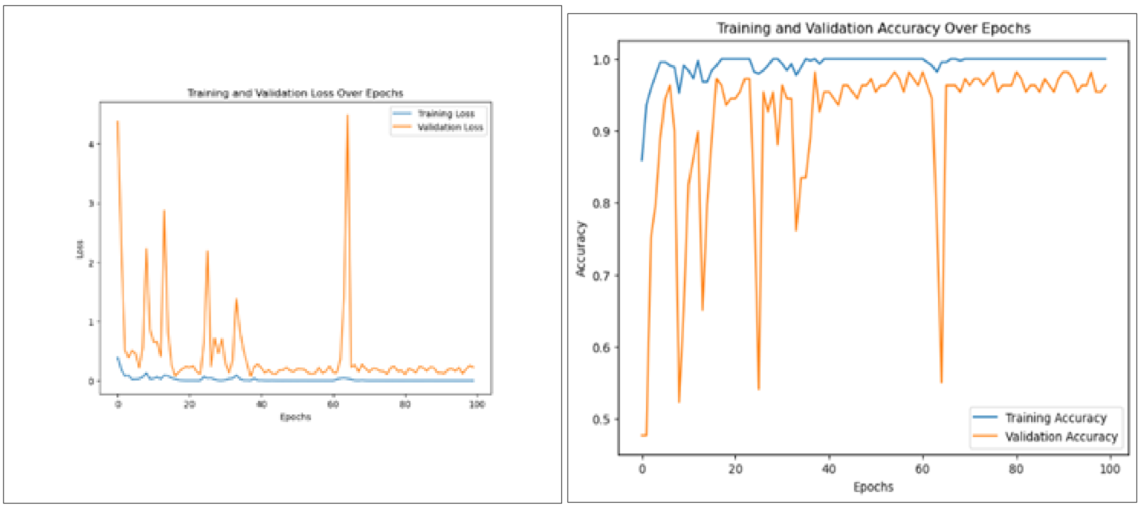

Figure 4 Model accuracy and loss curves

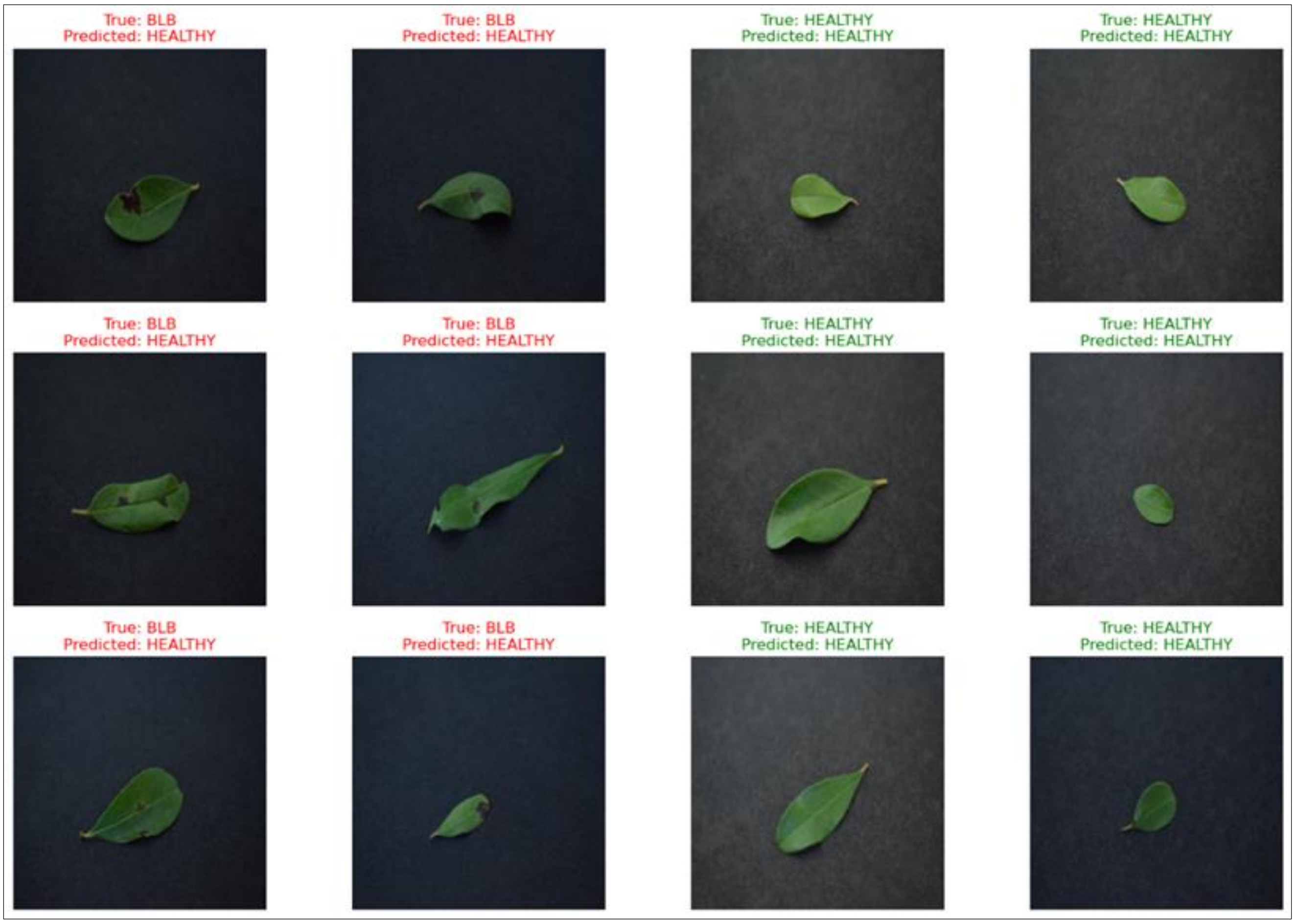

Figure 5 Prediction accuracy of the model

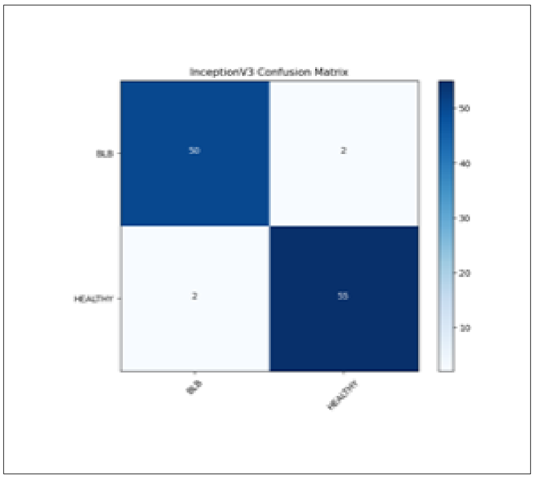

Figure 6 Confusion matrix for the Inception V3 model

15. Inception V3

Table 4 provides an overview of the performance metrics of various models utilized for predicting pomegranate BLB diseases. Among these models, the Inception V3 model achieved the highest F1 score, recall, precision, and accuracy, with values of 96.33 percent across all metrics. In comparison, other models such as VGG19 and VGG16 demonstrated lower performance, with accuracy scores of 52.29 percent. MobileNet exhibited comparatively better results, achieving accuracy scores 94.49 percent.These measurements provide information on the efficiency of different models in accurately classifying pomegranate diseases, highlighting the superiority of the InceptionV3 model in respect to overall classification performance. In a recent investigation conducted in 2024, a CNN demonstrated an impressive accuracy of 96.33 percent in classifying pomegranate BLB disease. This achievement highlights the CNN's effectiveness in distinguishing between healthy pomegranate leaves and those affected by the diseases.These results demonstrate the accuracy with which CNN can classify pomegranate disorders and the ongoing progress in disease detection techniques. Overall, the results from these studies collectively demonstrate the efficiency of CNNs in accurately classifying pomegranate diseases like BLB. Such advancements in machine learning techniques hold significant promise for improving the accuracy and efficiency of disease diagnosis in agriculture, leading to more effective disease management strategies.

16. Mobilenet

Convolutional neural networks like MobileNet are made specifically for embedded and mobile vision applications.Their foundation is a simplified architecture that builds lightweight deep neural networks with reduced latency for mobile and embedded devices using depthwise separable convolutions.

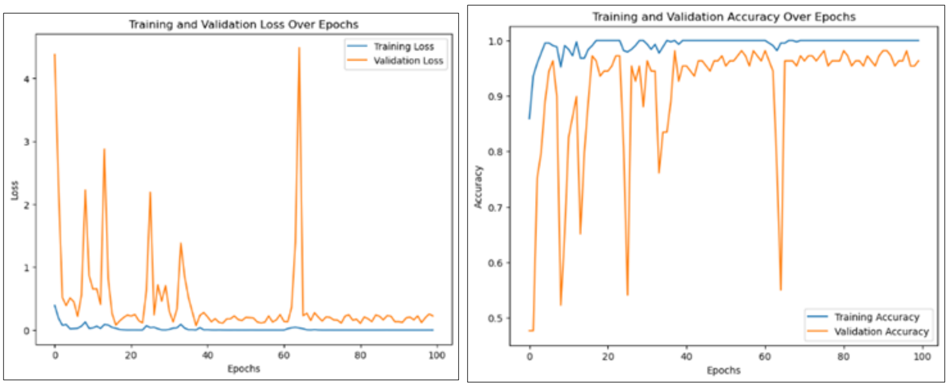

Figure 7 Model accuracy and loss curves

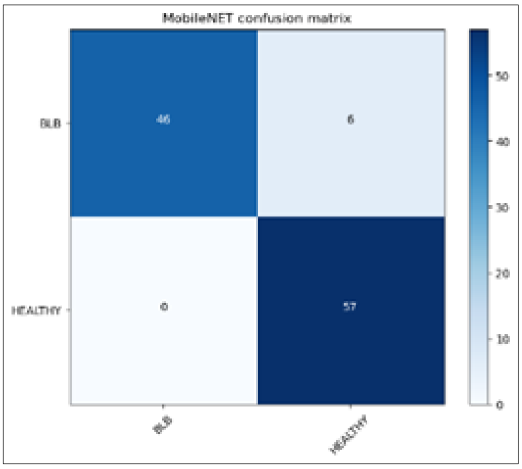

Figure 8 Confusion matrix for the Inception V3 model

17. VGG16

VGG16 is a convolutional neural network model that's used for image recognition. It's unique in that it has only 16 layers that have weights, as opposed to relying on a large number of hyper-parameters. It's considered oneof the best vision model architectures.

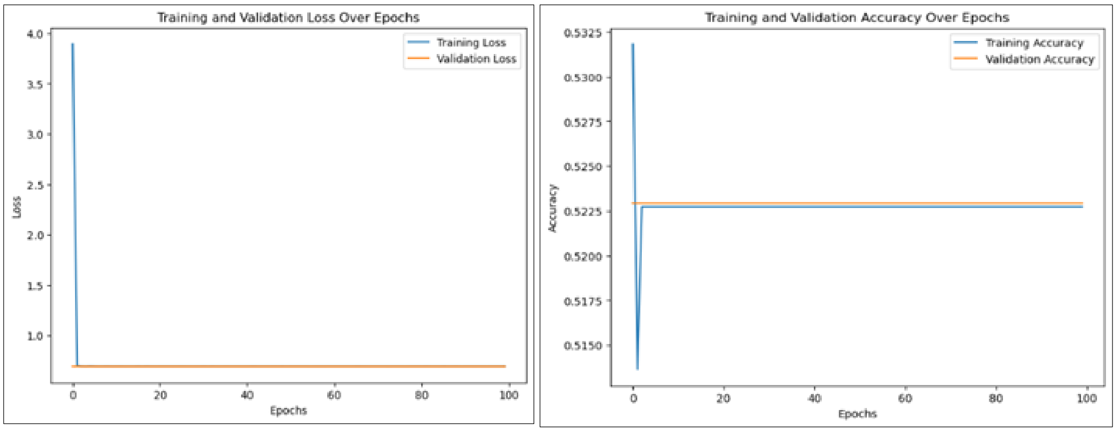

Figure 9 Model accuracy and loss curves

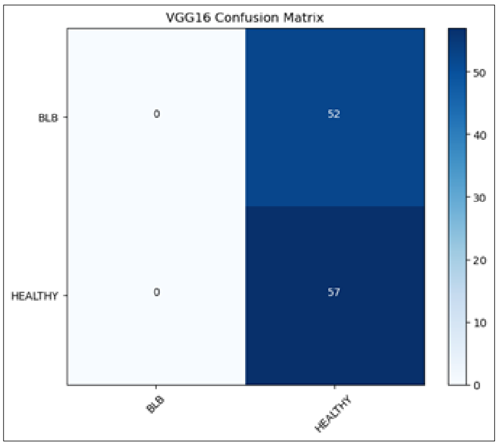

Figure 10 Confusion matrix for the Inception V3 model

18. VGG19

The VGG19 model (also known as VGGNet-19) has the same basic idea as the VGG16 model, with the exception that it supports 19 layers. The numbers “16” and “19” refer to the model’s weight layers (convolutional layers). In comparison to VGG16, VGG19 contains three extra convolutional layers.

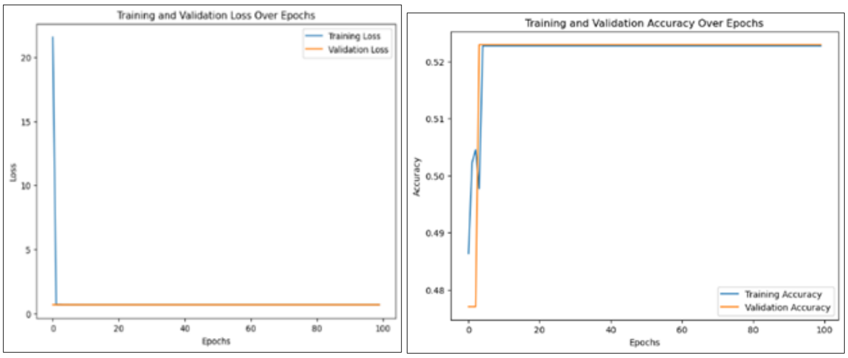

Figure 11 Model accuracy and loss curves

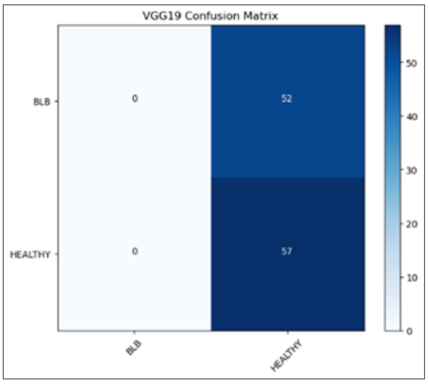

Figure 12 Confusion matrix for the Inception V3 model

19. Conclusion

This study demonstrates the transformative potential of Convolutional Neural Networks (CNNs) in the classification of pomegranate leaf diseases. Through the integration of data augmentation, deep learning techniques and transfer learning, our developed system showcases high accuracy and efficiency in early illness identification within pomegranate crops. With rigorous experimentation, With our Inception v3 model, we reached a remarkable accuracy of 96.33 percent in distinguishing between BLB diseases and healthy, with remarkable precision in identifying healthy leaves versus those affected. These results not only demonstrate CNN's efficacy in managing agricultural diseases but also highlight their wider applicability in tackling issues related to food security. Future studies need to concentrate on refining CNN models through transfer learning and the integration of additional data sources to enhance adaptability and precision in disease classification tasks. Ultimately, artificial intelligence is still developing, and this invention has great potential to improve global food security initiatives and transform agricultural diagnostics.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

References

[1] Afzaal H, Farooque AA, Schumann AW, et al. Detection of a Pomegranate Disease (Early Blight) Using Artificial Intelligence. *Remote Sens.* 2021;13:411.

[2] Barman U, Sahu D, Barman GG, Das J. Comparative assessment of deep learning to detect the leaf diseases of Pomegranate based on data augmentation. In: 2020 International Conference on Computational Performance Evaluation (ComPE). IEEE; 2020. p. 682-687.

[3] Belay AJ, Salau AO, Ashagrie M, et al. Development of a chickpea disease detection and classification model using deep learning. *Inf. Med. Unlocked.* 2020;20:100396.

[4] Hassan SM, Amitab K, Jasinski M, Leonowicz Z, Jasinska E, Novak T, Maji AK. ASurvey on Different Plant Diseases Detection Using Machine Learning Techniques. Electronics. 2022;11(17):2641.

[5] Ho Y, Wookey S. The real-world-weight cross-entropy loss function: Modeling the costs of mislabeling. IEEE Access. 2020;8:4806-4813.

[6] Islam, Sikder. Detection of Pomegranate diseases using image segmentation and multiclass support vector machine. In: 2017 IEEE 30th Canadian Conference on Electrical and Computer Engineering (CCECE). IEEE; c2017. p. 1-4.

[7] Khalifa NEM, Taha MHN, Abou El-Maged LM, Hassanien AE. Artificial intelligence in potato leaf disease classification: a deep learning approach. In: Machine Learning and Big Data Analytics Paradigms: Analysis, Applications and Challenges; c2021. p. 63-79.

[8] Kuricheti W, Nawaz M, Javed A, et al. A novel deep learning method for detection and classification of plant diseases. Complex Intell. Syst. 2022;8:507-524.

[9] Lee et al. Innovative Approach to Potato Disease Severity Classification. Agricul. Sci. J. 2023;15(2):210-225.

[10] Lee TY, Yu JY, Chang YC, Yang JM. Health detection for potato leaf with convolutional neural network. In: 2020 Indo–Taiwan 2nd International Conference on Computing, Analytics and Networks (IndoTaiwan ICAN). IEEE; c2020. p. 289- 293.

[11] Mora V, Ramasamy M, Damaj MB, Irigoyen S, Ancona V, Ibanez F,Avila CA, Mandadi KK. Pomegranate Zebra Chip: An Overview of the Disease, Control Strategies, and Prospects. Front Microbiol. 2021 Jul 22;12:700663.

[12] Ramya R, Kumar P. High-performance deep transfer learning model with batch normalization based on multiscale feature fusion for tomato plant disease identification and categorization. Environ. Res. Commun. 2023;5:125015.

[13] LambaM,GigrasY,DhullA.Classification of plant diseases using machine and deep learning. OpenComputerScience.2021;11(1):491–508. Available from:https://doi.org/10.1515/comp-2020-0122.

[14] SreekanthGR,SugantheR.Automatic Detection of Tea Leaf Diseases using Deep Convolution Neural Network. International Conference on Computer Communication and Informatics(ICCCI).2021.Availablefrom:https://doi.org/10.1109/ICCCI50826.2021.9402225

[15] Lamba M, Gigras Y, Dhull A. Classification of plant diseases using machine and deep learning. Open Computer Science. 2021;11(1):491–508. Available from: https://doi.org/10.1515/comp2020-0122.

[16] PawarS.Manoj Kharde DeepLearning-based Disease Detection using Pomegranate Leaf Image.Smart Technologies,Communication and Robotics.2022. Available from: https://doi.org/10.1109/STCR55312.2022.10009185.

[17] Mao Y, Zhang Z. Identification of Apple Leaf Diseases by Improved Deep Convolutional Neural Networks With an Attention Mechanism, Front. Plant Science. 2021. Available from: https://doi.org/10.3389/fpls.2021.723294.

[18] WuY.Identification of Maize Leaf Diseases based on Convolutional Neural Network. Journal of Physics:Conference Series.2021;1748(3):032004.Available from: https://doi.org/10.1088/17426596/1748/3/032004.

[19] Mangena VM. Recognition and Classification of Pomegranate Leaves Diseases by Image Processing and Machine Learning Techniques, Computers. Materials and Continua;66(3):2939–2955. Available from:https://doi.org/10.32604/cmc.2021.012466.

[20] Wakhare PB, Neduncheliyan S, Thakur KR. Study of Disease Identification in Pomegranate UsingLeaf Detection Technique. 2022 International Conference on Emerging Smart Computing and Informatics (ESCI). 2022;p. 1–6. Available from: https://doi.org/10.1109/ESCI53509.2022.9758262.