Journal of Scientific & Industrial Research
Vol. 84, April 2025, pp. 399-410
DOI: 10.56042/jsir.v84i04.8329

Semantic Segmentation and Transfer Learning based Disease Classification in Black Gram Plants

Srinivas Talasila[1]*, Vijaya Kumar Gurrala[1], M Sucharitha[2] & Rajendra Prasad Somineni[1]
[1]VNR Vignana Jyothi Institute of Engineering and Technology, Hyderabad 500 090, Telangana, India
[2]VIT-AP University, Amaravati 522 237, Andhra Pradesh, India

Received 26 January 2024; revised 12 November 2024; accepted 11 March 2025

Smart farming, also known as precision agriculture, entails the integration of computing technologies into agriculture to promote sustainable and environment friendly practices. The high prevalence of plant diseases significantly affects the crop quality and yield, creating a need for a supporting system. Such systems should identify plant diseases more effectively and provide recommendations for the required amount of fertilizers for the particular disease. Hence, in this article, a framework for leaf segmentation and disease classification is proposed, particularly for black gram plants. This system uses advanced deep learning algorithms to segment the plant leaves and classify them into different disease categories. Real-time images have a complex background, which is similar to the leaf, and may mislead the disease recognition algorithms. To overcome this challenge, a semantic segmentation algorithm, which is DeepLabv3+, is proposed to segment leaf regions from the input images. The ResNet-18 architecture is utilized to serve as the backbone of the DeepLabv3+ layers. And then EfficientNet-B0 model is used for the disease classification. The experimental results showed that this combination for both segmentation and classification tasks achieved an accuracy of 99.72%, a precision of 99.35%, a recall of 99.33% and an F1 score of 99.34%. Finally, for the benefit of the farmers, an application is developed to recognize the diseases and recommend fertilizers for the disease.

Keywords: Agriculture, DeepLabv3+ layers, Deep learning, EfficientNet-B0, Plant diseases

Introduction

Agricultural sector is crucial to its growth for each and every nation. India depends on agricultural productivity for food and economic stability. The country requires substantial quantity of food to feed its 1.43 billion people. Food shortages to meet supply-demand gaps are a global concern. Plant diseases in the leaves impede agricultural productivity. As a result, the cost of food products increases, forcing poor people to go hungry. As soon as illnesses arise, crops must be protected. Thus, early plant disease diagnosis is valued in agriculture. Smart farming, also known as precision agriculture, allows farmers to use fewer pesticides and fertilizers, thus lowering environmental impact. However, due to lack of information, farmers may not detect diseases promptly. They depend on experts and other professionals to increase their productivity. Faster internet access availability at hand will make it easier for farmers and agricultural experts to communicate and share relevant information. Farmers can increase their efficiency, profitability, and sustainability and ensure that they continue to provide high-quality food to consumers, with the application of right technology and data-driven solutions.

Crop/Plant diseases typically originate from the leaves and spread throughout the plant. Numerous researchers have developed several disease detection techniques using basic image processing, machine learning and deep learning technologies.[1–3] The findings in this field have not reached their optimal level due to a wide range of plant species and their disease characteristics. However, deep learning for plant disease detection has grown in popularity for its advancements in computer vision and AI.[4]

In this work, a framework for black gram disease classification is proposed. Black gram, or urad bean (*Vigna mungo*), is a staple food grown in rainy and winter seasons, cultivated across South Asia, particularly in India. It has high protein content and soil-enriching nitrogen-fixing properties. Pulses contributed 7-10% of total food grain production in the country and Black gram is the major among them. However, the technological advancements in this crop are limited. Various diseases, including viruses harm

*Author for Correspondence
E-mail: srinivas_t@vnrvjiet.in

black gram plant leaves, affecting productivity. Thus, early and accurate disease identification is of paramount importance. So, as part of this research work Black gram Plant Leaf Disease (BPLD) Dataset was collected during January-April 2020 & 2021 at Nagayalanka, India, and used to evaluate our proposed framework work.

Literature Review and Research Gap

Deep learning is exceptionally well suited for image segmentation and classification tasks. In the field of agriculture, plant diseases can be detected and classified more effectively using it. This can be done through the use of Convolutional Neural Networks (CNN) and transfer learning. The demands and challenges of CNNs have been discussed in numerous works.[5–7] For leaf region segmentation, CNNs may be trained on images of leaves to identify and segment relevant regions of the leaf, such as the leaf margin, midrib, and lamina. For disease classification, transfer learning can be used to train the pre-trained networks, and then trained network can be used for classification. The use of deep learning for leaf region segmentation and disease classification can lead to improved accuracy and efficiency over the conventional methods such as hand-crafted features and Support Vector Machines (SVM).[8] This advancement helps detect and prevent plant diseases, ultimately boosting crop yields and reducing food waste.

There have been many methods proposed for leaf region segmentation; some popular deep learning methods for leaf region segmentation include U-Net, Mask R-CNN, and SegNet. A model namely U-Net, which is a fully CNN that uses a combination of down-sampling and up-sampling to capture both the local and global context of the image, with ResNet34 as encoder in it was employed for recognizing the leaves from the input images.[9] Chowdhury *et al.*[10] and Shoaib *et al.*[11] suggested a few slight changes in the U-Net and utilized for their work. A Mask R-CNN for leaf segmentation, which is a two-stage framework that first detects the leaf region and then segments the leaves from the images, was adopted.[12,13] A PLRSNet leaf segmentation network was designed to extract the leaf regions from the real field images.[14] The designed PLRSNet was based on SegNet architecture, which has an encoder-decoder network with a depth of 2 that uses an encoder to capture the hierarchical features of the image and a decoder to reconstruct the segmentation mask. Many other leaf segmentation models were proposed such as KijaniNet, ISC-MRCNN, AISA algorithm, and U^2-Net models, respectively, to extract leaf regions from the complex background images.[15–18] All these approaches demonstrated the potentiality of deep learning models in segmenting leaf regions.

Classification of plant diseases using pre-trained CNNs involves the use of existing deep learning models that have already been trained on large datasets to identify features and patterns in images of plants with diseases. This approach provides a fast and effective solution for identifying different types of diseases in plants and reduces the time and resources required to train a new model from scratch. A hybrid model for categorizing olive diseases that combines CNN and vision transformer models was developed.[19] The proposed ViT model with the combination of VGG16 obtained an accuracy of 97%. For multi-crop disease classification, a VGG-ICNN model that appends three blocks of Inception v7 to the four convolutional layers of VGG16 was introduced.[20] The model was able to attain 99.16% on Plant Village Dataset. Li *et al.*[21] improved accuracy and made the classification task more effective by combining the AlexNet and Inception-V4 networks. An optimized DenseNet model using two hidden layers was built and attained 95.7% accuracy for identifying tomato plant diseases.[22] EfficientNet architectures have been designed to be more efficient and perform better than existing models while using fewer resources. It was introduced in 2019 by Google researchers and has been adopted for various computer vision tasks. EfficientNet variants such as EfficientNetV2, EfficientNet-B7, EfficientNet-B0, and EfficientNet-B4 were also used for plant disease classification.[18,23–25]

Only a few research works have been conducted so far for the classification of plant diseases, particularly those affecting black gram leaves. These research works employed a variety of image processing and deep learning approaches to analyze, identify and classify plant diseases. A model named VirLeafNet was developed based on convolutional neural networks to determine the severity of the yellow mosaic disease of the black gram crop.[26] Abed *et al.*[9] utilized ResNet34 architecture to classify diseases after segmenting the leaf regions using U-Net architecture. At the same time,the MobileNetV2 model was utilized to classify two diseases of bean crop from the ibean dataset.[27] Talasila *et al.*[28] utilized DeepLabv3+ layers with MobileNetv2 as backbone for leaf segmentation and proposed a customized DCNN model for disease classification. However, these works are confined to a few diseases because of the lack of availability of the various diseased images in the utilized dataset.

Deep learning-based image processing algorithms are widely recognized for their effectiveness in identifying and classifying plant diseases. CNNs are proven to be very effective due to their flexibility, generalizability, and ability to self-learn for extracting required features for the detection and classification tasks. The presented research works made it abundantly evident that the deep learning approaches are the superior methods for detecting plant leaf diseases. Consequently, gathering a lot of data has a great impact on getting accurate results. To overcome this issue, data augmentation has been employed to alter the datasets. Despite the fact that the issue of plant disease detection has been solved with the findings of earlier research works, there is still a need to be solved, as the lack of availability of crop datasets having different disease characteristics. Overall, this literature suggests that deep learning technologies are highly effective in the field of plant disease classification. Future research should continue to explore and optimize these algorithms to further improve their accuracy and applications in this field.

Research Contributions

The primary contributions of this research include:

- Segmenting the leaf regions from the field images using a semantic segmentation model, which is DeepLabv3+.
- Training and Testing the EfficientNet-B0 model using transfer learning technique for classifying the black gram plant leaf diseases.
- Comparing the findings of the proposed combination of semantic segmentation and transfer learning model with the recent works.
- Developing a MATLAB based application that suggests farmers about the disease identified.

Materials and Methods

This article proposes a smart, automated disease classification system considering real-time cultivation field images. As a majority of the existing research works concentrated on extracting lesions rather than extracting leaf regions from the images, in this work, designed an efficient and automated segmentation algorithm to extract single leaf regions from complex backgrounds. This proposed approach of disease detection is a blend of segmentation and classification tasks. The flow of the research methodology adopted for classifying the leaf disease in the black gram crop, along with various stages in the training and testing phases, is illustrated in Fig. 1. The proposed system aims to provide a real-time solution for plant leaf segmentation and disease classification. The system uses image processing techniques to segment the leaf from the background and extract features for classification. Initially, data is collected from the fields or publicly available sources. Image preprocessing is done to enhance the quality of the images. And then, a leaf segmentation algorithm is developed to extract the leaf region from the complex background. Finally, trained and tested the deep network classifier for five class classification.

Data Collection

For this work, the Black gram crop was chosen. India is the world's largest producer of black gram. In 2021, the production of black gram in India was estimated to be around 6.5 million metric tons. Black gram production is expected to rise due to an increase in demand for vegetative protein and lentil popularity in India. Thus, it is necessary to create cutting-edge technology for this crop.

A BPLD dataset, which has 1000 images of black gram plant leaves, is utilized to develop the model.[29] This dataset is accessible to everyone in the Mendeley data. The images were taken in real-time field conditions using the camera and smartphones that can capture high-resolution images. The original images have very high resolution, which were then resized to 512 × 512 pixels and are in jpg format.

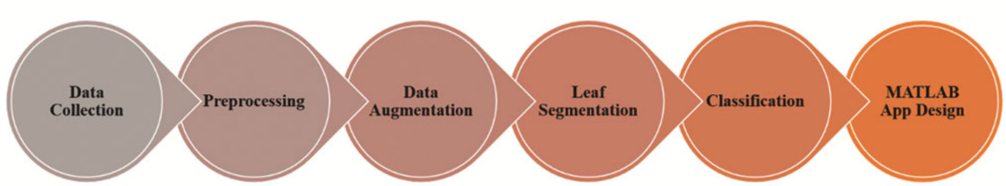

Fig. 1 — Flow of the proposed approach to disease detection

The BPLD dataset contains four disease categories and one healthy category of images as shown in Fig. 2. The presented black gram diseases in Fig. 2 can occur anytime between sowing and consumption of the product.

Pre-Processing

Image pre-processing is a crucial phase in deep learning, as it aids in improving the quality of the images and ensuring that the data fed to the model is suitable for training. Digital images need to be processed using the algorithms in the preprocessing stage to eliminate the visual distortion and noise which occurred while capturing the authentic field images. Using the Image segmenter tool in MATLAB, generated a ground truth label dataset for all the images in BPLD dataset for the leaf region segmentation task. Finally, images are rescaled to the required dimension 224 × 224 of the adopted deep networks for segmentation and classification tasks. Resizing the images to a consistent size helps in reducing computational time and increases accuracy. Later we adjusted the brightness and contrast of an image by redistributing the intensities of the pixels.

Data Augmentation

The quality and quantity of the training data play a significant role in finding efficient and accurate deep-learning models. However, the collection of such data is relevant to the time, cost and other resources. The lack of availability of data is the biggest problem in developing successful deep-learning models. Data augmentation is used to overcome this issue, which was used to create artificial data from the original data. The purpose of data augmentation is to help the model generalize better and reduce the chances of over fitting the training data. The model is exposed to a wider range of variations by creating new samples from the original data, leading to better accuracy and robustness. Shorten and Khoshgoftaar[30] provided a survey and detailed information on available data augmentation techniques, which improves the accuracy of the deep learning algorithms. They have categorized the augmentation techniques into basic image manipulations and deep learning approaches. When considering the basic manipulation to broaden the variability of the data, original images may have slight geometric alterations such as flipping, shifting, rotating, cropping, etc. By applying a few basic image alterations that are explained in detail[31], the 1000 images in the BPLD dataset were enlarged to 15000 images. The detailed information of images in the dataset is presented in Table 1. Adopted an 80:20 ratio on the augmented dataset to train and test segmentation and classification networks.

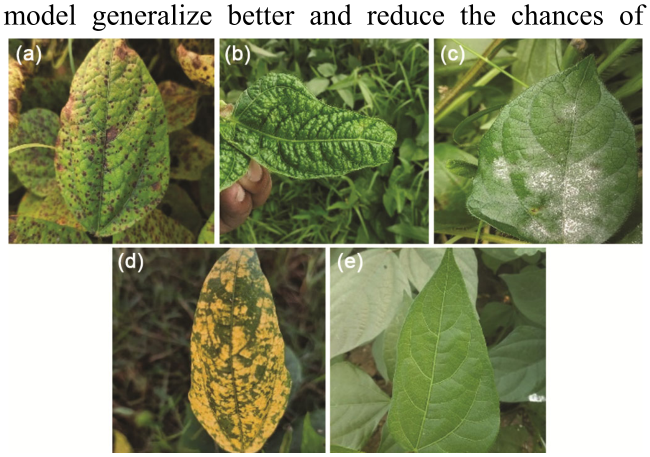

Fig. 2 — Black gram leaf diseases present in the dataset: (a) Anthracnose (b) Leaf crinkle (c) Powdery mildew (d) Yellow mosaic (e) Healthy

Segmentation

Plant disease classification highly relies on leaf region segmentation to extract the required leaf region from the real-time environment and identify the disease characteristics. Segmenting the leaf region may help the models to extract the required features to diagnose the diseases, which improves accuracy among the models. Many segmentation techniques like edge detection, thresholding, clustering, and other models are available, however, they struggle when the background closely resembles the leaf. Modern deep learning technologies, especially semantic segmentation models, can effectively segment leaves, even in the challenging backgrounds.

DeepLabv3+ segmentation approach was used in this work for leaf region segmentation. It is a deep learning-based image segmentation framework that can perform semantic segmentation tasks on a given image. This network is trained on large datasets of annotated images, where the pixels of each image are labelled according to the objects or parts of objects

Table 1 — Total number of samples in the BPLD Dataset before and after the data augmentation techniques applied, along with the number of training and testing images

Disease	Original samples	After augmentation	Training images	Testing images
Anthracnose	230	3450	2760	690
Leaf crinkle	150	2250	1800	450
Powdery mildew	180	2700	2160	540
Yellow mosaic	220	3300	2640	660
Healthy	220	3300	2640	660
Total	1000	15000	12000	3000

that they represent. DeepLabv3+ model can perform dense prediction of objects and their boundaries in an image. The current version of the DeepLab series is the DeepLabv3+. It was introduced by Chen *et al.*[32], which integrates encoder-decoder architecture with Atrous Spatial Pyramid Pooling (ASPP) module. It is an improvement over the original DeepLabv3 architecture, which uses an Xception backbone and includes a new decoder module to improve the quality of the segmentation predictions. Encoder-Decoder structure helps to get sharp object boundaries, whereas ASPP can extract contextual information at various dimensions. The structure of the DeepLabv3+ layers contains ASPP modules that perform four parallel convolution operations. One 1 × 1 convolution and three 3 × 3 convolutions with an atrous rate or dilation rate of 6, 12, and 18. It makes use of pre-trained CNNs for the encoding tasks.

In this work, we utilized the ResNet18 network as the backbone of DeepLabv3+ (Fig. 3). The ResNet18 architecture provides the DeepLabv3+ network with the ability to learn and recognize complex features in images, such as object edges and shapes, as well as to handle different image sizes and resolutions. The network is therefore well suited to handle a wide range of image segmentation tasks, including medical image analysis, autonomous driving, and robotics. The DeepLabv3+ with ResNet18 architecture represents a highly advanced and efficient tool for semantic image segmentation, offering state-of-the-art performance in various applications. By combining these two architectures, DeepLabv3+ and ResNet18 model can leverage the strengths of both to perform semantic segmentation in a more accurate and efficient manner. The ResNet18 (encoder) backbone provides a high-level feature representation that can be used to guide the pixel-level predictions made by the DeepLabv3+ (decoder) model.

Classification

For the classification of diseases, a CNN model was taken into consideration due to its superior performance in earlier research in this field. EfficientNet-B0 was utilized in this work for the classification task, which was developed by Tan and Le.[33] EfficientNet-B0 is the smallest and simplest model among the EfficientNet series, but still, it offers high accuracy and efficiency. It has 4.3 M parameters and a size of 12 MB, making it a superior option for deployment on low-memory devices. EfficientNet uses an efficient scaling method that adjusts the network size and depth based on the size of the input image. This allows the model to handle a range of image sizes, from small to large, without significant degradation in performance. The previous CNN architectures were typically built with an extremely high resolution, too much width, and depth. Increasing these attributes may enhance the model's efficiency but lead to a greater number of parameters, which makes them worthless. These attributes are increased in a systematic way in EfficientNet development, making it a more efficient model in CNNs. EfficientNet-B0 baseline model was taken here, as it has fewer parameters and high accuracy.

EfficientNet-B0 accepts 224 × 224 dimensioned images into the network. It used numerous 3 × 3 convolutional layers and MBConv modules to extract features. The input image is first processed to a 3 × 3 convolutional layer, and sixteen MBConv modules are used to get the features. Batch Normalization (BN) is carried out in the network following each convolution. The core of the EfficientNet-B0 model is

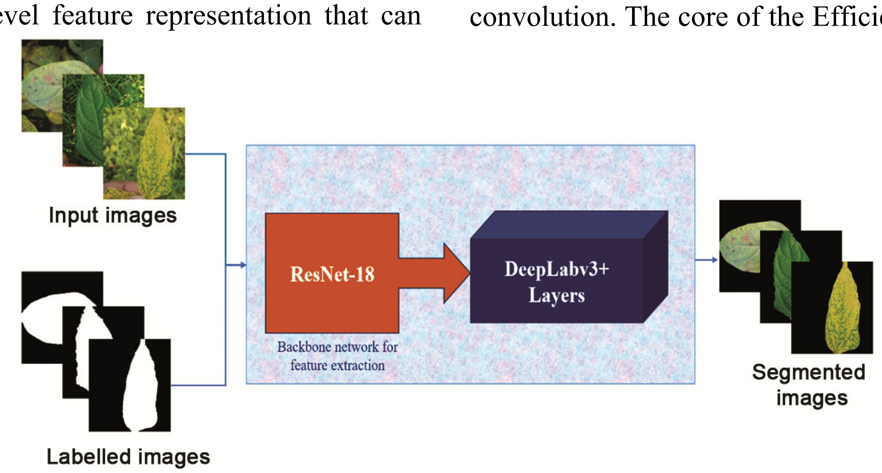

Fig. 3 — Leaf region segmentation based on DeepLabv3+ with ResNet18

made up of multiple MBConv blocks. Each block has several inverted residual bottleneck layers, followed by a depth wise separable convolution layer and a point wise convolution layer. The numbers of filters in each block increases as the network goes deeper. Skip connections are used between the MBConv blocks to allow information to bypass some of the layers. This helps the network to better preserve the low-level features from the early stages of the network. The head block consists of a global average pooling layer and a dense layer with the output number of nodes equal to the number of classes in the task. A softmax activation function follows this to produce the final prediction. EfficientNet-B0 model architecture is depicted in Fig. 4. The combination of these architectural elements makes EfficientNet-B0 well-suited for tasks such as image classification, object detection and semantic segmentation. This architecture was chosen because of its well-balanced resolution, depth and width, which results in a scalable, accurate and easy-to-implement model. EfficientNet-B0 outperformed previous cutting-edge algorithms developed using the ImageNet dataset. EfficientNet-B0 generated remarkable results even with transfer learning, demonstrating its usefulness beyond the typical ImageNet dataset.

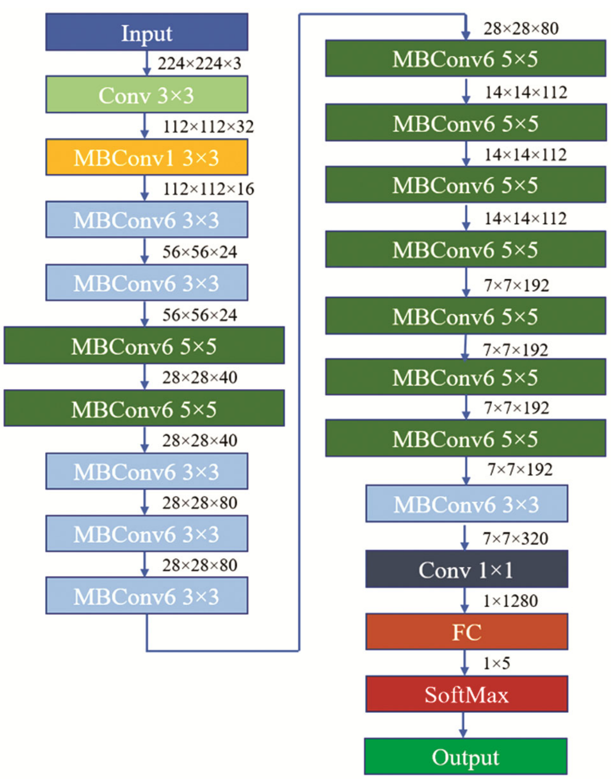

Fig. 4 — Network architecture of the EfficientNet-B0

Experimental Results & Discussion

The developed leaf region segmentation and classification algorithms were trained and tested on Windows 10 64-bit operating system in MATLAB 2022 software. Intel(R) Core (TM) i5-8250U CPU @1.60GHz1.80 GHz, 8GB RAM are specifications of the system environment. Along with NVIDIA Tesla P4 GPU was utilized to speed up the training process.

Segmentation of Leaf Regions with DeepLabv3+ Layers

This work focuses on extracting single leaves, which are relatively larger than leaves that are present in the background. This segmentation belongs to the binary segmentation, which has only two classes: leaf and background. As discussed earlier, the images in the BPLD dataset were captured from field conditions, DeepLabv3+ segmentation network was chosen for the leaf region segmentation. MATLAB image segmenter tool was utilized to create a labelled dataset for this binary segmentation. The original and labelled images were given as input to the DeepLabv3+ network for training. ResNet18 was used as a backbone for DeepLabv3+ in this work. ResNet18 network consists of a feature of identity mapping that enhances the network's capacity and generalizability. With only 18 layers, ResNet18 demonstrated its superior performance and greater accuracy.[34] ResNet18 would be a good choice as ResNet-18 provides a good balance of accuracy and computation efficiency, making it suitable for resource-constrained environments. To compare the performance of the proposed DeepLabv3+ with ResNet18 segmentation network, SegNet and U-Net architectures were taken.

All original and labelled images were resized to 224 × 224 to train the networks. Since the augmented dataset contains 15000 images, split into an 80:20 ratio, where training set entails 12000 images and testing set entails 3000 images. A set of experiments were conducted to optimize the hyper parameters and yielded the highest training accuracy 99.96% using SGDM optimizer, 0.001 initial learning rate, 32 mini-batch size, and 15 number of epochs. Except for U-Net's initial learning rate, which was set at 0.00001, the same hyper parameter combination was used to train the SegNet and U-Net architectures to compare the proposed network's performance.

Segmentation accuracy, Jaccard/IoU, Dice and boundary F1 Score metrics were used to evaluate the segmentation networks along with training accuracy and training loss. The mathematical expressions for the chosen performance metrics are

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots (1)$$

$$IoU = \frac{TP}{TP + FN + FP} \quad \ldots (2)$$

$$Dice = \frac{2 \times Jaccard}{1+jaccard} \quad \ldots (3)$$

$$BFScore = \frac{2 \times precision \times recall}{precision + recall} \quad \ldots (4)$$

where, $precision = \frac{TP}{TP + FP}$ and $recall = \frac{TP}{TP + FN}$

The performance comparison of SegNet, U-Net and proposed DeepLabv3+ with ResNet18 network in terms of training accuracy, training loss, segmentation accuracy, Jaccard/IoU, dice and boundary F1 score is presented in Table 2/Fig. 5. The exploratory findings demonstrated that the suggested segmentation network achieved 99.96% training accuracy, 0.0015 training loss, 99.54% testing accuracy, 97.08% intersection over union or Jaccard, 98.52% dice and 96.14% boundary F1 score. The findings exhibited the superiority of the network over the other competing models for segmentation.

The segmented sample outcomes of the networks are shown in Fig. 6, in which column 1 represents the original images in the BPLD dataset, column 2

Table 2 — Performance evaluation of the segmentation algorithms

Model	Training accuracy	Training loss	Testing accuracy	MeanIoU/Jaccard	DICE	BF Score
SegNet	93.14%	0.1782	94.32%	86.25%	92.62%	75.17%
U-net	95.29%	0.1199	92.68%	81.36%	89.72%	63.84%
DeepLabv3+ with ResNet18	99.96%	0.0015	99.54%	97.08%	98.52%	96.14%

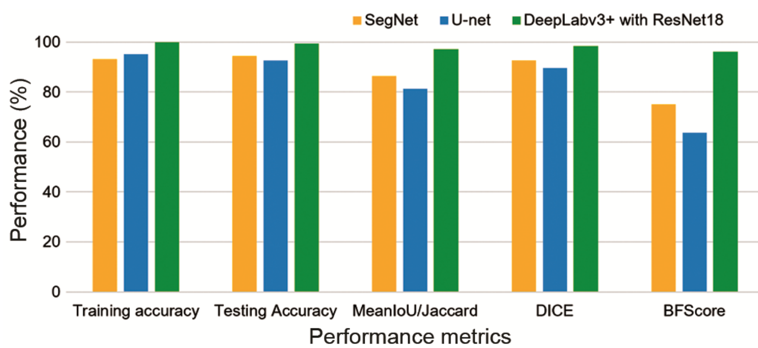

Fig. 5 — Performance evaluation of the segmentation algorithms

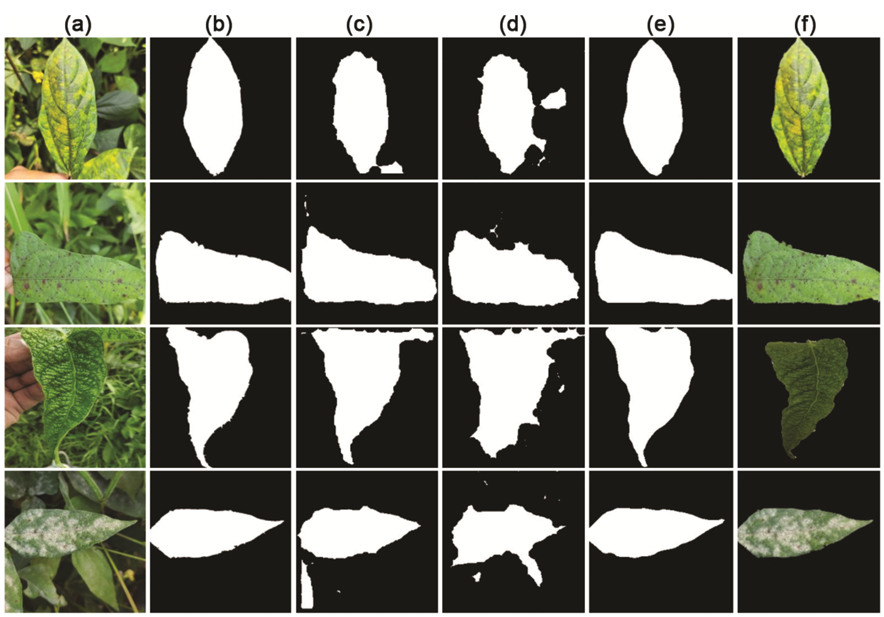

Fig. 6 — Segmented leaf region outcomes: (a) original images, (b) labelled images, (c) SegNet network outcomes, (d) U-Net network outcomes, (e) DeepLabv3+ with ResNet18 network outcomes (f) extracted leaf region outcomes after background segmentation

represents labelled images created by using MATLAB image segmenter tool, column 3 represents SegNet architecture outputs, column 4 represents U-Net architecture outcomes, column 5 represents DeepLabv3+ with ResNet18 network outputs and column 6 represented extracted leaf regions in RGB. Also, it has been visually confirmed that the proposed segmentation network was quite effective in segmenting leaf regions from complex backgrounds. The normalized confusion matrix of the designed DeepLabv3+ with ResNet18 network is illustrated in Fig. 7. The accuracy and error for each class (leaf and background) can be observed in the confusion matrix.

Disease Classification Using Segmented Leaf Regions and EfficientNet-B0

EfficientNet-B0 model was selected for the classification task with the goal of efficient classification and cost-effectiveness. EfficientNet-B0 could be a good choice for disease classification because it provides a balance between accuracy and computing economy, which is crucial when working with large datasets. To train and test the adopted classification network, segmented outputs were utilized. As the segmented dataset has 15000 leaf images, which were split into a ratio of 80:20 (12000 and 3000) for training and testing, respectively. An image size of 224 × 224 was used as input to the network. For validation while training the network, 10% of training images were leveraged. Using manual search method, hyper parameters are tuned, and the same were used for all experimentations. The chosen combination of hyper parameters is SGDM solver, 0.001 initial learning rate, 32 mini batch size, and 30 epochs. Transfer learning was employed to train models as well as competing models. Transfer learning involves freezing the pre-trained model's layers and retraining the last few layers on the new data to learn the new task. This allows the model to use information learned from the previous task and hence reduce the training data required and minimize over fitting. Finally, transfer learning is a powerful technique that can save time and resources while improving the performance of deep learning models on new tasks.

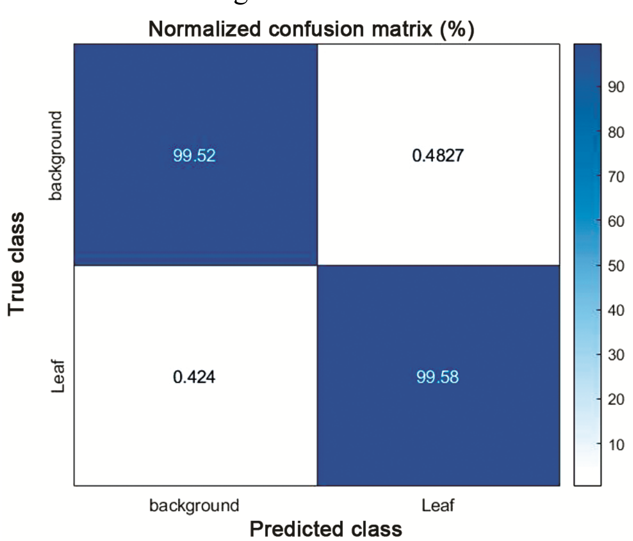

Fig. 7 — Normalized confusion matrix of the proposed DeepLabv3+ with ResNet18 network

To evaluate the performance of the classification network, performance metrics such as accuracy, precision, recall and F1 Score were utilized and are mathematically represented as

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad \ldots (5)$$

$$Recall = \frac{TP}{TP + FN} \quad \ldots (6)$$

$$Precision = \frac{TP}{TP + FP} \quad \ldots (7)$$

$$F1\_score = \frac{2 \times Precision \times Recall}{Precision + Recall} \quad \ldots (8)$$

To compare the performance of the adopted EfficientNet-B0 classification network, state-of-the-art networks such as GoogLeNet, MobileNetv2, ShuffleNet and SqueezeNet models were employed. All these networks were trained using the same hyper parameter combinations. The exploratory findings in Table 3 revealed that the proposed EfficientNet-B0 exhibited superior performance for classifying five categories of black gram crop diseases. Additionally, compared and tabulated the results of classification experiments when using field images directly. The

Table 3 — Performance comparison of the classification networks for both using segmented leaf regions and field images

Model	Using segmented leaf regions				Using field images			
	Accuracy	Precision	Recall	F1_Score	Accuracy	Precision	Recall	F1_Score
GoogLeNet	99.27%	98.21%	98.29%	98.23%	98.63%	97.04%	95.82%	96.26%
MobileNetv2	99.53%	98.93%	98.89%	98.90%	98.97%	97.45%	97.33%	97.38%
ShuffleNet	99.64%	99.16%	99.16%	99.16%	98.79%	96.99%	96.97%	96.94%
SqueezeNet	99.45%	98.66%	98.73%	98.69%	98.24%	95.86%	95.35%	95.51%
EfficientNet-B0	99.72%	99.35%	99.33%	99.34%	98.71%	96.91%	96.67%	96.73%

research demonstrates that employing segmented leaf regions instead of field-conditioned images improved the networks' classification performance. The superiority of the EffiicientNet-B0 over competing models is observable. Segmented leaves improved the accuracy of the network by about 1–3% as seen in Table 3. The proposed EfficientNet-B0 was able to achieve a greater classification accuracy of 99.72%, precision of 99.35%, recall of 99.33% and F1 score of 99.34%. The classification outcomes of each individual disease class present in the BPLD dataset were tabulated in Table 4 for all the networks.

The confusion matrix of the proposed EfficientNet-B0 model performance on the test set was represented in Fig. 8, from which the model misclassified 21 samples out of 3000 samples in the test set can be observed.

A summary of several recent research works that employed leaf region segmentation on the collected image and then applied classification of the disease is illustrated in Table 5. The comparison shows the potential of the presented research work. This research work is very effective and valuable for classifying black gram diseases, particularly when the images are from field conditions. The proposed work is explicitly based on two architectures, namely DeepLabv3+ for segmentation and EfficientNet-B0 for classification. The adopted combination of

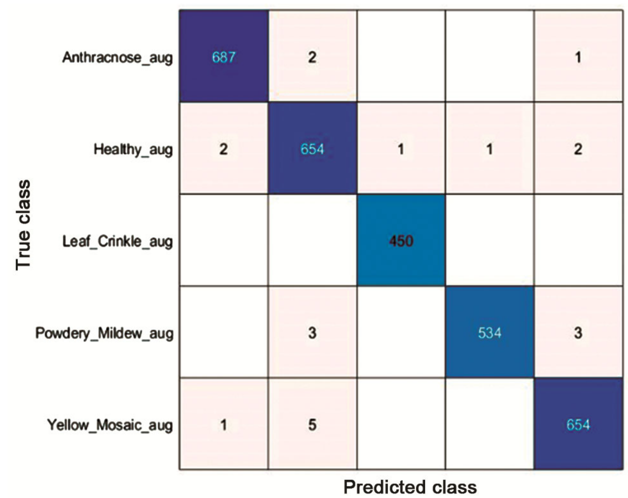

Fig. 8 — Confusion matrix of the EfficientNet-B0 classification model performance on the test set

Table 4 — Performance comparison of the classification networks for each individual disease class

Model	Disease	Accuracy	Precision	Recall	F1_Score
GoogLeNet					
	Anthracnose	99.30%	99.41%	97.54%	98.46%
	Healthy	99.07%	99.07%	96.67%	97.85%
	Leaf crinkle	99.60%	97.40%	1.00%	98.68%
	Powdery mildew	99.63%	99.81%	98.15%	98.97%
	Yellow mosaic	98.73%	95.34%	99.09%	97.18%
MobileNetV2					
	Anthracnose	99.83%	1.00%	99.28%	99.64%
	Healthy	98.90%	96.04%	99.09%	97.54%
	Leaf crinkle	99.93%	99.56%	1.00%	99.78%
	Powdery mildew	99.70%	99.81%	98.52%	99.16%
	Yellow mosaic	99.30%	99.23%	97.58%	98.40%
ShuffleNet					
	Anthracnose	99.93%	99.71%	1.00%	99.86%
	Healthy	99.13%	97.60%	98.48%	98.04%
	Leaf crinkle	99.93%	99.78%	99.78%	99.78%
	Powdery mildew	99.90%	99.63%	99.81%	99.72%
	Yellow mosaic	99.30%	99.08%	97.73%	98.40%
SqueezeNet					
	Anthracnose	99.83%	99.57%	99.71%	99.64%
	Healthy	98.93%	97.29%	97.88%	97.58%
	Leaf crinkle	99.77%	98.68%	99.78%	99.23%
	Powdery mildew	99.83%	99.45%	99.63%	99.54%
	Yellow mosaic	98.90%	98.31%	96.67%	97.48%
EfficientNet-B0					
	Anthracnose	99.80%	99.57%	99.57%	99.57%
	Healthy	99.47%	98.49%	99.09%	98.79%
	Leaf crinkle	99.97%	99.78%	1.00%	99.89%
	Powdery mildew	99.77%	99.81%	98.89%	99.35%
	Yellow mosaic	99.60%	99.09%	99.09%	99.09%

Table 5 — Summary of recent research works that utilized leaf region segmentation and then disease classification

Dataset	Crop	Number of images	Segmentation network employed	Classification network employed	Overall classification accuracy
Self-collected from fields[12]	Sunflower	858	Mask-RCNN	ResNet152	96.6%
Self-collected from fields[16]	15 Species	4000	Mask-RCNN	VGG16	91.5%
PlantVillage dataset[11]	tomato	18161	Modified U-Net	InceptionNet1	99.12%
Self-collected & PlantVillage Dataset[18]	Cardamon and Grape	1724 & 4062	U^2-Net	EfficientNetV2	98.26%
PlantVillage dataset[35]	Multiple	4588	Edge and Morphological	DenseNet121	98.9%
PlantVillage dataset[10]	tomato	18161	Modified U-Net	EfficientNet-B4	99.89%
ibean dataset[9]	Bean	1295	U-Net	DenseNet121	98.31%
PlantVillage dataset[17]	Multiple	38072	AISA algorithm	MobileNet	more than 80%
BPLD dataset (Current work)	Black gram	1000	DeepLabv3+ with ResNet18	EfficientNet-B0	99.72%

DeepLabv3+ with ResNet18 Segmentation model and EfficientNet-B0 classification model attained 99.72% classification accuracy on BPLD dataset.

The findings and conclusions of all experiments indicate that the proposed methodology can enable farmers and plant pathologists to identify black gram diseases accurately and effectively. Further, it will allow them to implement essential disease control measures. Moreover, researchers or app developers can create mobile applications that will help farmers detect diseases as quickly as possible whenever they occur. Considering the above-noted points, a MATLAB based application is developed that enables farmers to detect black gram leaf diseases in their earliest occurrence.

Application Development

Nowadays, with the growing availability of the internet and smart devices has led to an increase in the number of apps designed to make work easier for end users. So, we intend to develop an application for this work, which incorporates a trained segmentation network to extract leaf regions from the images and a classification network for classifying diseases present on the leaves. A MATLAB platform was utilized to develop the application of the presented research work. MATLAB is a powerful tool for developing applications in various domains. It is easy-to-use interface and rich library of functions make it an ideal choice for application development. By utilizing the trained algorithms, created a black gram crop leaf segmentation and disease classification system that enables the farmer to upload leaf images taken from the real-time cultivation fields and provides detailed disease information and pesticide recommendations.

This designed MATLAB application has three buttons, i) Input Image: where the farmer can upload the images; ii) Leaf Region Segmentation: which will extract leaf region from the input images using the developed DeepLabv3+ with ResNet18 semantic segmentation algorithm; iii) Disease Prediction: will predict the disease using the trained EfficientNet-B0 classification model. Here, leaf region segmentation output will be the input for the classification model. The disease management section of the interface will automatically display the disease information and fertilizer recommendations when the disease has been identified. The designed MATLAB app interface is shown in Fig. 9. Designing this type of app-based plant disease detection system is helpful for farmers who need to quickly and accurately identify diseases in their crops and to provide treatments for diseases.

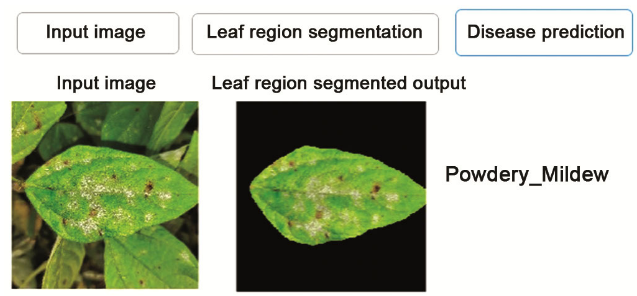

Fig. 9 — Designed MATLAB App interface

Finally, the proposed model accurately identifies the diseases in black gram, enabling accurate and timely detection. The developed application provides disease management, such as recommended fertilizers to cure the occurring disease in the crop. With the provided recommendations, farmers can make reliable decisions on optimizing the usage of fertilizers and pesticides. Moreover, the developed system not only promotes crop health by recommending fertilizers but also minimizes the risk of chemical overuse. Reducing excessive chemicals helps in preserving soil health and protects the ecosystem, which further leads to supporting more sustainable farming. Further, the proposed system lowers the input costs and provides high yields, offering economic benefits to the farmers.

Conclusions

A framework for detection of black gram crop leaf diseases is presented in this article and developed an app incorporating the proposed algorithms using MATLAB. BPLD dataset was utilized for this work. The proposed fusion of models: DeepLabv3+ with ResNet18 and EfficientNet-B0 achieved an outstanding classification accuracy of 99.72%. Moreover, the developed application is successful in segmenting leaf regions from field images, identifying the disease accurately and providing recommendations to the farmers about disease control measures. This research did not attempt measuring disease severity and detecting several diseases on a single leaf because of the limited available data. Besides, the dataset does not include images of all phases of the plant's growth and phases of disease growth. In future, we intend to increase the dataset with more number of diseases and to develop algorithms that detect multiple diseases on a single leaf and the severity of the identified disease.

Data availability

The data used in this work is available in Mendeley data at https://doi.org/10.17632/zfcv9fmrgv.3

References

1 Kundu R, Chauhan U & Chauhan S P S, Plant leaf disease detection using image processing, *Int Conf Innov Pract Technol Manag (IEEE)*, **2** (2022) 393–396, https://doi.org/10.1109/iciptm54933.2022.9754170.

2 Ahmed I & Yadav P K, Plant disease detection using machine learning approaches, *Expert Syst*, **40(5)** (2023) e13136, https://doi.org/10.1111/exsy.13136.

3 Talasila S, Rawal K & Sethi G, Black gram disease classification using a novel deep convolutional neural network, *Multimed Tools Appl*, **82(28)** (2023) 44309–44333, https://doi.org/10.1007/s11042-023-15220-4.

4 Bhargava A, Shukla A, Goswami O P, Alsharif M H, Uthansakul P & Uthansakul M, Plant leaf disease detection, classification, and diagnosis using computer vision and artificial intelligence: A review, *IEEE Access*, **12** (2024) 37443–37469, https://doi.org/10.1109/access.2024.3373001.

5 Sarkar C, Gupta D, Gupta U & Hazarika B B, Leaf disease detection using machine learning and deep learning: Review and challenges, *Appl Soft Comput*, **145** (2023) 110534, https://doi.org/10.1016/j.asoc.2023.110534.

6 Ngugi H N, Ezugwu A E, Akinyelu A A & Abualigah L, Revolutionizing crop disease detection with computational deep learning: a comprehensive review, *Environ Monit Assess*, **196** (2024) 302, https://doi.org/10.1007/s10661-024-12454-z.

7 Ahmad A, Saraswat D & El Gamal A, A survey on using deep learning techniques for plant disease diagnosis and recommendations for development of appropriate tools, *Smart Agric Technol*, **3** (2023) 100083, https://doi.org/10.1016/j.atech.2022.100083.

8 Xu M, Park J E, Lee J, Yang J & Yoon S, Plant disease recognition datasets in the age of deep learning: Challenges and opportunities, *Front Plant Sci*, **15** (2024) 1452551, https://doi.org/10.3389/fpls.2024.1452551.

9 Abed S H, Al-Waisy A S, Mohammed H J & Al-Fahdawi S, A modern deep learning framework in robot vision for automated bean leaves diseases detection, *Int J Intell Robot Appl*, **5(2)** (2021) 235–251, https://doi.org/10.1007/s41315-021-00174-3.

10 Chowdhury M E H, Rahman T, Khandakar A, Ayari M A, Khan A U, Khan M S, Al-Emadi N, Reaz M B I, Islam M T & Ali S H M, Automatic and reliable leaf disease detection using deep learning techniques, *Agric Eng*, **3(2)** (2021) 294–312, https://doi.org/10.3390/agriengineering3020020.

11 Shoaib M, Hussain T, Shah B, Ullah I, Shah S M, Ali F & Park S H, Deep learning-based segmentation and classification of leaf images for detection of tomato plant disease, *Front Plant Sci*, **13** (2022) 1031748, https://doi.org/10.3389/fpls.2022.1031748.

12 Dawod R G & Dobre C, Automatic segmentation and classification system for foliar diseases in sunflower, *Sustainability*, **14(18)** (2022) 11312, https://doi.org/10.3390/su141811312.

13 Yang K, Zhong W & Li F, Leaf segmentation and classification with a complicated background using deep learning, *Agronomy*, **10(11)** (2020) 1721, https://doi.org/10.3390/agronomy10111721.

14 Talasila S, Rawal K & Sethi G, PLRSNet: A semantic segmentation network for segmenting plant leaf region under complex background, *Int J Intell Unmanned Syst*, **11(1)** (2023) 132–150, https://doi.org/10.1108/ijius-08-2021-0100.

15 Ngugi L C, Abdelwahab M & Abo-Zahhad M, Tomato leaf segmentation algorithms for mobile phone applications using deep learning, *Comput Electron Agric*, **178** (2020) 105788, https://doi.org/10.1016/j.compag.2020.105788.

16 Yang X, Chen A, Zhou G, Wang J, Chen W, Gao Y & Jiang R, Instance segmentation and classification method for plant leaf images based on ISC-MRCNN and APS-DCCNN, *IEEE Access*, **8** (2020) 151555–151573, https://doi.org/10.1109/access.2020.3017560.

17 Xiong Y, Liang L, Wang L, She J & Wu M, Identification of cash crop diseases using automatic image segmentation algorithm and deep learning with expanded dataset, *Comput Electron Agric*, **177** (2020) 105712, https://doi.org/10.1016/j.compag.2020.105712.

18 Sunil C K, Jaidhar C D & Patil N, Cardamom plant disease detection approach using EfficientNetV2, *IEEE Access*, **10** (2021) 789–804, https://doi.org/10.1109/access.2021.3138920.

19 Alshammari H, Gasmi K, Ben Ltaifa I, Krichen M, Ben Ammar L & Mahmood M A, Olive disease classification based on vision transformer and CNN models, *Comput Intell Neurosci*, **2022(1)** (2022) 3998193, https://doi.org/10.1155/2022/3998193.

20 Thakur P S, Sheorey T & Ojha A, VGG-ICNN: A lightweight CNN model for crop disease identification,

Multimed Tools Appl, **82(1)** (2023) 497–520, https://doi.org/10.1007/s11042-022-13144-z.

21 Li Z, Li C, Deng L, Fan Y, Xiao X, Ma H, Qin J & Zhu L, Improved AlexNet with Inception-V4 for plant disease diagnosis, *Comput Intell Neurosci*, **2022(1)** (2022) 5862600, https://doi.org/10.1155/2022/5862600.

22 Yulita I N, Amri N A & Hidayat A, Mobile application for tomato plant leaf disease detection using a dense convolutional network architecture, *Computation*, **11(2)** (2023) 20, https://doi.org/10.3390/computation11020020.

23 Kaur P, Harnal S, Tiwari R, Upadhyay S, Bhatia S, Mashat A & Alabdali A M, Recognition of leaf disease using hybrid convolutional neural network by applying feature reduction, *Sensors*, **22(2)** (2022) 575, https://doi.org/10.3390/s22020575.

24 Noon S K, Amjad M, Ali Qureshi M & Mannan A, Computationally light deep learning framework to recognize cotton leaf diseases, *J Intell Fuzzy Syst*, **40(6)** (2021) 12383–12398, https://doi.org/10.3233/jifs-210516.

25 Atila Ü, Uçar M, Akyol K & Uçar E, Plant leaf disease classification using EfficientNet deep learning model, *Ecol Inform*, **61** (2021) 101182, https://doi.org/10.1016/j.ecoinf.2020.101182.

26 Joshi R C, Kaushik M, Dutta M K, Srivastava A & Choudhary N, VirLeafNet: Automatic analysis and viral disease diagnosis using deep-learning in Vigna mungo plant, *Ecol Inform*, **61** (2021) 101197, https://doi.org/10.1016/j.ecoinf.2020.101197.

27 Elfatimi E, Eryiğit R & Elfatimi L, Beans leaf diseases classification using mobilenet models, *IEEE Access*, **10** (2022) 9471–9482, https://doi.org/10.1109/access.2022.3142817.

28 Talasila S, Rawal K & Sethi G, Black gram disease classification using a novel deep convolutional neural network, *Multimed Tools Appl*, **82(28)** (2023) 44309–44333, https://doi.org/10.1007/s11042-023-15220-4.

29 Talasila S, Rawal K, Sethi G, Sanjay M S S & Reddy M S P, Black gram Plant Leaf Disease (BPLD) dataset for recognition and classification of diseases using computer-vision algorithms, *Data in Brief*, **45** (2022) 108725, https://doi.org/10.1016/j.dib.2022.108725.

30 Shorten C & Khoshgoftaar T M, A survey on image data augmentation for deep learning, *J Big Data*, **6(1)** (2019) 1–48, https://doi.org/10.1186/s40537-019-0197-0.

31 Talasila S, Rawal K & Sethi G, Conventional data augmentation techniques for plant disease detection and classification systems, *Smart Innov Syst Technol*, **289** (2022) 279–287, https://doi.org/10.1007/978-981-19-0011-2_26.

32 Chen L C, Zhu Y, Papandreou G, Schroff F & Adam H, Encoder-decoder with atrous separable convolution for semantic image segmentation, *Proc European Conf Comput Vis* (Springer*)* 2018, 833–851, https://doi.org/10.1007/978-3-030-01234-2_49.

33 Tan M & Le Q, EfficientNet: Rethinking model scaling for convolutional neural networks, *arXiv preprint*, (2019) 1905, https://doi.org/10.48550/arXiv.1905.11946.

34 He K, Zhang X, Ren S & Sun J, Deep residual learning for image recognition, *Proc IEEE Comput Soc Conf Comput Vis Pattern Recognit* (IEEE) 2016, 770–778, https://doi.org/10.1109/cvpr.2016.90.

35 KcK, Yin Z, Li D & Wu Z, Impacts of background removal on convolutional neural networks for plant disease classification in-situ, *Agriculture*, **11(9)** (2021) 827, https://doi.org/10.3390/agriculture11090827.