Proceedings of the International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI-2025)
DVD Part Number: CFP25VH0-DVD; ISBN: 979-8-3315-0981-1

Cuscuta Detection and Classification of Blackgram Plant Leaf Diseases using Deep-Transformation Algorithm

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***Abstract*— Cuscuta is a parasitic plant that highly impacts the yielding of black gram (Vigna mungo) by reducing the quality based on required subsistence. Early detection of Cuscuta affliction becomes more complex, which may lead to heavy loss to the framers. This paper proposed a new Deep-Transformation Algorithm (DTA) to overcome various issues in finding the affected regions accurately and effectively classifying Cuscuta on black gram plants. In this context, the pre-trained model VGGNet is used to train on Cuscuta images that obtain the disease patterns using multiple layers. The preprocessing technique, the contrast enhancement model CLAHE (contrast limited adaptive histogram equalization), improves the confined regions and avoids over-saturation. The other segmentation method, such as Watershed segmentation, is used to segment the regions based on Cuscuta stems and leaves. Finally, the proposed DTA is the combination of Pipeline with a fine-grained neural network applied on testing set images, which obtains superior performance in terms of classification accuracy with 99.78%, which is high compared with other existing models.**

Keywords*— Cuscuta, Black Gram (Vigna mungo), VGGNet, Deep-Transformation Algorithm (DTA), CLAHE.

I. Introduction

Agriculture contributes to feeding humanity as well as a major driver of socioeconomic stability globally. But, plant diseases are a significant problem for the agricultural industry, leading to reduced quality and lower yields of crops. Plant diseases can cause radical losses in production and productivity, therefore, early detection with correct results is necessary to limit these defects leading then to sustainable agricultural techniques. Historically, the detection of plant diseases depends on the inspection by experts or farmers that is a time-consuming, expensive and error-prone task. In addition, with there being less expertise and resources available in far-off areas or those not developed fully, there are increased instances of delayed diagnoses or wrong diagnoses. This creates a need for automated, reliable and scalable solutions. Blackgram (Vigna mungo), or urad bean, and black lentil, is an important legume crop grown in various regions because of its nutritional and economic value. But its productivity is greatly hampered by many diseases like powdery mildew, Cercospora leaf spot and mosaic diseases due to viruses and fungi. Therefore, early and correct diagnoses of these diseases are urgent needs for better crop management and yield loss prevention.

Figure 1: Sample Cuscuta (dodder) Image

Artificial intelligence (AI) has already made great strides in detecting and managing plant disease and parasitic infestation. Cuscuta (dodder) is one of these parasitic plants that represent a significant biotic stress for crop productivity, e.g. blackgram (Vigna mungo). Cuscuta encircles the stems of host plants, drawing nutrients from within and resulting in catastrophic yield losses. Quick detection and accurate identification of Cuscuta infestation is the need of the hour, for minimizing its ill impact and achieving sustainable crop production. The large data based and computational power driven approaches namely deep learning (DL) and transformation-based algorithms (TBA) has been proven as a competent tool to explain the complex agricultural problems. In this study, we apply a Deep-Transformation Algorithm to effectively identify and classifying Cuscuta infestations in blackgram plants. We have developed an improved method that integrates deep neural networks with advanced image processing techniques to achieve a quick but solid real-time monitoring and resource management.

II. Literature Survey

YASIN et al. [10] proposed the BPLD, which focuses on classifying Black Gram Plant Disease. Various plant leaf diseases belong to the black gram. In this context, various DL algorithms are used to classify BPLD. From these algorithms, the Darknet-53 and ResNet-101 obtain superior accuracy performance of 98.98%. Sunil et al. [11] proposed the literature on plant diseases and classifications using various ML and DL algorithms. Many studies discussed several multiple plants, and approximately 104 research works were considered to analyze the performance of these algorithms. Venkatesh et al. [12] introduced advanced ML-based disease detection for plant leaf diseases. In this context, the black gram plant is used for the analysis based on classification. The RF used for the training acquired an accuracy of 99.18% and a testing accuracy of 97.34%; compared with other models, the proposed approach obtains superior outcomes. Mehdhar et al. [13] introduced the ensemble approach that combined three CNN models (MobileNetv2, NasNetMobile, and traditional CNN). The proposed approach is first trained with two models at the base level and transforms these predictions to the XGboost model that shows the final prediction. The XGBoost, combined with a search grid algorithm, obtains an accuracy of 98% in terms of classification. Joshi et al. [14] proposed an integrated model that combined automated DL algorithms to classify Vigna mungo leaves collected from various online sources. VirLeafNet-1, VirLeafNet-2, and VirLeafNet-3 have the highest accuracy at 91.234%, 96.429%, and 97.403%, respectively, on several leaf images. Ramanjot et al. [15] discussed various papers related to plant diseases. The selected papers are from 2010 to 2022 and are published in various online sources. All these articles are relevant to plant diseases and classification using ML and DL algorithms. Meena et al. [16] presented various trends that help to detect and predict plant diseases using advanced DL and image processing techniques. The proposed approach uses the artificial feature selection algorithm that identifies plant diseases based on spots that occur in the plant diseases. These models improve the detection and classification of plant diseases with better performance. The final accuracy obtained was 96.25% with accurate region detection. Johri et al. [17] discuss several DL-based algorithms that detect and predict plant diseases. The proposed DL models, compared with various algorithms, provide accurate results in terms of classification. Abbas et al. [18] proposed the C-GAN, which is combined with transfer learning. The proposed approach detects the regions of tomato plants accurately. The training model DenseNet21 is used to train on actual tomato leaves and also artificial images. The data augmentation technique increases the network performance based on the accuracy of 99.51% with the classification of 5 types of images.

III. PRE-TRAINED MODEL VGGNET

In this step, the automation of both detection and classification of Cuscuta infestations can be efficiently done using deep CNN like VGGNet or/and with the help of transfer learning/pre-trained networks for robustness feature extraction. The advantages of using the pre-trained VGGNet model show the huge impact on identifying the disease patterns. The VGGNet proposed exploiting deeper architectures and using smaller convolutional filters to capture fine-grained image details. The key factors of the pre-trained model VGGNet is explained as:

Architecture: VGGNet has 16 to 19 layers, and most of the convolution filters are small (3x3). This architecture is deep enough to extract complex features from Black gram images.

Pre-trained Models: Models for VGGNet are often pre-trained on vast data sources, such as ImageNet, which comprises millions of images spanning thousands of categories. These pre-trained model weights are a good starting point for solving image classification issues.

Transfer Learning: In this step, the features learned to adapt the network to specific features obtained from the input Black grain images.

Convolutional Layers (Feature Extraction): These layers extract the sequence features from input images. The Convolution Operation is represented as:

$$\mathrm{Y_{a,b,c}} = \sum_{x=0}^{X-1}\sum_{y=0}^{Y-1}\sum_{z=0}^{Z-1} \mathrm{A_{(a+x\_(b+y)z}} \cdot \mathrm{W_{x,y,z,c}} + \mathrm{N_c} \quad (1)$$

Rectified Linear Unit (ReLU) Activation: This is the second step and it is applied as:

$$\mathrm{f(x)} = \max(0, x) \quad (\mathbf{2})$$

Pooling Layers (Dimensionality Reduction): This layer mainly reduces the spatial dimensions while retaining the more significant features:

$$\mathrm{Y_{a,b,c}} = \max_{(x,y)\in \mathrm{Pool(a,b)}} \mathrm{X_{a,y,z}} \quad (3)$$

Fully Connected Layers (FCL) (Classification): From Steps 1 and 2, the features are smoothed and fed into FCLs. The softmax function is represented as:

$$\mathrm{P(y = c|X)} = \frac{e^{z_c}}{\sum_{k=1}^{K} e^{z_k}} \quad (4)$$

Transfer Learning: The parameters in VGGNet are optimized for traditional features from the input image. The fine-tuned network from the black gram dataset is replaced with the final classification layers to detect the Cuscuta.

- The softmax layer is replaced to measure the total classes (e.g., "healthy," "Cuscuta-infested").
- Fine-tune the network on the Blackgram dataset.

$$\mathrm{L} = -\frac{1}{\mathrm{N}} \sum_{a=1}^{N}\sum_{b=1}^{C} \mathrm{y_{a,b}} \log(\hat{\mathrm{y}}_{a,b}) \quad (5)$$

Output Interpretation: The final output is a class prediction.

$$\mathrm{Class} = \arg\max_{c} \mathrm{P(y = c|X)} \quad (6)$$

IV. DATASET DESCRIPTION

The collection contains images of black gram crops gathered in Avanigadda Mandal, Krishna District, Andhra Pradesh, India, one of the most badly afflicted areas by Cuscuta. In this context, the images of the black gram plant are divided into Cuscuta and Healthy categories. Each category has 400 images, totaling 800 images. The training set includes 400 images, while the testing set contains 400.

V. PRE-PROCESSING WITH CONTRAST LIMITED ADAPTIVE HISTOGRAM EQUALIZATION (CLAHE)

CLAHE is an image processing enhancement that enhances the contrast of a given image. While classical histogram equalization restores the entire image, the CLAHE method works within the image's small defined regions (or tiles/blocks). This local enhancement aids in keeping the details of different illumination (of the image during day and night). Furthermore, it adds contrast limiting to prevent noise or small details from being overly amplified, which may cause over-saturation. It is the most suitable pre-processing technique for the dataset images to detect Cuscuta (a parasitic plant) on Blackgram plants.

During image enhancement, oversaturation causes loss of information in regions where pixel values reach intensity saturation. CLAHE restricts the enhancement of contrast for pixel distributions close to saturation, preserving relevant information on bright and dark regions. CLAHE outputs more suitable images as input for machine learning or computer vision algorithms, facilitating accurate segmentation of the Cuscuta areas. Imaging plants in soil translates to an enhancement of the image that is critical for feature extraction, which ultimately leads to high-quality classification among infected and non-infected plants. The field images of Blackgram plants are mostly obtained through non-uniform lighting conditions, as shown. CLAHE overcomes these variations, thus providing uniform improvement throughout the image. It restricts the gain of noise, which is a widespread problem in traditional histogram equalization. The following steps shows the filtering of noise from the input image.

Step 1: Split the Image into regions

The input image split into regions which is represented as, $R_{a,b}$ with size m x n. These regions processed separately.

Step 2: Measuring the Histogram for Each Region

For every region $R_{a,b}$, the histogram H_k for intensity level k is measured:

$$H_k = \sum_{(a,b)\epsilon R_{a,b}} \delta(I(a,b) - k), \quad (7)$$

where $\delta(a) = \begin{cases} 1, & \text{if } a = 0, \\ 0, & \text{otherwise} \end{cases}$

Step 3: Contrast Limiting

In this step, the over-improvement prevents the noise; it fastens the histogram at a predefined limit, T, called the clip limit. It represents the fastened histogram as:

$$H_k^{clip} = \min(H_k, T) \quad (8)$$

The over pixels fasten the histogram, which is redistributed among all intensity levels to manage the overall pixel count in the region.

Step 4: Plotting Pixel Intensity Levels

This is the last step, that intensity value I(a, b) of a pixel in the region is plotted to a new value $I'(a,b)$ utilizing CDF:

$$I'(a,b) = \text{round}((L-1) \cdot CDF_{I(a,b)} \quad (9)$$

A. *Watershed Segmentation*

Many traditional models of Cuscuta detection, like manual processing, take a lot more time, are labor intensive, and pose a risk of human error. However, automated techniques based on image processing and computer vision are emerging as more effective and reliable tools for detecting and measuring infestations. Of these methods, watershed segmentation has attracted much interest for its capacity to segment touching or overlapping regions in complex images. The watershed segmentation typically considers the grayscale images as topographic surfaces in which pixel intensities are interpreted as elevation. The algorithm identifies ridges and basins to segment the area, and it helps separate clusters of Cuscuta, which usually grow entangled near the black gram plants. Thus, these evolved preprocessing techniques and the proposed DTA can lead to accurate recognition and spatial representation of parasitic infections in agricultural fields through watershed segmentation. The present study aims to use watershed segmentation to detect and characterize Cuscuta infestations caused by black gram (Vigna mungo). Using these methods, we strive to create a rapid and automated approach to identify Cuscuta from the host plant so that effective control measures can be taken earlier and better management practices developed.

In this context, the gradient image is treated as topographic surface:

- ➢ The Bright regions contain high gradients called as ridges.
- ➢ The Dark regions contain low gradients known as basins.

B. *Flooding simulation:*

Initially, the image is "flooded" till basins belong to several regions meet.

C. *Label Propagation:*

At time of flooding, the labels for various regions evolve at the time of flooding, represented by:

$$L(a,b,t) = \begin{cases} L_f & \text{if flooding reaches a marker pixel at time t,} \\ \min(L_n) & \text{if neighboring labels } L_n \text{ are propogated} \end{cases} \quad (10)$$

Finally, the Equation shows the segmented images.

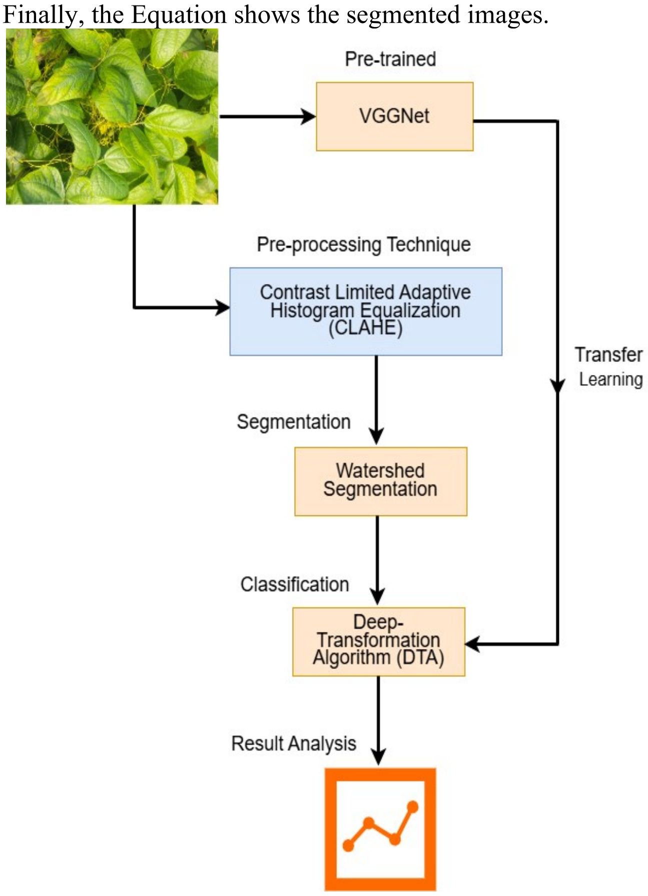

Figure 2: Architecture of DTA

VI. FINE-GRAINED NEURAL NETWORK (FGNN) FOR CLASSIFICATION

In this context, the Deep-Transformation Algorithm (DTA) combined with FGNN and transfer learning based VGGNet layers. This challenge led to the DTA, representing a novel computational approach. The DTA aimed to detecting and analyzing Cuscuta behavior morphological images at a micro level achieving precise identification and intervention. It scans high-resolution images of plants to recognize minute differences associated with parasitic developments. Using transfer learning, DTA uses the VGGNet layers trained on large image databases (ImageNet) and fine-tunes Cuscuta detection from a specific plant (black gram). It minimizes the requirement of large domain-specific labeled data and still achieves high accuracy and robustness. An AI-powered approach to agricultural management improves detection accuracy and enables early intervention strategies, limiting damage to cropland. This DTA framework holds excellent potential for open and agroecological agriculture, protecting key crop varieties under the threat of parasitic nematodes and supporting food production in general. This study highlights the methodology and performance analysis of Cuscuta infestation detection and classification along with the working potential of the DTA approach in Cuscuta-affected black gram plants. The following steps explain the classification of infected and healthy images.

Step 1: The first layer is input layer represented as:

$$X \in R^{N \times d}, \text{where:} \quad (11)$$

N: No of data samples.

d: Dimensionality of every input feature vector.

Step 2: The transfer learning Equations include (5), and (6):

Step 3: Fine-Grained Classification layer:

$$\hat{y} = \text{softmax}(ZW_{out} + b_{out}) \quad (12)$$

VII. Performance Metrics

The proposed approach's performance is measured using confusion matrix parameters. The Black gram images from the dataset have no labels, and the proposed approach analyzes the Cuscuta infestations based on normal and abnormal classification. The testing set contains 400 images, and these images are non-labeled. The following metrics show the performance of several algorithms.

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

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

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

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

A. Results and Discussions

In this section, Table 1 shows the performance of various algorithms belonging to DL and compared with DTA. It compares algorithms like CNN and ANN with the DTA. Among all the algorithms, the DTA obtains an accuracy of 99.78%, which is high compared with CNN's accuracy of 97.45% and ANN's accuracy of 98.34%. These performances show the potentiality of the proposed approach in detecting the Cuscuta infestation.

Table 1: Quantitative performance of various Algorithms

	Accuracy	Precision	Recall	F1-Score
CNN	97.45	96.34	95.67	94.34
ANN	98.34	98.56	97.67	97.12
DTA	99.78	99.78	99.51	99.81

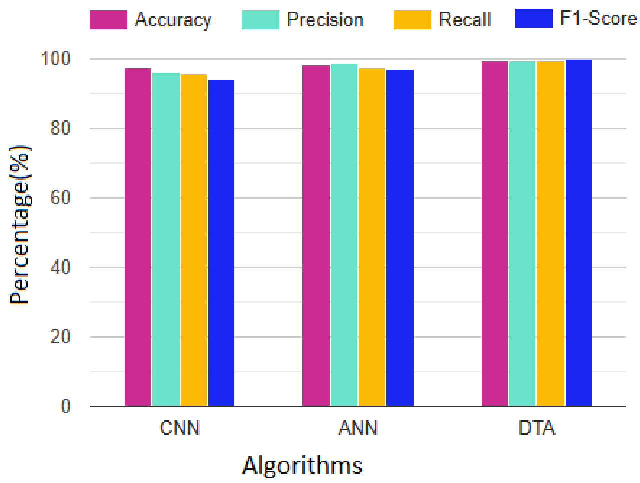

Figure 3: Quantitative Performance of Various Algorithms

VIII. Conclusion

This study showed the ability of DTA to identify and classify Cuscuta infestations occurring in black gram (Vigna mungo) plants. Using deep learning technology, the proposed model attained high rates of accurately detecting and classifying Cuscuta presence across infestation stages. DTA accurately detected Cuscuta intermixed with complicated backgrounds and under different field conditions. This system correctly classified infestation severity levels, which will help implement early-stage detection when intervention is most effective. The DTA outperformed traditional DL algorithms (the performance was evaluated based on accuracy of 99.78%, precision of 99.78% , recall of 99.51 and F1-Score 99.81. By providing a scalable and reliable tool for farmers and agronomists to monitor Cuscuta infestation, the proposed solution addresses the issue above to reduce crop losses due to the harmful weedy behavior of Cuscuta species and promote sustainable agricultural practices in general. Its integration with mobile-based applications or drones for real-time monitoring can revolutionize pest management in Blackgram cultivation.

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