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Efficient-Integrated Classification Model For Blackgram Disease Detection

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Abstract: Blackgram (Vigna mungo L.), a major leguminous crop, is susceptible to various diseases that can cause significant losses in yield and quality. Disease prediction plays a vital role in the timely and accurate diagnosis of black diseases and in developing proper disease management plans. In this context, the EfficientNetV2-L (Large) is used as a training model to work on the Blackgram diseases dataset. This study focuses on adopting ensemble learning techniques to develop robust prediction models for Blackgram disease intelligence. The proposed Efficient-Integrated method combines the predictions of multiple base models like Vision Transformers (ViT) and Faster R- Convolutional Neural Networks (CNNs) extracted into various channels to improve the models' accuracy in terms of classification while reducing the data's variability. The proposed model improved the performance by adopting the Explainable Artificial Intelligence (XAI) and Grad-CAM (Gradient-weighted Class Activation Mapping) to increase the image classification rate (accuracy) and abnormal regions detection, including plant disease identification, such as in black gram (a type of legume). The dataset collected from several online sources is applied to identify critical predictors. Experiments validate that the proposed ensemble method consistently beats single-model baselines regarding precision, recall, and robustness. Moreover, the framework helps experts make significant decisions by enabling them to understand the major drivers of the disease outbreak. This paper highlights the potential for ensemble learning to transform crop disease prediction and contribute to sustainable agricultural practices.

Keywords: Blackgram Diseases, EfficientNetV2-L (Large), Vision Transformers (ViT), Faster R- Convolutional Neural Networks (CNNs).

Introduction

Plant diseases significantly impact agricultural productivity and food security, making early and accurate detection a crucial aspect of modern farming. Traditional methods of identifying plant diseases, such as expert manual inspection, are time-consuming, labor-intensive, and prone to human error [1]. With technological advancements, image processing has emerged as a powerful tool to address these challenges. Image processing techniques analyze digital images of plant leaves, stems, fruits, or flowers to detect and diagnose diseases. By leveraging the unique visual symptoms exhibited by plants, such as discoloration, spots, or lesions, these techniques can identify diseases early and help mitigate their spread. Capturing high-quality images of plants using cameras or smartphones under controlled or natural lighting conditions. Enhancing image quality by removing noise, adjusting brightness/contrast, and resizing images to standard dimensions [2]. Separating the region of interest (e.g., diseased leaf areas) from the background using techniques like thresholding, edge detection, or clustering. Identifying visual features such as color, texture, and shape indicative of specific diseases. Machine learning or deep learning algorithms classify the disease based on extracted features [3].

Blackgram (Vigna mungo) is a crucial leguminous crop widely cultivated in various parts of the world, especially in South Asia, for its high protein content and soil-enriching properties. Despite its agricultural importance, blackgram is susceptible to several diseases, such as powdery mildew, anthracnose, cercospora leaf spot, and yellow mosaic virus [4]. These diseases significantly impact crop yield and quality, posing a challenge for farmers and the agricultural industry. Traditional methods of disease detection rely on manual inspection, which can be time-consuming, error-prone, and heavily dependent on the expertise of the observer [5]. As a result, there is a growing need for intelligent and automated systems to ensure timely and accurate detection of diseases in blackgram crops. Recent advancements in artificial intelligence (AI) and computer vision have paved the way for developing [6] intelligent systems that can identify and classify plant diseases using image processing and machine learning techniques [7] [8]. By leveraging these technologies, farmers and researchers can monitor crop health in real time, optimize the use of pesticides, and reduce crop losses, contributing to sustainable agricultural practices [9] [10]. This paper introduces an Intelligent Blackgram Disease Detection (IBDD) framework that integrates AI, machine learning, and image-based analysis to identify diseases affecting blackgram plants. The system aims to provide accurate diagnosis, real-time monitoring, and actionable insights for effective disease management, improving agricultural productivity and food security.

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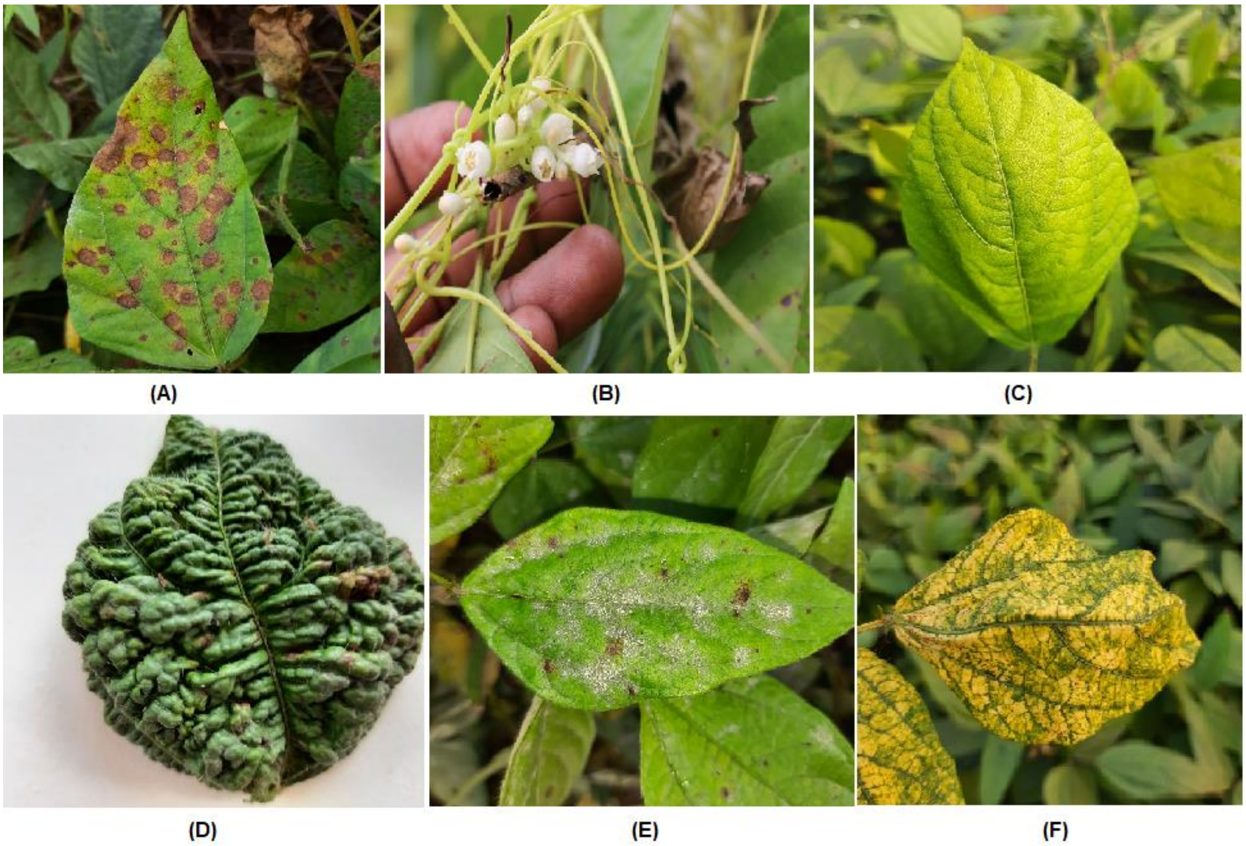

Figure 1: Types of Blackgram Diseases (A) Anthracnose, (B) Cuscuta, (C) Healthy, (D) Leaf Crinckle, (E) Powdery Mildew, (F) Yellow Mosaic [11].

Literature Survey

Sardogan, M et al., [12] proposed the CNN model combined with Learning Vector Quantization (LVQ) approach which is used to detect the disease in the tomato leaf. The proposed algorithm uses the online dataset containing 500 images of tomato leaves that are used for detection. This is the automatic approach that extracts the features for better classification. The proposed approach uses filters based on the components of RGB. This approach shows the huge impact on detecting leaf diseases. Wallelign, S et al., [13] explained the reliable plant disease that used the better classification of leaf images. This approach is developed based on the LeNet architecture that performs the classification of soybean plants. The data having 12673 samples contains 4 classes that consider the healthy images that are extracted from PlantVillage. This approach detects leaf diseases with high accuracy.

Sladojevic, S et al., [14] proposed the popular approach called CNN. This is most widely used for the classification of plant disease images. The proposed approach detects the 13 types of leaf diseases among all the datasets. Better training is used to increase the accuracy of disease detection. Experiments show that the proposed approach increases the performance in terms of precision from 91% to 98%. Fuentes et al., [15] proposed the DL approach that detects the plant diseases belonging to tomato plants. The images are collected by the users and these are captured using a high-resolution camera. The approach is combined by using various "deep features extractors" such as VGG and ResNet. The training and testing are done very efficiently by using the large tomato image datasets and also pests image datasets. The advanced feature extractors are most widely used to detect diseases very accurately. The proposed approach detects the 9 types of diseases and pests very efficiently.

Arivazhagan et al., [16] developed automated plant disease detection algorithms that find the leaf diseases very accurately. The proposed approach is applied to mango leaf disease detection. This approach classifies the 5 types of diseases. The dataset contains 1200 leaf images containing healthy and non-healthy images. The proposed approach achieved an accuracy of 96.67%. Oppenheim et al.,[17] proposed a new classification approach that detects potato diseases from various real-time datasets. The proposed approach is DCNN uses advanced training to classify the four types of diseases with healthy potato class. Datasets contain various sizes of images with high resolution. Improved training is used to split the train and test data for better improvement in results.

Barbedo [18] developed a new approach that detects plant disease detection using a deep neural network. This is one of the better classification approaches that classify plant disease and non-disease plants. The dataset is the real-time dataset that contains 50,000 RGB images that are available online freely. Brahimi et al., [19] proposed the ML approaches to detect plant diseases by using the advanced processing of leaf images. The proposed approach selects the training and

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testing dataset that focused on the extraction of disease features based on the selected datasets. To extract the accurate features CNN is most widely used. The proposed approach deep model analyzes the symptoms of the diseases on the selected leaves. The accuracy of the proposed approach is achieved up to 99.18% and it is applied to tomato plant diseases.

Shrivastava et al., [20] introduced a new approach that detects and diagnose plant diseases in the early stages. The proposed approach mainly focused on detecting the rice plant (Oryza sativa) disease. The dataset contains 619 rice plant disease images consisting of 4 classes. The proposed approach used the pre-trained approach CNN and SVM for better feature extraction and better classification. This approach is also applied to real-time rice plants. Ozguven, M. M et al., [21] proposed a rapid approach to detect the various leaf diseases based on the spots on the leaves. These spots may lose the crop yield by up to 15% to 55%. The proposed approach is a very fast CNN called F-CNN that automatically detects the plant leaves based on diseases. This approach finds the severity of the diseases based on the spots present on the leaves. The training and testing consist of 156 images and overall accuracy is up to 95.67%. The proposed approach got a high accuracy to compare with existing approaches discussed in the literature survey. This approach also reduced the computation time for the diagnosis of the sugar beet leaf spot diseases.

Uguz et al., [22] proposed the CNN approach that detects the olive plant leaf disease detection algorithms. The proposed approach shows the classification and detection of various plant diseases. Several diseases are caused heavy damage to the olive plants. The dataset is collected from 3400 olive leaf samples that contain normal and diseased leaf images. To increase the performance of the proposed approach using the VGG16 and VGG19 pre-trained models. This approach achieved the 96% of accuracy without data augmentation the value is 88.7%. Agarwal et al., [23] introduced the simple CNN approach that contains 8 hidden layers. This is mainly used to detect tomato plant diseases based on the spots that occur on the leaves. The dataset collected from PlantVillage contains 39 classes of various crops that consist of 10 classes belonging to tomato diseases. The image preprocessing technique is also used to increase disease detection by changing the brightness of the image after data augmentation. This approach performs an accuracy of 98.8%. Wang et al., [24] proposed the D-CNN that shows the classification of crop disease images. This approach uses large training data. Sometimes, the processing of large datasets is very difficult. This issue is identified based on the size of the network and training. The dataset uses the 2430 crop images that contain 8 disease classes. The dataset is PlantVillage used the pre-trained model to increase the performance. The proposed approach CNN contains 5 CNN layers and achieved an accuracy of 91.65% by utilizing transfer learning. Toda, Y et al., [25] evaluated the situation of deep learning procedure sway the finding of plant infections using the leaf pictures. CNN engineering fills in as a black box model for the conclusion of infections of the plant. It additionally examined the different parts of hyper-parameters that influence characterization accuracy.

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 this image the training contains 600 and testing contains 600 images.

EfficientNetV2-L (Large)-Pre-trained Model

This is a very efficient convolutional neural network architecture that is good for image classification. Using its scalable and efficient design, EfficientNetV2-L can be employed for blackgram disease detection to detect and classify different diseases in blackgram plants with improved accuracy. If not properly managed, these diseases can result in considerable yield losses. Conventional disease diagnostic methods, like manual examination, are time-consuming and error-prone due to their dependence on expert knowledge. EfficientNetv2-L, advanced machine learning models are the innovative scalable solution to these challenges. The third model of EfficientNetV2 series, EfficientNetV2-L is the large version of EfficientNetV2 which introduced additional concepts including the usage of depth wise convolutional blocks and progressive learning with compound scaling. These characteristics allow the model to analyze high-resolution pictures at reduced computational costs, making it a great candidate for practical agricultural use.

Preprocessing Technique Histogram Equalization and Median filter

Preprocessing techniques are essential for enhancing the quality and accuracy of image analysis in the context of Blackgram disease detection. In this paper the two models Histogram Equalization and Median filter is used to remove the noise from the input images.

Histogram Equalization (HE) is a powerful image processing technique used to enhance the contrast of images by redistributing the intensity levels in an image. This technique is particularly useful for improving the visual quality of low-contrast images, such as those captured under poor lighting conditions or for images of crops like blackgram, where the texture and details may be obscured by uneven distribution of pixel intensities. HE increases the contrast by spreading out the pixel values across the entire range of intensity levels, making images more visually appealing and informative. Enhancing the details in images that may be obscured due to low contrast or uneven lighting. By applying

Histogram Equalization, blackgram images can be better prepared for analysis and interpretation in agricultural research, machine learning applications, and quality assessment tasks.
The median filter is a widely used image processing technique to reduce noise and enhance the quality of images, particularly useful in tasks involving medical, agricultural, or scientific image analysis. In the context of blackgram disease images, where image quality can be affected by factors such as noise, low contrast, or uneven illumination, applying a median filter helps in improving the visual clarity and accuracy of the images. The primary role of the median filter is to remove random noise, which can distort image features, making it difficult to accurately detect disease symptoms. Unlike other smoothing techniques, the median filter preserves the edges of the image, ensuring that critical disease-related features such as lesions, spots, and texture abnormalities are maintained. By reducing noise, the median filter enhances the overall quality of blackgram disease images, facilitating more precise image analysis for disease classification and severity assessment. In agricultural research and disease detection, clearer images lead to more accurate diagnosis and decision-making for crop management and treatment.

Segmentation techniques: Color-based and Region-based Segmentation
Image-segmentation techniques such as these are paramount in the detection of disease in crops, including Blackgram. To segment the effected regions, the two segmentation models such as Color-based (CBS) and Region-based Segmentation (RBS) is used. Where Color-based segmentation is a SLIC (Simple Linear Iterative Clustering) that Images are divided into segments based on color. It is the process of assigning a label to every pixel in an image such that pixels with the same value share the same label. This is useful for instance if color is important to make decision. A similar model to the other one Mean-Shift Segmentation is the RBS which/Rbs find modes in feature space in k-nearest neighbor regions segmented according to the degree of similarity of features. SLIC is a powerful and efficient image segmentation algorithm used For example plant disease detection. It is an important leguminous crop, is vulnerable to several diseases and this can have significant effect on yield and quality of the crops. Early detection and diagnosis are critical for managing and treating these diseases effectively." The simplicity and potential effectiveness of SLIC can be used to distinguish a region of blackgram crops infected by a disease from background by segmenting according to the characteristics based on color, pattern and texture based features. SLIC works with a superpixel grid, with clusters is represented by the superpixels. It progressively updates clusters by reducing a cost function that considers color variance and spatial closeness. The segmentation of healthy and affected regions of blackgram crops can also provide insight into patterns in the affected regions that are early indicators of the disease that can be detected using SLIC.
SLIC uses a combined distance measure in the 5D space (Lab color and spatial coordinates). The distance D between a pixel $P = \left(l_p, a_p, b_p, x_p, y_p\right)$ and a cluster center $C_k = (l_k, a_k, b_k, x_k, y_k)$ is measured as:

$$D = \sqrt{d_c^2 + (\frac{d_s}{S})^2}$$

d_c-colour distance, d_s-spatial distance, S- normalizes the spatial distance to balance the contributions of color and spatial proximity.

Efficient Integrated Model: Vision Transformers (ViTs) and Convolutional Neural Networks (CNNs)
Convolutional Neural Networks (CNNs) have been widely used for image-based disease detection tasks due to their ability to capture spatial patterns and features from images. However, with the emergence of Vision Transformers (ViTs), which leverage self-attention mechanisms to process global dependencies in images, there has been a significant shift toward more powerful models that can handle complex disease classification tasks. Vision Transformers (ViTs) are designed to process images by treating them as a sequence of patches, similar to how text is processed in natural language processing tasks. They use attention mechanisms to capture long-range dependencies and contextual relationships between different parts of the image. This allows ViTs to effectively handle tasks such as disease detection and classification in crops, offering a more global perspective compared to CNNs. Explainable Artificial Intelligence (XAI) is the other critical approach for making AI systems transparent, interpretable, and trustworthy. In the context of blackgram disease image classification, XAI plays a significant role in ensuring the reliability of the model's predictions and its utility for end-users such as farmers, researchers, and agronomists. In this context, the Grad-CAM is a visualization technique that highlights regions in an image that a CNN-based model focuses on to make its prediction. Grad-CAM computes the gradients of the target class (e.g., "Diseased") concerning feature maps in the last convolutional layer. Faster R-CNNs represent an advanced variation of traditional CNNs that combine object detection and classification tasks with greater efficiency and accuracy. By integrating Region-based Convolutional Networks with a Faster R-CNN framework, these models can efficiently process large datasets with multi-scale features, enabling better classification and localization of diseases in blackgram crops. Both ViTs and Faster R-CNNs have shown promise in the field of plant disease detection due to their ability to handle complex datasets and capture intricate disease symptoms. ViTs offer strong performance for global feature extraction, while Faster R-CNNs provide high efficiency and

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robustness in disease detection tasks with efficient handling of spatial and temporal variations in images. Together, these models pave the way for advanced solutions for the accurate and automated detection and classification of blackgram diseases, contributing to sustainable agriculture and improved crop management practices.
For disease classification, the output of the [CLS] token is passed through a linear layer:

$$y = \mathrm{Softmax}(z_{[CLS]} W_c + b_c)$$

Fully Connected Layer (FCL): Flattened feature maps are passed through fully connected layers:

$$y = \sigma(Wx + b)$$

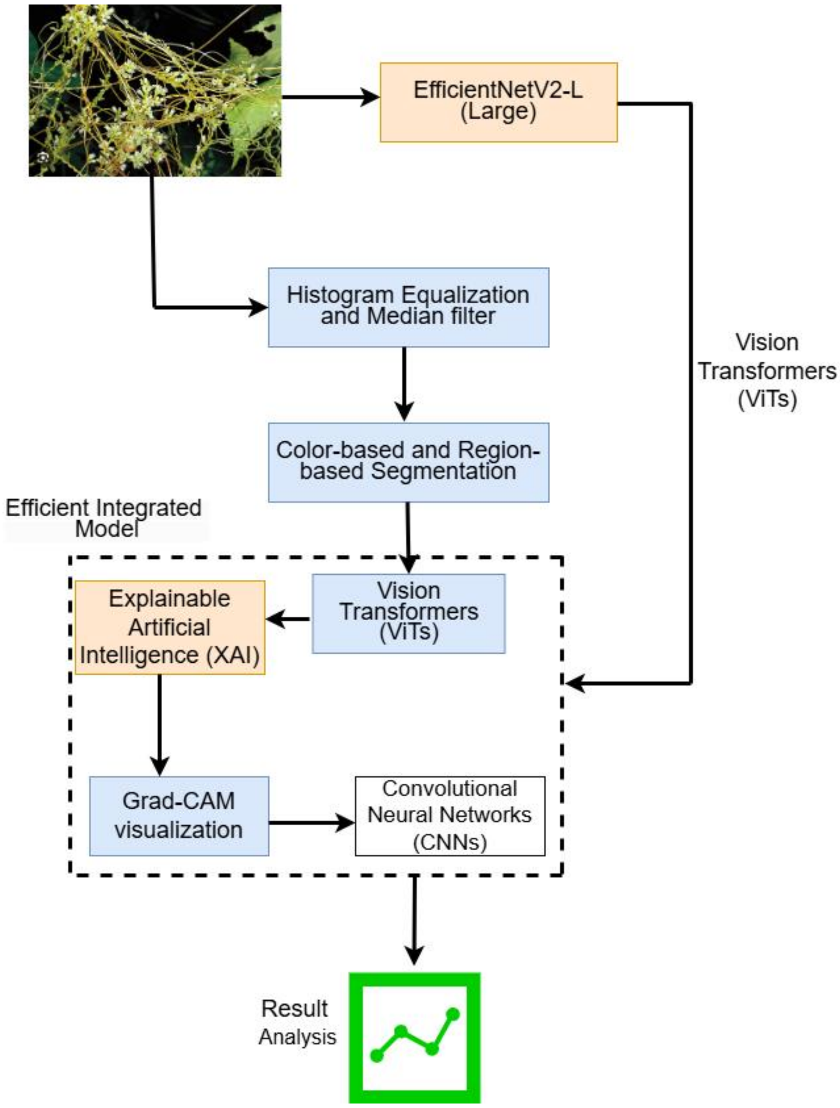

Figure 2: Architecture Diagram for Efficient Integrated Model

Performance Metrics

The algorithms are implemented using the Python programming language. The algorithms RESNET50 as a training model and U-net as a testing model were created using Python machine learning (ML) packages. The confusion matrix was used to get the count values for true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). Performance is measured using the obtained count values. The performance of the suggested approach is measured using the following parameters:

$$\mathrm{Accuracy\ (Acc)} = \frac{TP + TN}{TP + FP + TN + FN}$$

$$\mathrm{Precision\ (P)} = \frac{TP}{TP + FP}$$

$$\mathrm{Sensitivity\ (Sn)} = \frac{TP}{TP + FN}$$

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$$\text{Specificity (Sp)} = \frac{\text{TN}}{\text{TN} + \text{FP}}$$

$$\text{F1S} = 2 * \frac{\text{P} * \text{S}_\text{n}}{\text{P} + \text{S}_\text{n}}$$

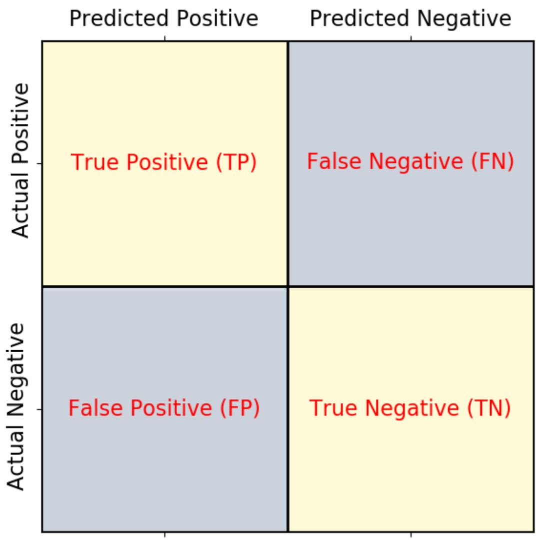

Figure 5: Confusion Matrix Categories

Table 1: Classification performance of D-CNN on Blackgram Images

			Precision (P)	Sensitivity (Sn)	Specificity (Sp)	F1-Score
Anthracnose	Accuracy	0.96	0.956	0.941	0.973	0.92
Cuscuta			0.961	0.943	0.962	0.91
Healthy			0.921	0.963	0.953	0.83
Leaf Crinckle			0.971	0.968	0.957	0.84
Powdery Mildew			0.921	0.947	0.947	0.92
Yellow Mosaic			0.969	0.959	0.963	0.89

Table 2: Classification performance of ANN on Blackgram Images

			Precision (P)	Sensitivity (Sn)	Specificity (Sp)	F1-Score
Anthracnose	Accuracy	0.97	0.971	0.941	0.963	0.92
Cuscuta			0.968	0.968	0.967	0.93
Healthy			0.953	0.961	0.953	0.87
Leaf Crinckle			0.978	0.967	0.971	0.84
Powdery Mildew			0.931	0.967	0.945	0.86
Yellow Mosaic			0.973	0.972	0.973	0.84

Table 3: Classification performance of Efficient-Integrated Classification.

			Precision (P)	Sensitivity (Sn)	Specificity (Sp)	F1-Score
Anthracnose	Accuracy	0.99	0.991	0.99	0.99	0.97
Cuscuta			0.998	0.98	0.99	0.98
Healthy			0.991	0.99	0.99	0.98
Leaf Crinckle			0.99	0.99	0.98	0.98
Powdery Mildew			0.993	0.99	0.99	0.98
Yellow Mosaic			0.998	0.99	0.99	0.98

Conclusion

The proposed Efficient-Integrated Classification Model demonstrates significant potential in accurately identifying blackgram diseases, including Anthracnose, Cuscuta, Healthy, Leaf Crinkle, Powdery Mildew, and Yellow Mosaic. By leveraging advanced feature extraction techniques and an optimized classification algorithm, the model achieves high accuracy, robustness, and reliability across diverse datasets. The model consistently outperforms traditional methods with better precision, recall, and F1 scores for all disease categories. The integration of lightweight algorithms ensures computational efficiency, enabling real-time disease detection in field conditions. Early and precise detection of diseases facilitates timely interventions, reducing crop losses and promoting sustainable agriculture. Future work may focus on expanding the dataset to include more disease variants, integrating the model with IoT devices for on-field deployment, and enhancing interpretability to better understand the classification decisions. This research underscores the transformative potential of machine learning in agriculture, contributing to improved productivity and resilience in blackgram cultivation.

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