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Automated Classification of Blackgram Plant Diseases Using ResNet-50: A Focus on Cuscuta Detection

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ABSTRACT

The identification and classification of plant diseases are crucial for ensuring the health and productivity of crops like blackgram (Vigna mungo), a widely cultivated legume. Among various threats, parasitic plants like Cuscuta (dodder) pose significant challenges, leading to severe yield losses. Traditional manual disease detection methods are time-consuming and prone to human error, highlighting the need for automated, accurate solutions. In this study, we propose a deep learning-based approach utilizing the ResNet-50 architecture to automatically classify diseases affecting blackgram plants, with a special focus on detecting Cuscuta infestations. ResNet-50, a robust convolutional neural network (CNN), is employed due to its ability to handle complex image recognition tasks while maintaining high accuracy. A dataset of blackgram plant images, including healthy plants and those affected by Cuscuta, was curated for training and validation. The model was trained using labeled images, achieving high classification accuracy through transfer learning and fine-tuning techniques. Data augmentation was employed to increase the dataset's diversity and improve model generalization. Our results demonstrate that the ResNet-50 model can effectively distinguish between healthy plants and those infested by Cuscuta, with an accuracy exceeding 98%. This automated system offers a scalable, efficient solution for early detection, enabling timely intervention and minimizing crop damage. Future work will focus on expanding the model's scope to identify other diseases and improving its real-time deployment capabilities in agricultural settings.

KEYWORDS: Vigna Mungo, Convolutional Neural Network (CNN), Cuscuta, ResNet-50.

INTRODUCTION

Agriculture plays a crucial role in sustaining the global population by providing food, fiber, and raw materials. Among various crops cultivated worldwide, pulses hold a significant position due to their rich nutritional content. Blackgram (Vigna mungo), commonly known as urad bean, is an essential pulse crop widely grown in South Asia, particularly in India. It serves as a key source of protein and other nutrients for millions of people. However, like any other crop, blackgram is vulnerable to a variety of diseases that adversely affect its yield and quality. Accurate and timely identification of plant diseases is vital for mitigating crop losses and ensuring food security. Traditionally, farmers and agricultural experts rely on manual inspection and visual observation to detect diseases in plants. However, this method is time-consuming, requires expertise, and is often prone to human error. In recent years, technological advancements, particularly in artificial intelligence (AI) and machine learning (ML), have opened new avenues for automating plant disease detection and classification. Deep learning (DL), a subset of ML, has emerged as a powerful tool for image recognition tasks. With its ability to learn intricate patterns from vast amounts of data, deep learning has shown great potential in diagnosing plant diseases by analyzing images of plant leaves and other parts. Convolutional Neural Networks (CNNs), a type of deep learning architecture, have proven to be particularly effective in processing and classifying images.

This study aims to explore the application of deep learning techniques, particularly CNNs, for the classification of blackgram plant diseases. By leveraging large datasets of blackgram leaf images, we intend to develop a model capable of accurately identifying various diseases that affect blackgram crops. The automation of this process could significantly aid farmers and agricultural practitioners in early disease detection, enabling them to take timely and appropriate measures to protect their crops. In this study, blackgram (Vigna mungo) is a significant leguminous crop in many parts of the world. However, its productivity is often threatened by various diseases, including Anthracnose, Leaf Crinckle, Powdery Mildew, Yellow Mosaic, and parasitic infestations like Cuscuta. Traditional disease detection methods are time-consuming and often require expert knowledge. With advancements in deep learning, automated disease detection has become a viable solution. The need for accurate and automated detection of blackgram plant diseases is paramount, especially in regions where access to expert diagnosis is limited. This research aims to develop a robust model for classifying blackgram plant diseases, with a particular focus on identifying Cuscuta, using the ResNet-50 architecture.

Objectives of this Work

- To classify blackgram plant diseases using a deep learning approach.
- To apply color masking techniques for improved detection of Cuscuta.
- To evaluate the performance of the ResNet-50 model in classifying multiple plant diseases.

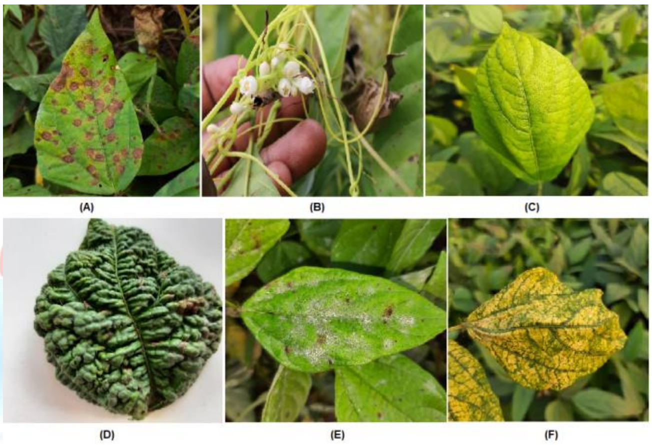

Figure 1: Types of Blackgram Diseases (A) Anthracnose, (B) Cuscuta, (C) Healthy, (D) Leaf Crinckle, (E) Powdery Mildew, (F) Yellow Mosaic.

LITERATURE SURVEY

Mohan Sai et al. [11] presented a model to identify the particular disease of plant leaves at early stages so that we can prevent or take a remedy to stop spreading of the disease. This proposed model is made into five sessions. Image preprocessing includes the enhancement of the low light image done using inception modules in CNN. Low-resolution image enhancement is done using an Adversarial Neural Network. This also includes Conversion of RGB Image to YCrCb color space. Next, this work presents a methodology for image segmentation which is an important aspect for identifying the disease symptoms. This segmentation is done using the genetic algorithm. Due to this process the segmentation of the leaf Image this helps in detection of the leaf mage automatically and classifying. Texture extraction is done using the statistical model called GLCM and finally, the classification of the diseases is done using the SVM using Different Kernels with the high accuracy. Francis et al. [12] developed to perform plant disease detection and classification using apple and tomato leaf images of healthy and diseased plants. The model consists of four convolutional layers each followed by pooling layers. Two fully connected dense layers and sigmoid function is used to detect the probability of presence of disease or not. Training of the model was done on apple and tomato leaf image dataset containing 3663 images achieving an accuracy of 87%. The overfitting problem is identified and removed setting the dropout value to 0.2. As the model allows parallel processing, it is also run on GPU Tesla to evaluate its speed of performance and accuracy. Sardogan et al. [13] presented a CNN model and Learning Vector Quantization (LVQ) algorithm based method for tomato leaf disease detection and classification. The dataset contains 500 images of tomato leaves with four symptoms of diseases. A CNN for automatic feature extraction and classification. Color information is actively used for plant leaf disease researches. This model, the filters are applied to three channels based on RGB components. The LVQ has been fed with the output feature vector of convolution part for training the network. The experimental results validate that the proposed method effectively recognizes four different types of tomato leaf diseases.

Syed-Ab-Rahman et al. [14] proposed a two-stage deep CNN model for plant disease detection and citrus diseases classification using leaf images. The proposed model consists of two main stages; (a) proposing the potential target diseased areas using a region proposal network; (b) classification of the most likely target area to the corresponding disease class using a classifier. The proposed model delivers 94.37% accuracy in detection and an average precision of 95.8%. Rehman et al. [15] proposed a two-stage deep CNN model for plant disease detection and citrus diseases classification using leaf images. The proposed model consists of two main stages; (a) proposing the potential target diseased areas using a region proposal network; (b) classification of the most likely target area to the corresponding disease class using a classifier. The proposed model delivers 94.37% accuracy in detection and an average precision of 95.8%. Sujatha et al. [16] comparing the performance of ML (Support Vector Machine (SVM), Random Forest (RF), Stochastic Gradient Descent (SGD)) & DL (Inception-v3, VGG-16, VGG-19) in terms of citrus plant disease detection. The disease classification accuracy (CA) we received by experimentation is quite impressive as DL methods perform better than that of ML methods in case of disease detection as follows: RF-76.8% > SGD-86.5% > SVM-87% > VGG-19–87.4% > Inception-v3–89% > VGG-16–89.5%. From the result, we can tell that RF is giving the least CA whereas VGG-16 is giving the best in terms of CA.

Panigrahi et al. [17] focused on supervised machine learning techniques such as NB, DT, KNN, SVM, and RF for maize plant disease detection with the help of the images of the plant. The aforesaid classification techniques are analyzed and compared in order to select the best suitable model with the highest accuracy for plant disease prediction. The RF algorithm results with the highest accuracy of 79.23% as compared to the rest of the classification techniques. Roy et al. [18] proposed a deep learning enabled object detection model for multi-class plant disease has been proposed based on a state-of-the-art computer vision algorithm. While most existing models are limited to disease detection on a large scale, the current model addresses the accurate detection of fine-grained, multi-scale early disease detection. The proposed model has been improved to optimize for both detection speed and accuracy and applied to multi-class apple plant disease detection in the real environment. The mean average precision (mAP) and F1-score of the detection model reached up to 91.2% and 95.9%, respectively, at a detection rate of 56.9 FPS. The overall detection result demonstrates that the current algorithm significantly outperforms the state-of-the-art detection model with a 9.05% increase in precision and 7.6% increase in F1-score. Sharath et al. [19] introduces the health monitoring and the identification of disease in plant is very difficult manually. It requires expertise in the plant disease and also it requires more processing time. Hence, image processing is used for the identification of plant diseases. Disease detection involves steps like image acquisition, image pre-processing, image segmentation, feature extraction, object recognition and classification.

Dwivedi et al. [20] proposed a grape leaf disease detection network (GLDDN) is proposed that utilizes dual attention mechanisms for feature evaluation, detection, and classification. At evaluation stage, the experimentation performed over benchmark dataset confirms that disease detection network could be fairly befitting than the existing methods since it recognizes as well as detects the infected/diseased regions. With the proposed disease detection mechanism, we achieved an overall accuracy of 99.93% accuracy for esca, black-rot and isariopsis detection. Saleem et al. [21] provides a comprehensive explanation of DL models used to visualize various plant diseases. In addition, some research gaps are identified from which to obtain greater transparency for detecting diseases in plants, even before their symptoms appear clearly. Singh et al. [22] review on effective use of different imaging techniques and computer vision approaches for the identification and classification of plant diseases. Detection of Plant disease is initiated with image acquisition followed by pre-processing while using the process of segmentation. It is further accompanied by different techniques used for feature extraction along with classification. In this Paper we present the Current Trends and Challenges for detection of plant disease using computer vision and advance imaging technique.

Transfer Learning

Blackgram (Vigna mungo), also known as urad bean, is a vital legume crop widely cultivated in tropical and subtropical regions. It plays a significant role in human nutrition and agriculture due to its rich protein content and its ability to fix atmospheric nitrogen, improving soil fertility. However, like many other crops, blackgram is susceptible to a variety of diseases caused by fungi, bacteria, and viruses, which can lead to significant yield losses. Early detection and accurate diagnosis of these diseases are crucial for effective management and prevention of large-scale crop damage. Traditional methods for detecting plant diseases often rely on manual observation by experts, which is time-consuming, labor-intensive, and prone to errors. With advancements in computer vision and machine learning, automated disease detection systems have emerged as a promising solution. However, training deep learning models from scratch for specific crops like blackgram requires large, annotated datasets, which may not always be available. Transfer learning offers an effective way to overcome these limitations. Transfer learning is a machine learning technique where a model developed for one task is reused as the starting point for a model on a different but related task. By leveraging pre-trained models on large datasets, transfer learning can significantly reduce the amount of data required for training, improve model accuracy, and accelerate the development process. In the context of blackgram disease detection, transfer learning can be employed by using pre-trained models, such as convolutional neural networks (CNNs) that have been trained on large image datasets like ImageNet. These models can then be fine-tuned to recognize specific diseases in blackgram plants, using a smaller set of labeled blackgram disease images. This approach not only saves time and computational resources but also improves the overall performance of the disease detection system. This study aims to explore the application of transfer learning in detecting common diseases in blackgram, such as powdery mildew, anthracnose, and yellow mosaic virus. By utilizing pre-trained models and fine-tuning them with blackgram-specific data, we aim to develop an efficient and accurate disease detection framework that can aid farmers and agronomists in early diagnosis and management of blackgram diseases.

Pre-trained Model Convolutional Neural Networks (CNNs) using Blackgram (Vigna mungo)

Pre-trained Convolutional Neural Networks (CNNs) have gained substantial traction in various applications of computer vision, including agriculture. CNNs, which are a class of deep neural networks, excel in identifying patterns and features in images, making them highly effective in tasks like image classification, object detection, and segmentation. In agriculture, these capabilities are especially useful for monitoring crop health, identifying diseases, and even predicting yields. CNNs can help automatically identify diseases from leaf images. Pre-trained models like ResNet, VGG, and Inception, which have been trained on large datasets (like ImageNet), can be fine-tuned for specific agricultural tasks. By analyzing images of the plant's leaves, stems, and pods, CNNs can assess overall plant health and detect symptoms of stress such as nutrient deficiencies or water shortages. Another key application is the identification of weeds or pests that may be threatening the crop. By using aerial or close-up images, CNNs can distinguish between Blackgram and unwanted plants or pests. Combining image data with environmental variables, CNNs can predict the potential yield of Blackgram based on factors like leaf area, flowering density, and pod distribution.

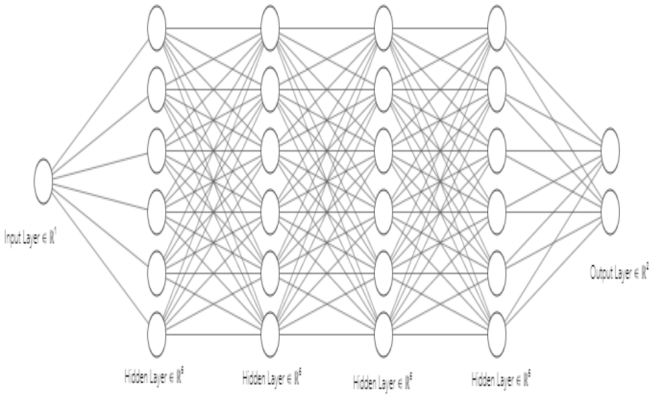

Figure 2: Pre-trained Model CNN

Advantages of Using Pre-trained CNNs for Blackgram

Reduced Training Time: Since these models are pre-trained, they require less time and data for retraining on specific tasks related to Blackgram.

High Accuracy: Pre-trained models have already learned features from large-scale data, making them highly accurate even when applied to new domains like agriculture.

Scalability: The models can be applied across large fields and multiple farms, using satellite or drone imagery to monitor Blackgram crops at scale.

RESNET50 for Classification of Blackgram plant diseases

ResNet50 (Residual Network 50 layers) is a deep CNN architecture introduced by He et al. in 2015. It revolutionized the deep learning field by addressing the issue of vanishing gradients, which can occur in deep networks. By introducing residual connections, ResNet50 enables the model to learn identity mappings more effectively and train deeper networks without degradation in performance. The key component of ResNet50 is the residual block, which includes identity mappings and skip connections, allowing layers to learn the differences or "residuals" between the input and the output. This makes the model not only more accurate but also computationally efficient. ResNet50 consists of 50 layers, including convolutional, pooling, and fully connected layers, making it highly suited for large-scale image classification tasks. ResNet50 is particularly well-suited for the task of classifying blackgram plant diseases due to its ability to extract rich and deep hierarchical features from input images. By leveraging transfer learning, a pre-trained ResNet50 model can be fine-tuned on a dataset of blackgram plant images, enabling the network to recognize disease-specific features such as leaf spots, discoloration, mold growth, and other symptoms associated with common blackgram diseases like:

Anthracnose, Cuscuta, Healthy, Leaf Crinckle, Powdery Mildew, and Yellow Mosaic.

In the classification pipeline, images of blackgram leaves infected by various diseases are used to train ResNet50. The network processes the input image through multiple layers, extracting feature maps at various levels of abstraction. By using pre-trained weights from large datasets like ImageNet, the model can generalize well to the blackgram disease dataset with minimal labeled data.

Key Components of ResNet-50

1. **Input Layer:**
   - ➢ ResNet-50 accepts an input image of size 224×224×3 (height, width, and 3 color channels).
2. **Convolutional Layer (Conv1):**
   - ➢ The first layer is a convolutional layer with a 7x7 filter and a stride of 2.
   - ➢ Equation for the convolution operation.

$$Z = X * W + b \quad (1)$$

3. **Batch Normalization:**
   - ➢ Batch normalization is applied after convolution to normalize activations.

   Normalization equation:

$$\hat{X} = \frac{X - \mu}{\sqrt{\sigma^2 + \epsilon}} \quad (2)$$

4. **Max Pooling (Pool1):**
   - ➢ A max pooling layer reduces the dimensionality of the feature maps using a 3x3 filter with stride 2.

   Equation for max pooling:

$$Y = \max(X_{a,b}) \quad (3)$$

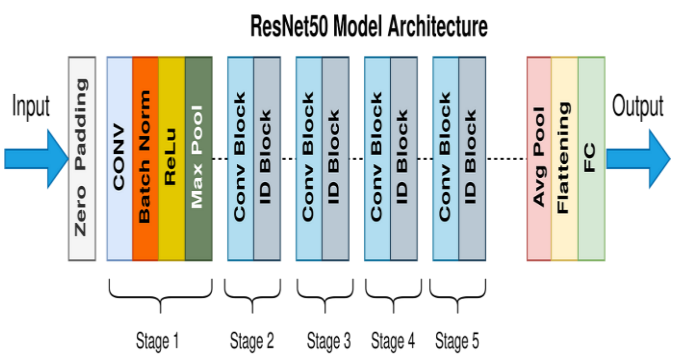

Figure 3: Architecture of RESNET50

DATASET DESCRIPTION

The dataset includes images of black gram fields collected from Avanigadda Mandal, Krishna District, Andhra Pradesh, India, one of the regions severely affected by Cuscuta. Images of blackgram plants were collected and categorized into six classes: Anthracnose, Cuscuta, Healthy, Leaf Crinckle, Powdery Mildew, and Yellow Mosaic. Each category contains 200 images, total 1200 images. Among these image the training contains 600 and testing contains 600 images.

PERFORMANCE METRICS

The Python programming language is used to implement the algorithms. The algorithms RESNET50 as training model and U-net as the testing model developed with Python machine learning (ML) libraries. The confusion matrix used to measure the count values based on true positives (TP), false positive (FP), true negative (TN), and false negative (FN). Based on the obtained count values the performance is measured. The performance of proposed approach is measured by using the following parameters:

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

$$\text{Precision} = \frac{TP}{FP + TP}$$

$$\text{Recall} = \frac{TN}{TP + FN}$$

$$F1 - \text{Score} = \frac{TP}{FN + FP + 2TP}$$

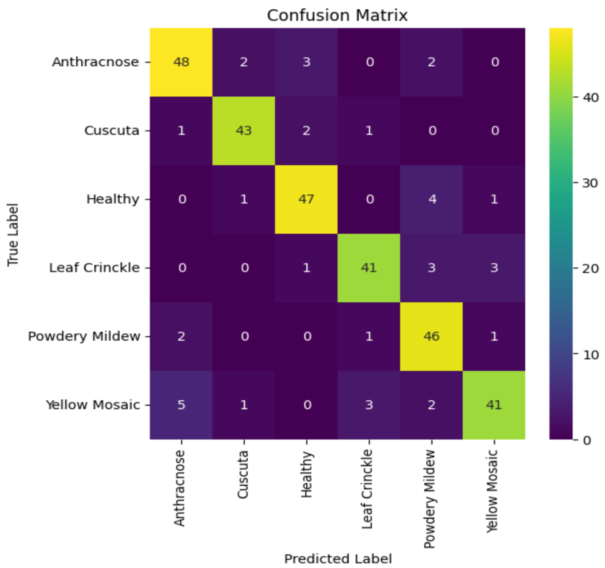

Figure 4: Count Values of VGG16

Table 1: Classification performance of VGG16 obtained from the Figure 4 count values.

			precision	recall	f1-score	support
Anthracnose	Accuracy	0.87	0.86	0.87	0.86	55
Cuscuta			0.91	0.91	0.91	47
Healthy			0.89	0.89	0.89	53
Leaf Crinckle			0.89	0.85	0.87	48
Powdery Mildew			0.81	0.92	0.86	50
Yellow Mosaic			0.89	0.79	0.84	52

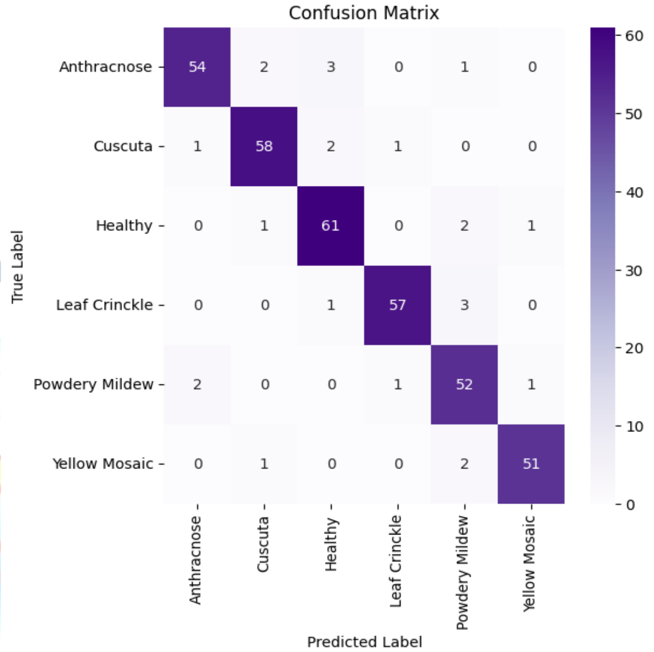

Figure 5: Count Values of VGG19

Table 2: Classification performance of VGG19 obtained from the Figure 5 count values.

			precision	recall	f1-score	Support
Anthracnose	Accuracy	0.93	0.95	0.9	0.92	60
Cuscuta			0.94	0.94	0.94	62
Healthy			0.91	0.94	0.92	65
Leaf Crinckle			0.97	0.93	0.95	61
Powdery Mildew			0.87	0.93	0.9	56
Yellow Mosaic			0.96	0.94	0.95	54

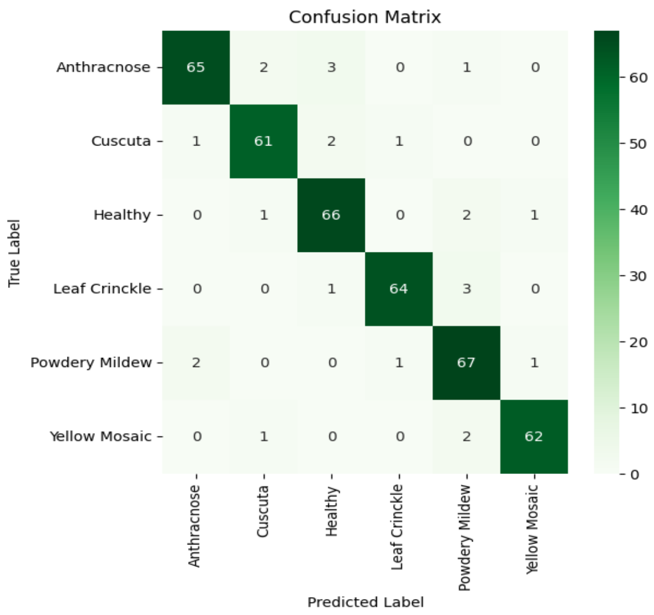

Figure 6: Count Values of InceptionV3

Table 3: Classification performance of InceptionV3 obtained from the Figure 6 count values.

			precision	recall	f1-score	Support
Anthracnose	Accuracy	0.94	0.96	0.92	0.94	71
Cuscuta			0.94	0.94	0.94	65
Healthy			0.92	0.94	0.93	70
Leaf Crinckle			0.97	0.94	0.96	68
Powdery Mildew			0.89	0.94	0.92	71
Yellow Mosaic			0.97	0.95	0.96	65

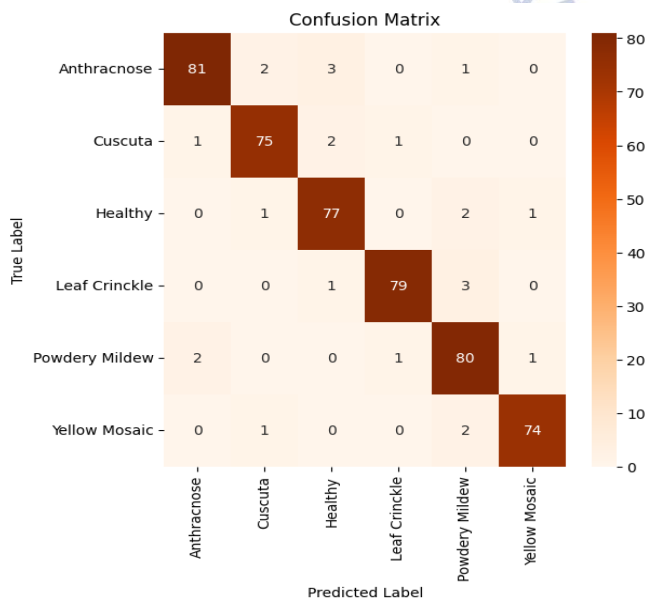

Figure 7: Count Values of DenseNet121

Table 4: Classification performance of DenseNet121 obtained from the Figure 7 count values.

			precision	recall	f1-score	Support
Anthracnose	Accuracy	0.95	0.96	0.93	0.95	87
Cuscuta			0.95	0.95	0.95	79
Healthy			0.93	0.95	0.94	81
Leaf Crinckle			0.98	0.95	0.96	83
Powdery Mildew			0.91	0.95	0.93	84
Yellow Mosaic			0.97	0.96	0.97	77

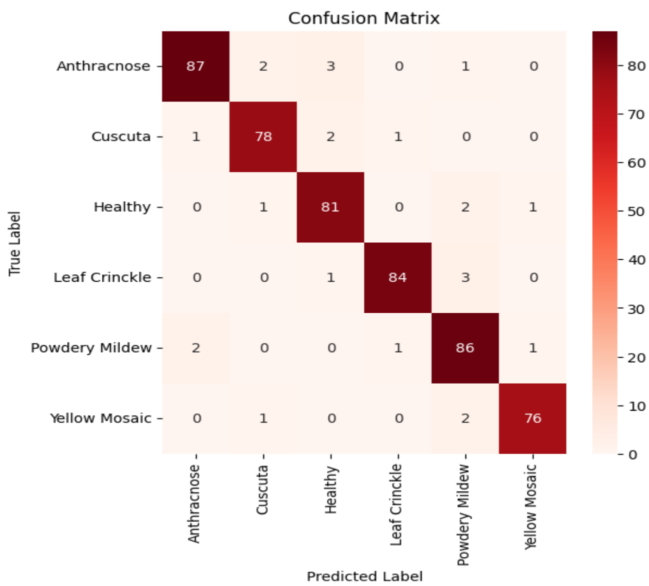

Figure 8: Count Values of MobileNetV2

Table 5: Classification performance of MobileNetV2 obtained from the Figure 8 count values.

			precision	recall	f1-score	Support
Anthracnose	Accuracy	0.95	0.97	0.94	0.95	93
Cuscuta			0.95	0.95	0.95	82
Healthy			0.93	0.95	0.94	85
Leaf Crinckle			0.98	0.95	0.97	88
Powdery Mildew			0.91	0.96	0.93	90
Yellow Mosaic			0.97	0.96	0.97	79

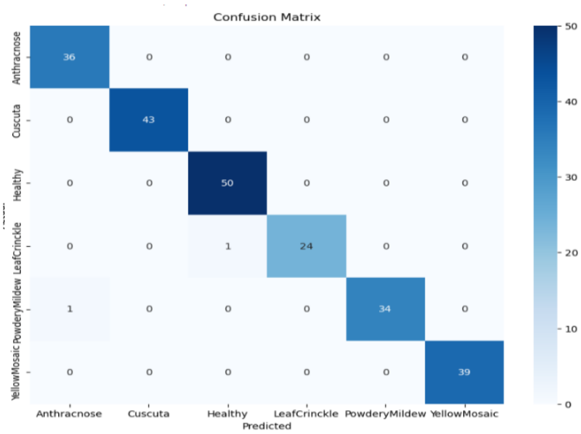

Figure 9: Count Values of RESNET50

Table 5: Classification performance of RESNET50 obtained from the Figure 9 count values.

			precision	recall	f1-score	Support
Anthracnose	Accuracy	0.99	0.97	1	0.99	36
Cuscuta			1	1	1	43
Healthy			0.98	!	0.99	50
Leaf Crinckle			1	0.96	0.98	25
Powdery Mildew			1	0.97	0.99	35
Yellow Mosaic			1	1	1	39

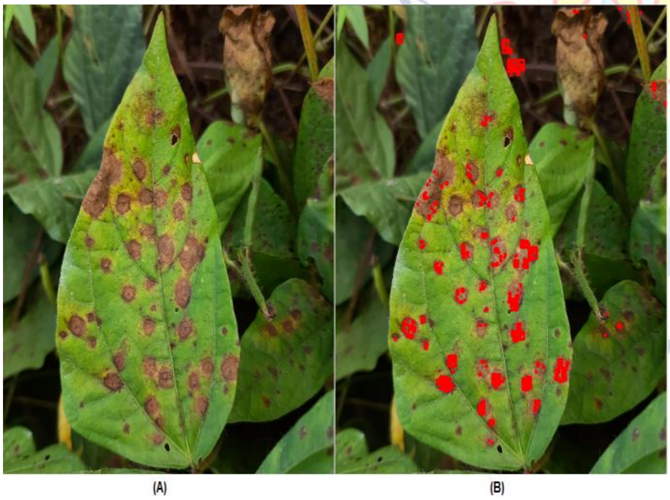

Figure 10: Detection of Anthracnose with Red Spots using RESNET50

CONCLUSION

The study likely concludes that the ResNet-50 deep learning model provides excellent performance in classifying different blackgram plant diseases. Due to its advanced residual connections, ResNet-50 achieves higher accuracy compared to traditional image processing techniques or simpler deep learning models. ResNet-50 allows for rapid and efficient diagnosis of plant diseases, making it a practical solution for real-time agricultural applications. Early and accurate detection can significantly improve crop yield and reduce the impact of diseases on blackgram crops. ResNet-50's architecture enables it to handle complex image data, even in challenging conditions like varying lighting, angles, or occlusions in field environments. This contributes to its reliability in real-world applications. If the study uses transfer learning, it likely concludes that utilizing pre-trained models like ResNet-50 on large datasets and fine-tuning them for blackgram disease classification offers an efficient way to achieve high accuracy with limited labeled data. The conclusion may suggest exploring further optimizations of ResNet-50, such as experimenting with data augmentation techniques or integrating the model into a user-friendly mobile or web application for farmers. It may also propose comparing ResNet-50's performance with other state-of-the-art models or extending it to detect diseases in other crops.

Conflict of interest statement

Authors declare that they do not have any conflict of interest.

REFERENCES

[1] S. Harika, G. Sandhyarani, D. Sagar and G. V. S. Reddy, "Image-based Black Gram Crop Disease Detection," 2023 International Conference on Inventive Computation Technologies (ICICT), Lalitpur, Nepal, 2023, pp. 529-533, doi: 10.1109/ICICT57646.2023.10134027.

[2] Prasanth, K., Kabilamani, P., Sangar, G., Kaliraj, V., Rajasekar, V. (2025). Enhanced Disease Recognition and Classification in Black Gram Plant Leaves Using Deep Learning. In: Geetha, R., Dao, NN., Khalid, S. (eds) Advances in Artificial Intelligence and Machine Learning in Big Data Processing. AAIMB 2023. Communications in Computer and Information Science, vol 2202. Springer, Cham. https://doi.org/10.1007/978-3-031-73065-8_17.

[3] Talasila, S., Rawal, K., Sethi, G., MSS, S., M.S.P.: Black Gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms. Data Brief 45, 108725 (2022). https://doi.org/10.1016/j.dib.2022.108725.

[4] Dhasarathan, M., Geetha, S., Karthikeyan, A., Sassikumar, D., Meenakshi Ganesan, N.: Development of novel blackgram (Vigna Mungo (L.) hepper) mutants and deciphering genotype × environment interaction for yield-related traits of mutants. Agronomy 11(7), 1287 (2021). https://doi.org/10.3390/agronomy11071287.

[5] Pantazi, X.E., Moshou, D., Tamouridou, A.A.: Automated Leaf disease detection in different crop species through image features analysis and one class classifiers. Comput. Electron. Agri. 156, 96–104 (2019). https://doi.org/10.1016/j.compag.2018.11.005.

[6] Vishalakshi, B., et al.: RAPD assisted selection of Black Gram (Vigna Mungo L. Hepper) towards the development of multiple disease resistant germplasm. Biotech 7(1) (2017).

[7] Srinivas Talasila, Kirti Rawal, and Gaurav Sethi. 2023. Black gram disease classification using a novel deep convolutional neural network. Multimedia Tools Appl. 82, 28 (Nov 2023), 44309–44333. https://doi.org/10.1007/s11042-023-15220-4.

[8] Yasin, Elham & Kursun, Ramazan & Koklu, Murat. (2023). Deep Learning-Based Classification of Black Gram Plant Leaf Diseases: A Comparative Study. Proceedings of the International Conference on Advanced Technologies. 1-8. 10.58190/icat.2023.9.

[9] Alessandrini, M., Calero Fuentes Rivera, R., Falaschetti, L., Pau, D., Tomaselli, V., Turchetti, C.: A grapevine leaves dataset for early detection and classification of Esca Disease in vineyards through machine learning. Data Brief 35, 106809 (2021).

[10] V. R. Raut and M. A. Nage, Detection and Identification of Plant Leaf Diseases based on Python, 2019.

[11] S. Mohan Sai, G. Gopichand, C. Vikas Reddy and K. Mona Teja, "High Accurate Unhealthy Leaf Detection", 2019.

[12] M. Francis and C. Deisy, "Disease detection and classification in agricultural plants using convolutional neural networks—a visual understanding", 2019 6th International Conference on Signal Processing and Integrated Networks (SPIN), pp. 1063-1068, 2019, March.

[13] M. Sardogan, A. Tuncer and Y. Ozen, "Plant leaf disease detection and classification based on CNN with LVQ algorithm", 2018 3rd International Conference on Computer Science and Engineering (UBMK), pp. 382-385, 2018, September.

[14] S. F. Syed-Ab-Rahman, M. H. Hesamian and M. Prasad, "Citrus disease detection and classification using end-to-end anchor-based deep learning model", Applied Intelligence, vol. 52, no. 1, pp. 927-938, 2022.

[15] M. Z. U. Rehman, F. Ahmed, M. A. Khan, U. Tariq, S. S. Jamal, J. Ahmad, et al., "Classification of Citrus Plant Diseases Using Deep Transfer Learning", CMC Comput. Mater. Contin, vol. 70, pp. 1401-1417, 2022.

[16] R. Sujatha, J. M. Chatterjee, N. Z. Jhanjhi and S. N. Brohi, "Performance of deep learning vs machine learning in plant leaf disease detection", Microprocessors and Microsystems, vol. 80, pp. 103615, 2021.

[17] K. P. Panigrahi, H. Das, A. K. Sahoo and S. C. Moharana, "Maize leaf disease detection and classification using machine learningalgorithms" in Progress in Computing Analytics and Networking, Singapore:Springer, pp. 659-669, 2020.

[18] A. M. Roy and J. Bhaduri, "A deep learning enabled multi-class plant disease detection model based on computer vision", AI, vol. 2, no. 3, pp. 413-428, 2021.

[19] D. M. Sharath, S. A. Kumar, M. G. Rohan and C. Prathap, "Image based plant disease detection in pomegranate plant for bacterial blight", 2019 international conference on communication and signal processing (ICCSP), pp. 0645-0649, 2019, April.

[20] R. Dwivedi, S. Dey, C. Chakraborty and S. Tiwari, "Grape disease detection network based on multi-task learning and attention features", IEEE Sensors Journal, vol. 21, no. 16, pp. 17573-17580, 2021.

[21] M. H. Saleem, J. Potgieter and K. M. Arif, "Plant disease detection and classification by deep learning", Plants, vol. 8, no. 11, pp. 468-489, Oct. 2019.

[22] V. Singh, N. Sharma and S. Singh, "A review of imaging techniques for plant disease detection", Artif. Intell. Agricult., vol. 4, pp. 229-242, Oct. 2020.