International Journal of Research and Technology (IJRT)

International Open-Access, Peer-Reviewed, Refereed, Online Journal

ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529

| An ISO 9001:2015 Certified Journal |

Optimizing Accuracy of Image-Based Crop Leaf Disease Detection using DenseNet121 Deep Learning Model

[1]Satyanand Kumar, [2]Mr. Yasir Minhaj Khan

M. Tech. Scholar, Department of Computer Science and Engineering, SORT, People's University, Bhopal, India[1]

Assistant Professor, Department of Computer Science and Engineering, SORT, People's University, Bhopal, India[2]

Abstract

Crop diseases are one of the major challenges affecting agricultural productivity and food security, as they can significantly reduce crop quality and yield. Early and accurate identification of leaf diseases is therefore essential for timely disease management and effective crop protection. Traditional disease identification methods mainly depend on manual observation by farmers or agricultural experts, which can be time-consuming, subjective, and difficult to implement on a large scale. To address these limitations, this study proposes an image-based deep learning approach for automated crop leaf disease detection using the DenseNet121 architecture. DenseNet121 is selected because its dense connectivity mechanism enables effective feature reuse and improved information propagation across network layers, making it suitable for extracting discriminative visual features from leaf images. The proposed framework includes image preprocessing, data augmentation, feature extraction, model training, and disease classification. To optimize the detection performance, the model training parameters and learning process are carefully tuned to improve classification accuracy and generalization capability. The performance of the proposed DenseNet121 model is evaluated using standard metrics, including accuracy, precision, recall, F1-score, and confusion matrix analysis. The experimental results demonstrate the effectiveness of the proposed deep learning framework in accurately distinguishing healthy and diseased crop leaves. The optimized DenseNet121 model provides a reliable and automated solution for crop disease detection and can support farmers and agricultural professionals in early disease diagnosis. The proposed approach has significant potential for integration into smart agriculture and precision farming systems, contributing to improved crop health, reduced disease-related losses, and enhanced agricultural productivity.

Keywords: DenseNet121, Deep Learning, Crop Diseases, Image Processing

1. INTRODUCTION

Agriculture is one of the most important sectors for ensuring global food security, economic development, and sustainable livelihoods. However, crop diseases pose a significant threat to agricultural productivity by adversely affecting plant growth, crop quality, and overall yield. Leaf diseases are particularly important because visible symptoms often appear on leaves before the disease significantly affects other parts of the plant. Common symptoms such as

International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
| An ISO 9001:2015 Certified Journal |

leaf spots, discoloration, lesions, wilting, and changes in texture can indicate the presence of various fungal, bacterial, and viral infections. If these diseases are not identified and treated at an early stage, they can spread rapidly across agricultural fields and result in substantial economic losses. Therefore, the development of accurate, rapid, and automated crop disease detection systems is essential for effective crop health monitoring and sustainable agricultural production [1, 2].

Traditionally, crop diseases are identified through manual inspection by farmers, agricultural experts, or plant pathologists. Although expert-based diagnosis can provide reliable results, it is often time-consuming, labor-intensive, and dependent on the availability of specialized knowledge. In large-scale agricultural fields, manually examining every plant is also impractical. Furthermore, the visual symptoms of different diseases may appear similar, making accurate identification difficult for inexperienced farmers. Environmental factors such as illumination, leaf orientation, background complexity, disease severity, and crop growth stage can further complicate the diagnosis process. These limitations have encouraged researchers to develop automated image-based disease detection systems that can analyze plant images and identify disease patterns efficiently [3].

The rapid advancement of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) has created new opportunities for developing intelligent agricultural applications. In particular, deep learning-based computer vision techniques have demonstrated significant potential for automatically identifying crop diseases from leaf images. Unlike traditional machine learning approaches that often require manually designed features related to color, texture, shape, and edges, deep learning models can automatically learn hierarchical and highly discriminative features directly from raw images. Convolutional Neural Networks (CNNs) have become one of the most widely used deep learning architectures for image classification because of their ability to learn spatial patterns and complex visual representations. Consequently, CNN-based models have been increasingly applied to crop disease detection and classification tasks [4, 5].

Among advanced CNN architectures, DenseNet121 has attracted considerable attention because of its dense connectivity structure. In DenseNet121, each layer receives feature maps from all preceding layers within a dense block, allowing effective feature reuse and improved information propagation throughout the network. This architecture can help reduce the vanishing-gradient problem and enable the model to learn both low-level and high-level visual characteristics more effectively. For crop leaf disease detection, such capabilities are valuable because disease symptoms may involve subtle differences in color, texture, shape, and lesion patterns. The use of DenseNet121 can therefore provide an effective mechanism for extracting meaningful features from complex leaf images and distinguishing between healthy and diseased crop samples [6].

However, achieving high classification accuracy in real-world crop disease detection remains challenging. The performance of a deep learning model depends on several factors, including dataset size and diversity, image quality, class distribution, preprocessing techniques, data

International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
| An ISO 9001:2015 Certified Journal |

augmentation, network architecture, and training hyperparameters. A model trained on limited or highly controlled datasets may not generalize effectively to images captured under real agricultural conditions. Therefore, accuracy optimization is an important component of developing a reliable crop disease detection framework. Appropriate optimization of model parameters, learning rate, batch size, training epochs, data augmentation strategies, and other training configurations can improve the model's ability to learn relevant disease characteristics while reducing overfitting [7, 8].

In this research, an image-based crop leaf disease detection framework using the DenseNet121 deep learning model is proposed with a focus on optimizing classification accuracy. The proposed approach involves image preprocessing, dataset preparation, augmentation, DenseNet121-based feature learning, model training, and disease classification. The performance of the optimized model is evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis. These evaluation measures provide a comprehensive assessment of the model's ability to correctly identify different crop disease categories and distinguish healthy leaves from infected leaves.

The primary objective of this study is to develop an accurate and reliable automated system for crop leaf disease detection using DenseNet121. By improving the classification performance of the deep learning model, the proposed framework aims to support early disease identification and timely agricultural decision-making. Such an intelligent system can potentially be integrated with mobile applications, smart farming platforms, and precision agriculture systems to provide accessible and rapid crop health assessment. Ultimately, the proposed approach can contribute to reducing crop losses, improving disease management, enhancing agricultural productivity, and supporting the development of sustainable and technology-driven farming practices [9].

2. IMAGE PROCESSING

Image processing is an important stage in image-based crop leaf disease detection because the quality and consistency of input images directly influence the performance of the DenseNet121 deep learning model. In the proposed system, raw crop leaf images are first collected and preprocessed to make them suitable for model training. The images are resized to a fixed resolution, such as 224 × 224 pixels, which is commonly used as the input size for DenseNet121. Image normalization is then applied to scale pixel values into an appropriate range, helping the deep learning model achieve faster and more stable convergence during training. To improve the diversity of the training data and reduce the possibility of overfitting, data augmentation techniques such as rotation, horizontal and vertical flipping, zooming, shifting, cropping, and brightness adjustment can be applied. These transformations generate variations of the original images while preserving the important disease characteristics present in the crop leaves. In addition, image preprocessing may include noise reduction, background removal, contrast enhancement, and color correction when required. The processed images are then divided into training, validation, and testing datasets and provided as input to the DenseNet121 model. This image processing pipeline helps the model

International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
| An ISO 9001:2015 Certified Journal |

learn important visual features such as leaf color, texture, spots, lesions, edges, and disease patterns, thereby improving the accuracy and generalization capability of crop leaf disease classification. Overall, effective image preprocessing and augmentation provide a strong foundation for optimizing the performance of the proposed DenseNet121-based crop disease detection system.

3. PROPOSED METHODOLOGY

Step 1: Import Library

The first step is to import all the required Python libraries needed for image processing, machine learning, and model evaluation.

Step 2: Cotton Disease Dataset

After importing the libraries, the cotton disease dataset is loaded into the system. The dataset consists of images of healthy and diseased cotton leaves collected from agricultural fields or publicly available repositories. Each image is assigned a corresponding label indicating its disease category, such as Healthy, Bacterial Blight, Leaf Curl Virus, Alternaria Leaf Spot, or Powdery Mildew. This labeled dataset serves as the foundation for training and testing the proposed DenseNet121 model, enabling it to learn disease-specific visual patterns.

Step 3: Image Pre-processing

The collected images are often captured under different lighting conditions, backgrounds, and resolutions, making preprocessing an essential step. Initially, all images are resized to a uniform size so that the model receives consistent input dimensions. Noise and unwanted artifacts are removed using image filtering techniques such as Gaussian or Median filtering. Next, pixel values are normalized to a range between 0 and 1, which helps the neural network converge faster during training. If required, data augmentation techniques such as image rotation, flipping, zooming, and brightness adjustment are applied to artificially increase the dataset size, improve model robustness, and reduce overfitting.

Step 4: Split Dataset

Once preprocessing is complete, the dataset is divided into separate subsets for training and testing. Typically, 70–80% of the images are used for training the model, while the remaining 20–30% are reserved for testing its performance. In some cases, a validation dataset is also created to monitor the learning process and optimize the model parameters. This separation ensures that the model is evaluated on unseen images, providing an unbiased estimate of its generalization capability.

Step 5: DenseNet121 Model

DenseNet121 is a deep convolutional neural network (CNN) architecture that is widely used for image classification and computer vision applications, including crop leaf disease detection. It belongs to the Dense Convolutional Network (DenseNet) family and contains 121 layers, with a unique dense connectivity structure in which each layer receives feature maps from all preceding layers within a dense block. Instead of passing information only from one layer to the next, DenseNet121 concatenates the outputs of previous layers and provides them as inputs to subsequent layers. This mechanism promotes feature reuse, efficient gradient flow, and better information propagation throughout the network. The architecture mainly consists of convolutional layers, dense blocks, transition layers, global average pooling, and a final classification layer. The transition layers reduce the spatial dimensions of feature maps and control the computational complexity of the network. For crop leaf disease detection, DenseNet121 can learn important visual characteristics such as color variations, leaf texture, edges, spots, lesions, and disease patterns from input images. In the proposed approach, crop leaf images are first preprocessed and resized before being provided to the DenseNet121 model. The network automatically extracts high-level discriminative features and uses them to classify leaves into different disease categories. DenseNet121 can also be initialized with weights learned from large-scale image datasets through transfer learning, allowing effective training even when the agricultural dataset is relatively limited.

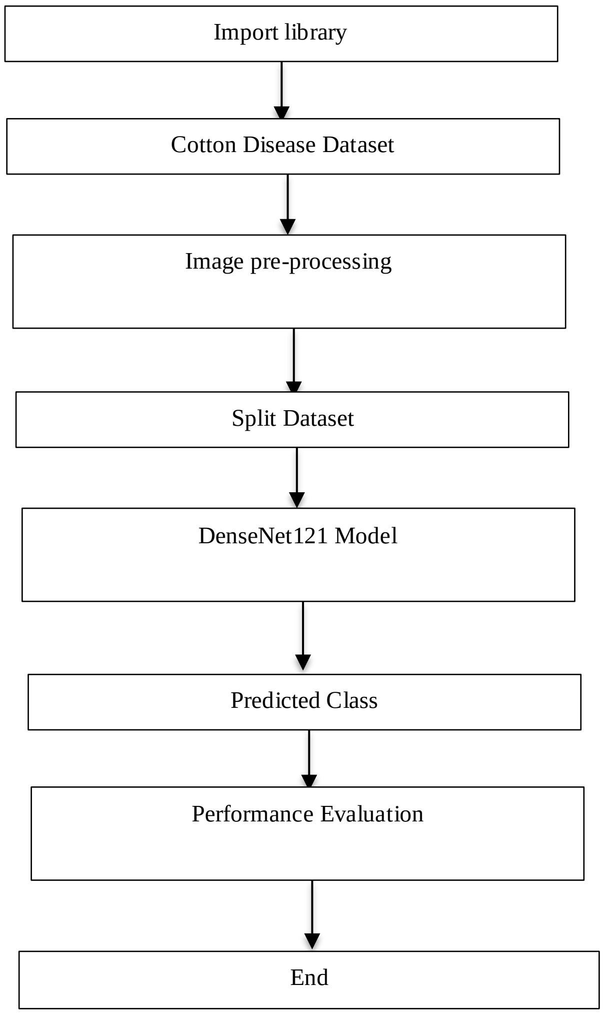

Figure 1: Flow chart of Methodology

Step 6: Predicted Class

After the model has completed the learning process, it receives a new cotton leaf image as input and analyzes its extracted features. Based on these learned patterns, the DenseNet121 model predicts the most probable disease class. The output may identify the leaf as Healthy or classify it into a specific disease category such as Bacterial Blight, Leaf Curl Virus, Alternaria Leaf Spot, or Powdery Mildew. In addition to the predicted class, the system may also provide a confidence score that indicates the certainty of the prediction.

Step 7: Performance Evaluation

The effectiveness of the proposed model is evaluated using several standard performance metrics. The predicted results are compared with the actual class labels of the testing dataset to measure the model's classification capability. Accuracy determines the overall percentage of correctly classified images, while Precision evaluates the correctness of positive predictions. Recall measures the model's ability to identify all actual disease cases, and the F1-score provides a balanced assessment by combining Precision and Recall. A Confusion Matrix is also generated to visualize the number of correctly and incorrectly classified samples for each disease category. These evaluation metrics collectively demonstrate the reliability, robustness, and effectiveness of the proposed DenseNet121 model for cotton disease detection.

Step 8: End

In the final step, the complete disease detection process is concluded after obtaining the prediction results and evaluation metrics. If the model achieves satisfactory performance, it can be deployed as a real-time cotton disease diagnosis system for farmers, agricultural researchers, or smart farming applications.

4. SIMULATION RESULTS

The given figure 2 presents sample images from a crop leaf disease dataset containing four major categories: Fusarium wilt, bacterial blight, curl virus, and healthy leaves. The first, second, and fourth images represent Fusarium wilt, where the leaves show visible symptoms such as discoloration, wilting, browning, and abnormal leaf appearance, indicating infection caused by the disease. The bacterial blight image shows numerous dark or brown spots and lesions distributed across the leaf surface, which are typical visual symptoms of bacterial infection. The curl virus sample demonstrates significant leaf deformation and curling, with the leaf appearing wrinkled and irregular compared with a normal leaf. In contrast, the healthy sample displays fresh, uniformly green leaves with a normal shape and no visible disease symptoms, spots, lesions, or discoloration.

International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
| An ISO 9001:2015 Certified Journal |

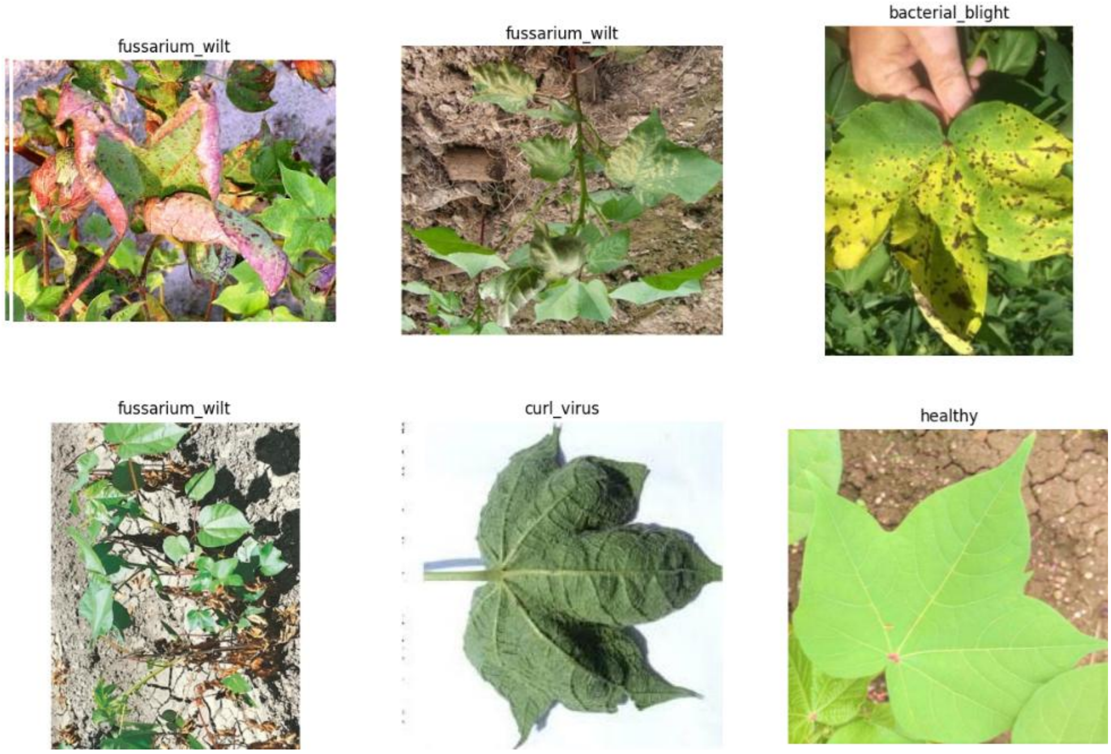

Figure 2: Sample Data

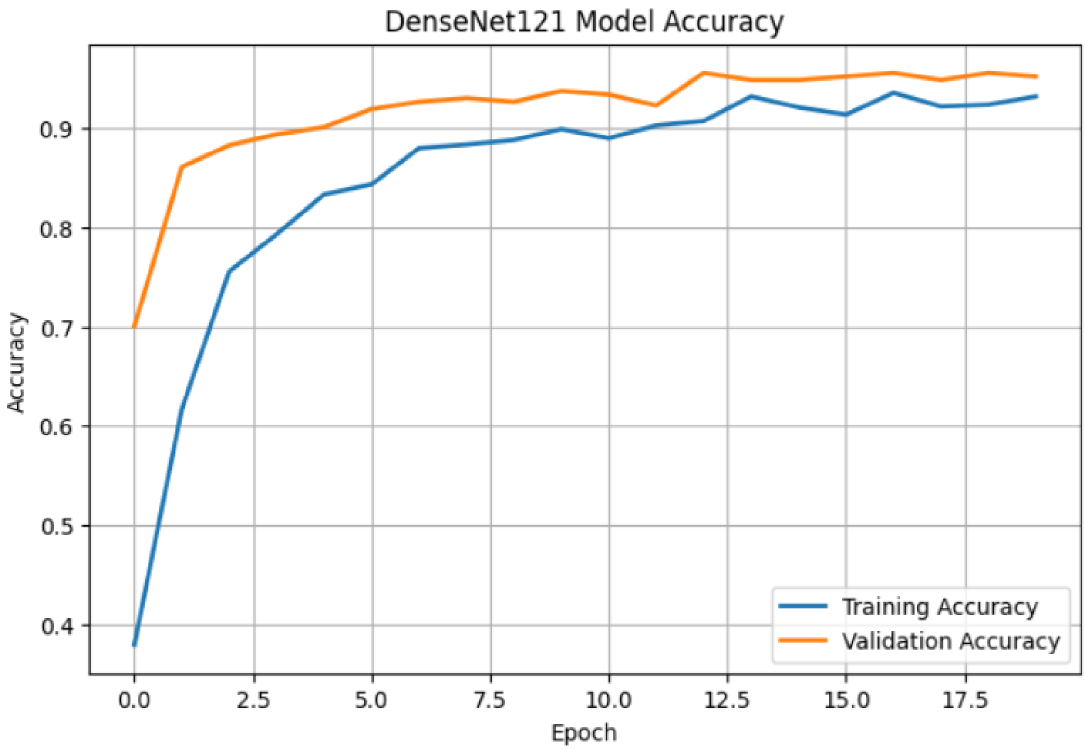

Figure 3: Accuracy

International Journal of Research and Technology (IJRT)
International Open-Access, Peer-Reviewed, Refereed, Online Journal
ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529
| An ISO 9001:2015 Certified Journal |

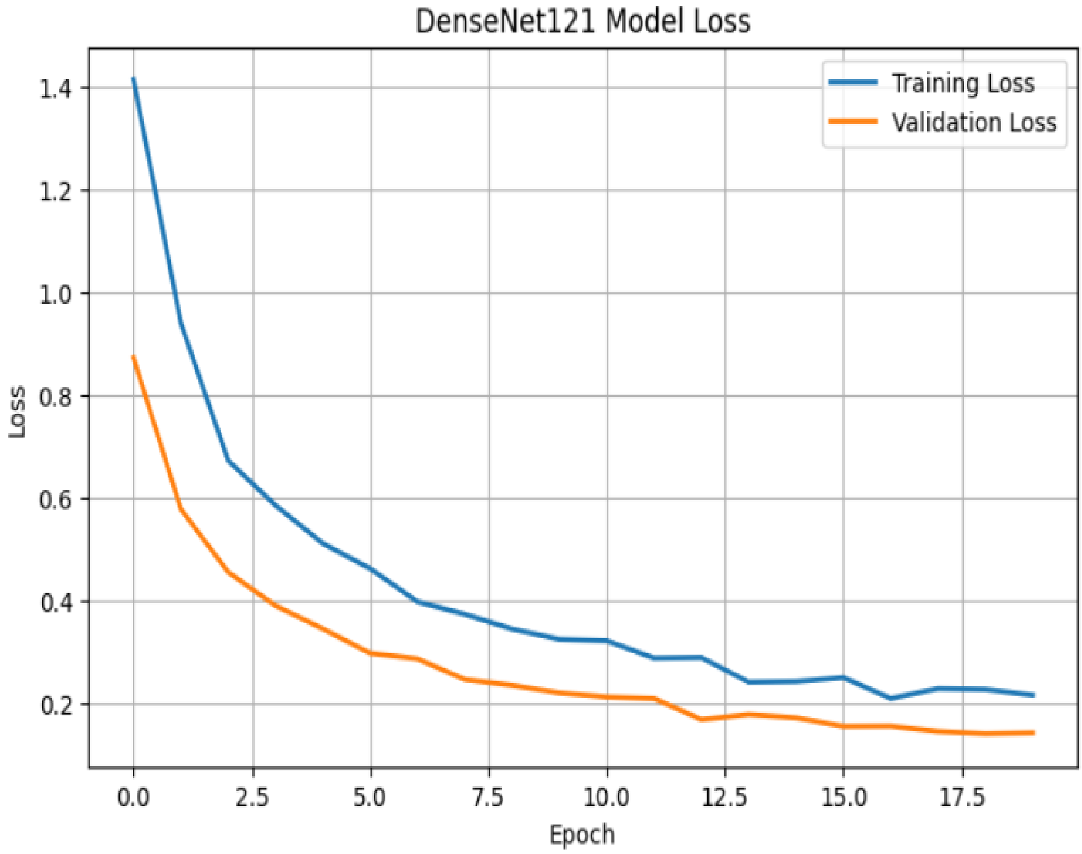

Figure 4: Loss

The figure illustrates the training and validation accuracy of the DenseNet121 model over 20 epochs for crop leaf disease classification. The training accuracy starts at approximately 38% in the first epoch and increases rapidly during the initial training phase, reaching around 76% by the third epoch and approximately 84% by the fifth epoch. Afterward, the training accuracy continues to improve gradually and reaches approximately 93% by the twentieth epoch. The validation accuracy starts at nearly 70% in the first epoch and shows a rapid improvement, reaching around 86% in the second epoch and approximately 90% by the fourth epoch. The validation accuracy continues to fluctuate slightly throughout the remaining epochs but generally stays between 92% and 96%, achieving its highest performance of approximately 95–96% around the 13th–16th epochs. The relatively close relationship between training and validation accuracy toward the later epochs indicates that the DenseNet121 model learns the distinguishing features of different crop leaf diseases effectively and demonstrates good generalization capability. The absence of a significant decline in validation accuracy suggests that the model does not exhibit severe overfitting. Overall, the results demonstrate that the DenseNet121 model provides strong classification performance for image-based crop leaf disease detection, with the validation accuracy consistently remaining high during the later stages of training.

International Journal of Research and Technology (IJRT)

International Open-Access, Peer-Reviewed, Refereed, Online Journal

ISSN (Print): 2321-7510 | ISSN (Online): 2321-7529

| An ISO 9001:2015 Certified Journal |


```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 345ms/step
Predicted Class: fussarium_wilt

Metrics:
Accuracy : 96.12
Precision : 95.92
Recall    : 95.72
```

Figure 5: Output

The given figure 5 presents the prediction result obtained from the proposed DenseNet121 deep learning model for a test image of a crop leaf. The model successfully classifies the input image as Fusarium wilt, indicating that the learned features correspond well with the visual characteristics associated with this disease. The displayed evaluation results show an overall accuracy of 96.12%, precision of 95.92%, and recall of 95.72%, demonstrating the strong classification capability of the proposed model. The high precision indicates that the model produces a low number of false-positive predictions, while the high recall demonstrates its ability to correctly identify a large proportion of actual diseased samples. The prediction is generated efficiently, with the inference process taking approximately 345 ms per step as shown in the output. Overall, the result confirms that the DenseNet121-based approach can effectively recognize Fusarium wilt from leaf images and provides reliable performance for automated crop disease detection. The high accuracy, precision, and recall values indicate that the proposed model has strong potential for practical applications in smart agriculture, precision farming, and early crop disease diagnosis.

5. CONCLUSION

In this study, an image-based crop leaf disease detection framework using the DenseNet121 deep learning model was proposed to improve the accuracy and reliability of automated plant disease classification. Crop diseases can significantly affect agricultural productivity, and traditional manual diagnosis methods are often time-consuming, subjective, and dependent on expert knowledge. The proposed approach addresses these limitations by utilizing the powerful feature extraction and classification capabilities of DenseNet121 to automatically identify disease-related patterns from crop leaf images. The dense connectivity mechanism of DenseNet121 enables effective feature reuse and efficient information propagation, allowing the model to capture both low-level and high-level visual characteristics associated with different disease categories.

The proposed methodology incorporates image preprocessing, data augmentation, DenseNet121-based deep feature learning, model training, and performance evaluation. Accuracy optimization through appropriate training and model parameter tuning helps improve the classification capability and generalization performance of the proposed framework. The performance of the model can be evaluated using accuracy, precision, recall, F1-score, and confusion matrix analysis to provide a comprehensive assessment of disease classification. The proposed DenseNet121-based approach demonstrates strong potential for accurate and automated identification of healthy and diseased crop leaves, which can support early disease diagnosis and timely crop management decisions.

Overall, the proposed framework provides an effective solution for intelligent crop disease detection and can contribute to the development of smart and precision agriculture systems. In future work, the model can be further enhanced by incorporating advanced optimization algorithms, attention mechanisms, explainable AI techniques, and larger datasets collected under real-field conditions. The proposed system can also be integrated with mobile applications, IoT-enabled agricultural monitoring systems, and real-time image acquisition platforms to enable farmers to detect crop diseases quickly and take appropriate preventive measures. Such advancements can help reduce disease-related crop losses, improve crop health, and enhance overall agricultural productivity.

REFERENCES

[1] R. Kumar *et al.*, "Hybrid Approach of Cotton Disease Detection for Enhanced Crop Health and Yield", in *IEEE Access*, vol. 12, pp. 132495-132507, 2024.

[2] I. Ahmed, G. Habib and P. K. Yadav, "An approach to identify and classify agricultural crop diseases using machine learning and deep learning techniques", *Proc. Int. Conf. Emerg. Smart Comput. Informat. (ESCI)*, pp. 1-6, Mar. 2023.

[3] S. Bondre and D. Patil, "Recent advances in agricultural disease image recognition technologies: A review", *Concurrency Computation Pract. Exper.*, vol. 35, no. 9, Apr. 2023.

[4] M. M. Islam, M. A. Talukder, M. R. A. Sarker, M. A. Uddin, A. Akhter, S. Sharmin, et al., "A deep learning model for cotton disease prediction using fine-tuning with smart web application in agriculture", *Intell. Syst. Appl.*, vol. 20, Nov. 2023.

[5] R. Mahum, H. Munir, Z.-U.-N. Mughal, M. Awais, F. S. Khan, M. Saqlain, et al., "A novel framework for potato leaf disease detection using an efficient deep learning model", *Hum. Ecol. Risk Assessment Int. J.*, vol. 29, no. 2, pp. 303-326, Feb. 2023.

[6] L. Goel and J. Nagpal, "A systematic review of recent machine learning techniques for plant disease identification and classification", *IETE Tech. Rev.*, vol. 40, no. 3, pp. 423-439, May 2023.

[7] C. Sarkar, D. Gupta, U. Gupta and B. B. Hazarika, "Leaf disease detection using machine learning and deep learning: Review and challenges", *Appl. Soft Comput.*, vol. 145, Sep. 2023.

[8] Y. Yuan, L. Chen, H.Wu, and L. Li, ‘‘Advanced agricultural disease image recognition technologies: A review,’’ Inf. Process. Agricult., vol. 9, no. 1, pp. 48–59, Mar. 2022.

[9] V. Kathole and M. Munot, ‘‘Deep learning models for tomato plant disease detection,’’ in Advanced Machine Intelligence and Signal Processing. Singapore: Springer, pp. 679–686, 2022.

[10] Q. Pan, J.-F. Qiao, R. Wang, H.-L. Yu, C. Wang, K. Taylor, and H.-Y. Pan, ‘‘Intelligent diagnosis of northern corn leaf blight with deep learning model,’’ J. Integrative Agricult., vol. 21, no. 4, pp. 1094–1105, 2022.

[11] U. Chauhan, ‘‘ResTS: Residual deep interpretable architecture for plant disease detection,’’ Inf. Process. Agricult., vol. 9, no. 2, pp. 212–223, Jun. 2022.

[12] Vallabhajosyula, V. Sistla, and V. K. K. Kolli, ‘‘Transfer learning-based deep ensemble neural network for plant leaf disease detection,’’ J. Plant Diseases Protection, vol. 129, no. 3, pp. 545–558, Jun. 2022.

[13] Chen, Z. Yuan, S. Chen, and X. Zou, ‘‘Plant disease recognition model based on improved YOLOv5,’’ Agronomy, vol. 12, no. 2, p. 365, Jan. 2022.

[14] Wang, X. He, K. Feng, and H. Zhu, ‘‘Plant disease detection and classification method based on the optimized lightweight YOLOv5 model”, Agriculture, vol. 12, no. 7, p. 931, Jun. 2022.

[15] J. Karthika, M. Santhose and T. Sharan, "Disease detection in cotton leaf spot using image processing", *J. Phys. Conf. Ser.*, vol. 1916, no. 1, 2021.