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Doodernet: Enhancing Black Gram Yield Through Early Detection Of Cuscuta Infestation

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Abstract
Cuscuta, commonly known as dodder, is a parasitic plant that poses a significant threat to crops worldwide, including black gram (Vigna mungo). Early detection and management of Cuscuta infestation are crucial to minimize yield losses and ensure optimal crop productivity. In this paper, the DodderNet is used to detect Cuscuta early in black gram plant farms. The proposed approach, DooderNet, combines preprocessing techniques, Image Annotation, segmentation, and U-Net. The pre-trained model RESNET50 is used to train on given Cuscuta images. It isn't easy to train these images with this model. The dataset consists of 200 high-resolution images of black gram fields in Avanigadda Mandal, Krishna District, Andhra Pradesh, India, and corresponding annotations in jpg image format. Finally, there are comparisons between various state-of-the-art convolutional neural network (CNN) architectures, including U-Net, DeepLab, and Fully Convolutional Network (FCN). The existing DeepLab and FCN, compared with DooderNet, show robust performance with an accuracy of 0.90%.
Keywords: *Cuscuta detection, Deep learning segmentation, Parasitic plant identification, Agricultural computer vision, U-Net architecture, Crop disease managementRetryClaude can make mistakes. Please double-check responses.*

1. INTRODUCTION

Plant disease prediction is one of the complex tasks in the present scenario [1] [2]. Early prediction of plant diseases is essential to prevent heavy loss if they are not detected in the early stages. In general, plants also suffer from various diseases that affect the regular growth of plants [3]. Diseases mainly occur in any part of plants like leaves, stems, and roots. There are multiple plants and crops, which makes it very difficult to detect and classify diseases with existing models. Most farmers fail to predict plant diseases early because of a lack of knowledge [4]. Many manual and traditional approaches are used to detect and diagnose plant diseases that obtain minimal accuracy [5]. Designing and developing dynamic plant diseases significantly reduces manual efforts and provides accurate analysis [6]. Agriculture becomes the primary source of income to the farmers in India. Sometimes, to improve the crop yield, farmers will use pesticides and chemicals to reduce the loss of plant growth and crop quality. Nowadays, chemicals are becoming more and more used for plant yielding. It has a significant impact on human life, which shows various side effects, causes heavy health issues, and leads to death [7]. Machine learning (ML) and deep learning (DL) algorithms used on various plants and fruit types, such as fruit [8], paddy [9], tomato [10], and peach [11]. There is a relationship between plant diseases and pesticide usage because farmers most widely use these pesticides to control damage in the early stages.

The genus Cuscuta, commonly known as Dodder, encompasses parasitic plants that belong to the family Convolvulaceae [12] [13]. It parasitizes various crops, including black gram (Vigna mungo), leading to severe yield losses and economic repercussions for farmers. In India, black gram is a staple legume crop cultivated extensively in regions such as Andhra Pradesh, which plays a crucial role in the agricultural economy [14]. However, Cuscuta infestation poses a significant challenge to black gram cultivation, adversely affecting plant growth, nutrient uptake, and yield quality. Early detection of Cuscuta infestation is important; it's urgent for effective management and mitigation of its impact on black gram yields. The current traditional checking and visual analysis methods, being labor-expensive, more computation time, and often insufficient for timely intervention, underscore the pressing need for automated solutions that leverage advanced technologies to enable early detection and monitoring of Cuscuta infestation in blackgram fields. In recent years, DL models, particularly CNN, which is more powerful for image analysis and pattern recognition tasks, including object detection and segmentation. These models can learn intricate patterns and features from large-scale datasets, making them well-suited for agricultural applications such as pest detection and disease diagnosis [15].

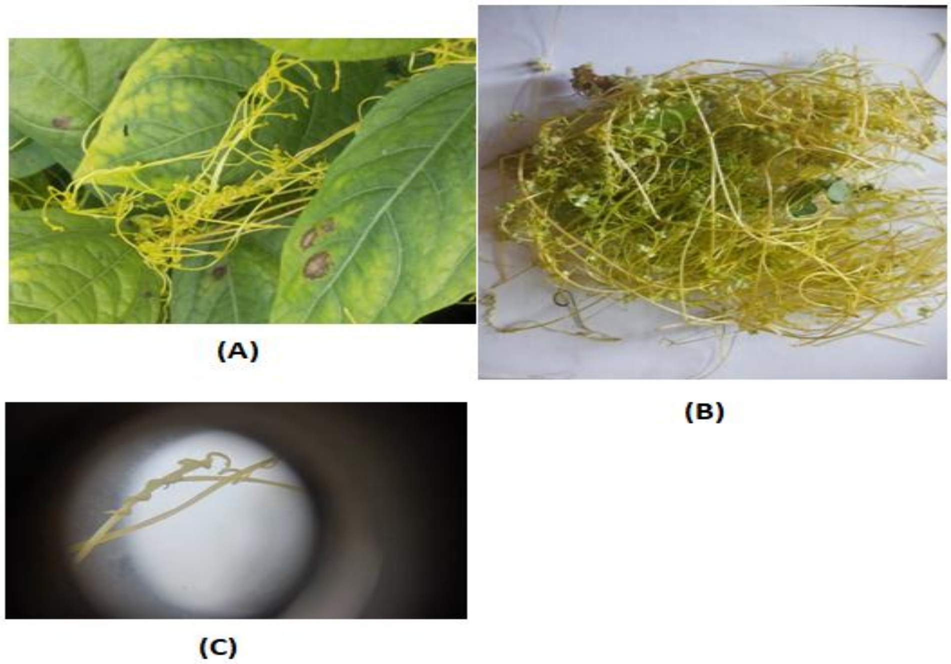

Figure 1(A): Type 1; Figure 1(B): Type 2, and Figure 1(C): Type 3.

This study aims to investigate the efficacy of various DL approaches for the early identification of Cuscuta infestation in black gram plant farms. We collected a comprehensive dataset comprising high-resolution images of black gram fields in Avanigadda Mandal, Krishna District, Andhra Pradesh, India. The corresponding annotations delineate the presence of Cuscuta-infested regions in each image, providing clear and precise information for analysis." We employ a range of CNN architectures, including U-Net [16], DeepLab [17], and FCN, to perform semantic segmentation of Cuscuta-infested areas. Through comparative analysis and performance evaluation, they provide valuable insights and practical recommendations for farmers and agricultural practitioners, inspiring them to adopt advanced technologies for improved pest management and crop yield optimization. The structure of the remaining paper is as follows: 1. Introduction; 2. Literature Survey, which shows the performance of various algorithms applied to plant disease images; 3. Methodology, which explains the proposed approaches used in this research; 4. Dataset description; 5. Performance metrics; 6. Results and Discussion; and 7. Conclusion.

2. LIETRATURE REVIEW

Elfatimi et al. [18] proposed the classified model for bean leaf diseases, which is a more effective model. The proposed approach is applied to various architectures. Differently, the comparison is analyzed based on the given parameters. The trained model MobileNetV2 architecture improves pattern detection with fast training times and high accuracy. The dataset consists of 3 classes, two abnormal classes, and one healthy class, and testing was conducted on 1296 bean images. The proposed model accuracy is 97% on the training dataset and 93% on the testing dataset. Jiang et al. [19] proposed a new model that detects apple leaf disease from the ALD dataset, available in Kaggle. These dataset images are developed using data augmentation, and annotation techniques are applied. The proposed approach, deep-CNN, combined with GoogLeNet Inception to increase the apple leaf detection rate called INAR-SSD. The performance of INAR-SSD shows the 78.80% mAP on ALDD with a speed of 23.13 FPS. The results show that the proposed approach achieved high performance with a rapid detection rate. The drawback of the INAR-SSD is it is limited to one plant disease detection only. Zhao et al. [20] presented the DoubleGAN, which creates high-resolution images of normal and diseased samples. The DoubleGAN works in two stages: In the first stage, the healthy leaves are trained using the Wasserstein-GAN. Then, the abnormal or diseased leaves are converted to 64*64 pixel images. In stage 2, superresolution-GAN is used to train on 256*256 pixel images to overcome unbalanced data. Finally, compared with DCGAN, DoubleGAN generated high-resolution images and obtained the accuracy of disease detection at 99.61%, and for plant species, it is 99.81%.

Wu et al. [21] introduced the data augmentation developed by GAN to detect leaf diseases. The DCGAN is used to augment the given dataset images, and the actual images are used as input for GoogLeNet. The accuracy of GoogLeNet is achieved at 94.12%. Combined with the DCGAN and t-SNE, the proposed approach is applied to high-quality images using the Visual Turing Test. The tomato leaf images were used for the experiments and achieved an accuracy of 94.33%, which is a high detection rate compared with other models. Tabbakh et al. [22] introduced a hybrid classification model to classify plant diseases. The proposed hybrid model performs well by combining Transfer Learning for pattern transfer—all the stages of the proposed approach analyzed on wheat datasets present in PlantVillage. The second step primarily focused on intense training to overcome overfitting. The third step is feature extraction using the ViT model, and the final step is classification using MLP. The final result obtained an accuracy of 98.82% for PlantVillage and 99.87% for the wheat dataset. Moupojou et al. [23] proposed the DL model that helps farmers to detect plant diseases effectively. The training was conducted on PlantVillage dataset that contains images of multiple plant diseases. There are 2569 images, and FieldPlant consists of 5170 plant diseases belonging to 27 plant diseases. The proposed approach obtained better accuracy through the comparison between various algorithms and among all the algorithms. Ahmad et al. [24] proposed the automated plant diseases classification approach developed using CNN. The CNN is more efficient regarding significant dataset-loading issues like memory management. The proposed approach also focused on solving the class imbalance issue. Transfer learning transfers the weights analysed on a huge dataset. We implemented the proposed approach on the PlantVillage and Pepper datasets, carefully analyzing the results to ensure accuracy and validity. The accuracy of PlantVillage was 99.1%, and for the pepper dataset, it was 99.71%. Sunil et al. [25] presented the new DL-based model called EfficientNet, which is used to classify the two diseases of cardamom plants. The U-Net model removes unwanted background images from the input image by selecting multiscale features. The EfficientNet obtained a high accuracy compared with CNN, with an accuracy of 98.28%.

Amin et al. [26] introduced the end-to-end DL model that finds the normal and abnormal corn plant leaves based on performance metrics. The fused, integrated method used the CNN model to extract the features from the cron leaf images. The performance of the proposed approach combined with data augmentation provides a better classification. The proposed classification accuracy is about 98.56%, which is high compared with ResNet152 and InceptionV3. Hassan et al. [27] proposed the novel DL approach combined with inception layer and residual connection. The accuracy of PlantVillage dataset is 99.39%, the rice disease dataset is 99.66%, and the cassava dataset is 76.59%. Li et al. [28] described the review process of various algorithms based on multiple plant diseases. The authors also presented the latest trends and challenges based on plant diseases and pesticides. Wang et al. [29] proposed the few-shot learning model by combining the Siamese network to overcome issues in the classification of leaf's issue with small dataset images. The feature extraction was implemented by using the CNN model. The proposed approach integrates the SSO and KNN classifiers. The experiments were conducted using three datasets, Flavia, Swedish, and Leafsnap, and obtained an accuracy of 97.87%. Yang et al. [30] proposed the CNN model to extract the spectral features from the corn seedlings. Finally, accuracy in classification and computational efficiency were analyzed to determine a 10-layer knot CNN model. CNN identified the cold damage levels in different maize seedlings, which were highly correlated based on chemical technique rankings. The difference between the correlation coefficient and CNN detection analysis with the chemical method for cold damage is 0.8219. The final results show better results based on cold damage in maize seedlings.

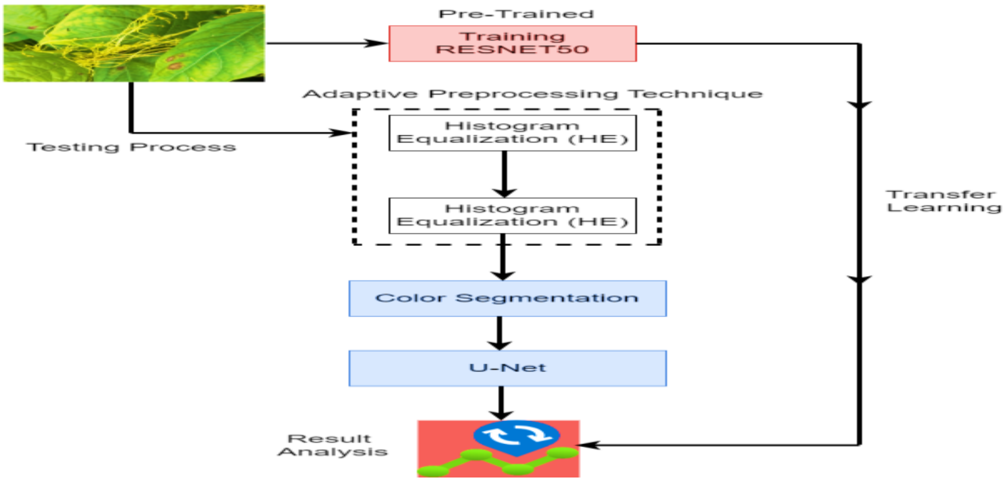

Figure 2: Architecture Diagram for Proposed Approach

3. 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. It consists of 220 high-resolution images of black gram fields using drones equipped with high-definition cameras, ensuring comprehensive coverage of the agricultural landscape. Among these, 190 images are training, and 30 images are valid. In addition to field images, separate images of Cuscuta samples were taken against white and black backgrounds to highlight the parasite's features. Microscopic images of Cuscuta were also captured to provide detailed structural information for training the models.

3.1 Dataset

Training Data: Images and labels were split into training and validation sets, stored in separate folders.

- **Training Images Folder**: D:/project/images/train
- **Training Annotations Folder**: D:/project/labels/train
- **Validation Images Folder**: D:/project/images/valid
- **Validation Annotations Folder**: D:/project/labels/valid

3.2 Data Preprocessing

Images were resized to 256×256256 \times 256256×256 pixels, and annotation masks were generated using the coordinates provided in JSON format. The images were converted to RGB format, and masks were created to represent the **Cuscuta** regions as binary values (1 for **Cuscuta**, 0 for the background).

3.3 Image Anotation

Each image in the dataset was annotated using the [PixLabAnnotate](https://annotate.pixlab.io/) tool, which allows for detailed and accurate labeling. Manual annotations were performed using rectangle and polygon tools to mark the Cuscuta-infested regions precisely. For each image, 2 to 76 annotations were made to ensure comprehensive coverage and accuracy. Annotations were saved in JSON format, providing detailed information about the location and extent of Cuscuta infestation within the black gram fields. Agricultural experts manually curated the annotations to ensure accuracy and consistency.

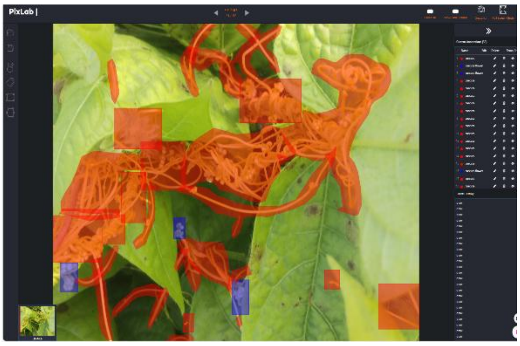

Figure 3 (a): Cuscuta infestation-1

Figure 3 (b): Cuscuta infestation-2

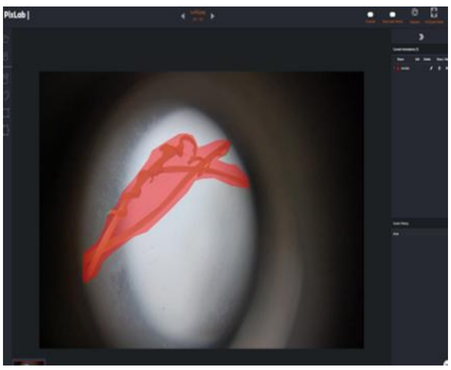

Figure 3 (c): Cuscuta infestation-3

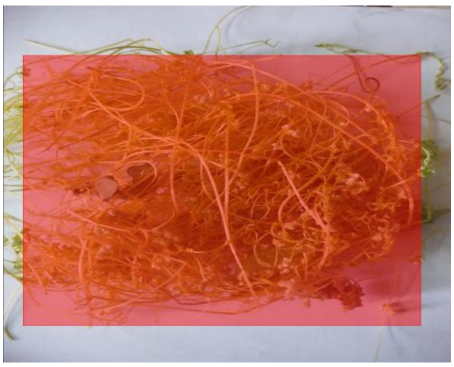

Figure 3 (d): Cuscuta infestation-4

4. RESNET50 (PRE-TRAINED MODEL)

RESNET50 is the pre-trained Residual Network, which consists of 50 layers. It is mainly used to develop to solve the vanishing gradient issue. The gradients directly flow through the network, which helps with more deep training. Training intensely on complex datasets becomes very effective in processing the Cuscuta images and requires fine-tuned visual recognition, like detecting advanced features connected with Cuscuta infestations. Deep learning (DL) has played a significant role in plant disease detection and classification in recent years. From there, CNN became one of the influential tools for the analysis of images based on its strengths in detecting automated features from raw image data. Early detection of Cuscuta infestation is crucial for preventing its growth and reducing its impact on crops. Many traditional methods work on manual disease detection methods, which take more computation time.

In this paper, the RESNET50 used to Cuscuta detection which involves in training the network on dataset labeled images, where the Cuscuta identified clearly. In training phase, the network study the difference between effected and non-effected reagions by identifying patterns specific to Cuscuta, which is limited factors like twining structure and color. After completion of training, the testing can be started on new images which automatically identified the Cuscuta infestations with high accuracy. The following layers present in RESNET50 architecture:

1. Input Layer

- The shape of input: The size of input image with shape 224x224x3 (width x height x channels).

2. Initial Convolution and Max-Pooling

- Conv1: A 7x7 convolution with 64 filters, stride of 2
- MaxPooling: A 3x3 layer with a stride of 2.

3. Residual Blocks (Bottleneck Layers)

- It consists of 4 phases; every phase contains several residual blocks. Every block has a "bottleneck" structure with 3 layers:
- 1x1 Convolution: Reduces the total channels.
- 3x3 Convolution: Performs spatial convolution.
- 1x1 Convolution: Restores total channels.

The layers are:

- Stage 1: contains 3 x 64 residual blocks
- Stage 2: contains 4 x 128 residual blocks.
- Stage 3: contains 6 x 256 residual blocks
- Stage 4: contains 3 x 512 residual blocks.

4. Average Pooling

- Global average pooling is applied after the last residual block to reduce the spatial dimensions to 1x1.

5. Fully Connected (FC) Layer

- A dense layer with 1000 units (for ImageNet) or adjusted to the number of classes in your specific dataset (e.g., 2 for detecting the presence or absence of Cuscuta infestation).

5. TESTING PHASE

In this phase, the following steps used to show the testing phase:

5.1 Adaptive Input Image Pre-processing:

Histogram Equalization (HE): HE is one of the image processing techniques that improve the contrast of input images by changing the intensity distribution of the histogram. Enhancing the image's contrast becomes very important because it helps visualize the abnormal conditions in the input image. All the input images suffer from low contrast rates due to their different lighting conditions, shadows, and the complicated nature of plant structures. HE mainly focused on improving the contrast and showing the difference between the parasitic Cuscuta and the host plants. The following equations are used to measure the HE:

1. Histogram Computation

The histogram for input image is measured. Let H(i) represents the total pixels with intensity level 'i'.

2. Measure Probability Density Function (PDF)

The probability of every intensity level is measured by using:

$$p(i) = \frac{h(i)}{N} \quad (1)$$

Where, N-total pixels.

3. Measure Cumulative Distribution Function (CDF)

The CDF is measured by using the following equation:

$$\mathrm{CDF}(i) = \sum_{j=0}^{i} p(j) \quad (2)$$

4. Mapping the Intensity Levels

Transmit every intensity level in the actual image to a new intensity level using the CDF:

$$\mathrm{NewIntensity}(i) = \mathrm{round}\left[(\mathrm{CDF}(i) - \mathrm{CDF}_{min}) \times \frac{L-1}{N-1}\right] \quad (3)$$

Bilateral Filtering (BF): It is a non-linear method that preserves input image edges and reduces the noise smoothing filter in image processing. In this paper, we underscore its significant role in detecting Cuscuta infestations, a crucial application where the aim is to remove the noise from the input images. BF considers both spatial proximity and intensity similarity of pixels. This dual consideration helps in smoothing the image while retaining important edges and details, which is crucial for accurate analysis of Cuscuta-infested areas. The key factors of BF are given below:

Spatial Domain Weighting: This component accounts for the geometric closeness of pixels, ensuring that a pixel's influence on its neighbor decreases with distance. This aspect helps maintain the integrity of edges and other crucial features in the image.

Intensity Domain Weighting: This component evaluates the intensity differences between pixels. Pixels with similar intensities are considered more related, contributing more significantly to the averaging process. This helps in smoothing out noise without blurring important details.

$$I_{filtered}(x) = \frac{1}{W_p} \sum_{x_i \epsilon S} I(x_i) \cdot G_s(\|x_i - x\|) \cdot G_r(\|I(x_i) - I(x)\|) \quad (4)$$

This study explores the effectiveness of BFin the context of Cuscuta infestation detection and analysis, with the ultimate goal of contributing to more reliable and efficient methods for managing these parasitic plants.

5.2 Feature Extraction using Color Segmentation

Color segmentation is a crucial technique in computer vision and image processing, employed to partition an image into distinct regions based on color similarities. This method plays a pivotal role in various agricultural applications, particularly in the detection and monitoring of plant health and infestations. One such application is the detection of Cuscuta infestations in blackgram crops. The distinguishing characteristic of Cuscuta is its unique coloration, which typically contrasts with the green hues of healthy crops. This contrast can be exploited using color segmentation techniques to accurately identify and isolate the regions infested by Cuscuta from the rest of the image. By extracting features based on color, the segmentation process can effectively highlight areas affected by the parasite, enabling targeted interventions.

This process typically involves converting the image into a color space that makes segmentation easier, and then applying thresholds to identify the regions of interest.

1. Color Space Conversion

The first step in color segmentation is often to convert the image from the RGB color space to another color space that separates color information from intensity information, such as HSV (Hue, Saturation, Value) or LAB (Lightness, A, B).

$$HSV = f(RGB) \quad (5)$$

$$LAB = g(RGB) \quad (6)$$

2. Thresholding for Color Segmentation

Once the image is in a suitable color space, thresholding is applied to isolate the colors corresponding to Cuscuta infestations.

A. HSV Thresholding:

$$\mathrm{Mask}(x,y) = \begin{cases} 1 \ \text{ if } H_{min} \leq H(x,y) \leq \ H_{max} \text{ and } S_{min} \leq S(x,y) \leq \ S_{max} \text{ and } V_{min} \\ 0 \ \text{ Otherwise,} \end{cases} \quad (7)$$

B. LAB Thresholding:

$$\mathrm{Mask}(x,y) = \begin{cases} 1 \ \text{ if } A_{min} \leq A(x,y) \leq \ A_{max} \text{ and } B_{min} \leq B(x,y) \leq \ B_{max}, \\ 0 \ \text{ Otherwise,} \end{cases} \quad (8)$$

3. Feature Extraction

After segmentation, various features can be extracted to characterize the detected Cuscuta regions:

$$\text{Area} = \sum_{x,y} \text{Mask}(x, y) \qquad (9)$$

$$\text{Centroid} = \left(\frac{\sum_{x,y} x \cdot \text{Mask}(x, y)}{\text{Area}}, \frac{\sum_{x,y} y \cdot \text{Mask}(x, y)}{\text{Area}}\right) \qquad (10)$$

$$\text{Perimeter} = \sum_{x,y} \text{Edge}(x, y) \qquad (11)$$

5.3 U-Net Architecture

It is most effective DL models for tasks involving image segmentation, including the detection and localization of specific objects within images. This model is actually developed for biomedical image segmentation; It is proven to be highly adaptable to other domains, including agriculture. U-Net is designed to capture fine-grained details in images, which is essential for accurately identifying the presence of Cuscuta vines intertwined with the host plants. Agricultural datasets, especially those focused on specific infestations like Cuscuta, are often limited in size. U-Net's ability to train effectively even on smaller datasets makes it an ideal choice for this application. The U-Net architecture extracts features at multiple scales, which allows it to detect both small and large instances of Cuscuta, ensuring robust detection across different scenarios.

1. Structure of U-Net

U-Net follows an encoder-decoder structure described in two main parts:

Encoder (Contracting Path): This consists of a sequence of convolutional layers that gradually reduce the input image's size while retaining important features. The encoder's function is to learn an image's spatial context by lowering its dimensionality. The encoder contains two 3 x 3 convolutions (unpadded), heed by a ReLU activation with 2 x 2 max-pooling operation 2 stride for compression.

$$\text{Convolutional Layer: } C_{l+1} = \text{ReLU}\big(\text{Conv}_{3x3}(C_l)\big) \qquad (12)$$

$$\text{Max Pooling: } P_{l+1} = \text{MaxPool}_{2\,x\,2}(C_{l+1}) \qquad (13)$$

2. Bottleneck

This part connects the encoder and decoder, consisting of convolutions that capture the most abstract features before upsampling starts.

Decoder (Expanding Path): The network's decoder component expands the encoded features to their original image size. It utilizes inverted convolutions and eliminates links from the encoder's corresponding layers to preserve fine features in the segmentation output. The decoder was developed using a feature map with a 2 x 2 convolution, which extracts the total features from the channels, a correlatively cropped feature map from the contraction path, and two 3 x 3 convolutions, each followed by a ReLU.

$$\text{Upsampling: } U_l = \text{UpConv}_{2x2}(B_l) \qquad (14)$$

$$\text{Concatenation: } M_l = \text{Concat}(U_l, C_{L-l}) \qquad (15)$$

$$\text{Convolutional layers: } C_{l-1} = \text{ReLU}(\text{Conv}_{3\times 3}(M_l)) \qquad (16)$$

3. Final Output Layer

This layer performs a 1 x 1 convolution, mapping each feature vector to the appropriate various classes.

$$\text{Output layer: } O = \text{Conv}_{1\times 1}(C_1) \qquad (17)$$

The U-Net architecture's symmetry and ability to capture both global context and fine details make it particularly effective for segmentation tasks, such as detecting Cuscuta infestation in agricultural settings.

6. RESULTS AND DISCUSSION

In this section, the experimental steup and conducted the experiments are explained, then the comparative results are given.

6.1Expeirmental Steup

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

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

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

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

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

6.2DISCUSSION OF RESULT ANALYSIS

Figure 3 shows the count values of DeepLab that are obtained from the analysis of confusion matrix. The overall count value shows the accurate values that shows huge impact on Cuscuta infestation from the given input images. The TP obtained the 100, FN is 20, FP is 10, and TN is 70. Figure 4 shows the count values of FCN with the values of TP-110, FN-17, FP-8, and TN-65. These values are obtained from the analysis of Cuscuta infestation dataset with the implementation of FCN. The final model implemented is U-Net obtained the values of TP-126, FN-14, FP-7, and TN-53. Here, the highest TP's are achieved by U-Net, because it is one of the more powerful models that performes better in terms of finding the accurate patterns. The FP obtained the lowest value with 7 samples. It is very low compare with other models. Showing the high TP's reflects the proposed U-Net shows the accurate and correctly finding the samples. The lowest number of TP's represents that the model not performed effectively compared with U-Net, because U-Net obtaines high values.

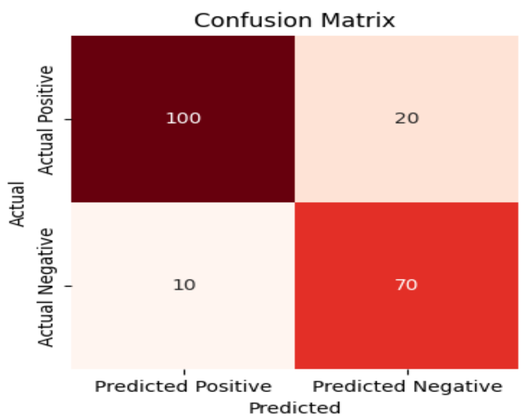

Figure 3: Count Values of DeepLab

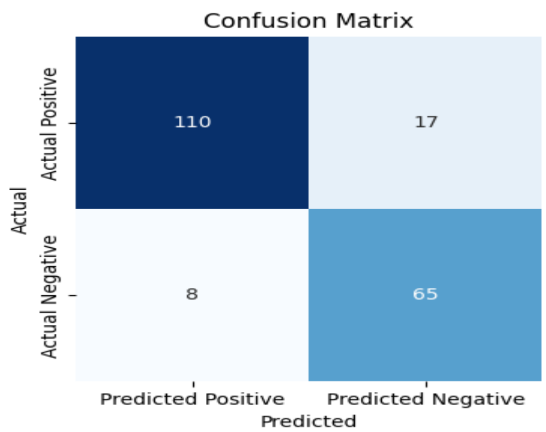

Figure 4: Count Values of FCN

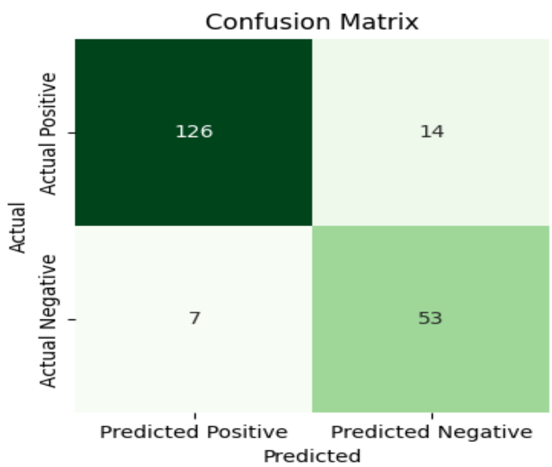

Figure 4: Count Values of U-Net

Table 1 shows the performance of algorithms based on confusion matrix count values obtained from various algorithms. Among all these models U-Net shows the highest performance in terms of disease detection rate. U-Net achieved the accuracy of 0.90%, which is high compare with DeepLab with the accuracy of 0.85%. Figure 5 visdualize the obtained values using Graph chart,

Table 1: Comparitive Performance of Algorithms based on Cuscuta infestation

	Accuracy	Precision	Recall	F1-Score
DeepLab	0.85	0.83	0.91	0.87
FCN	0.88	0.87	0.93	0.90
U-Net	0.90	0.90	0.95	0.92

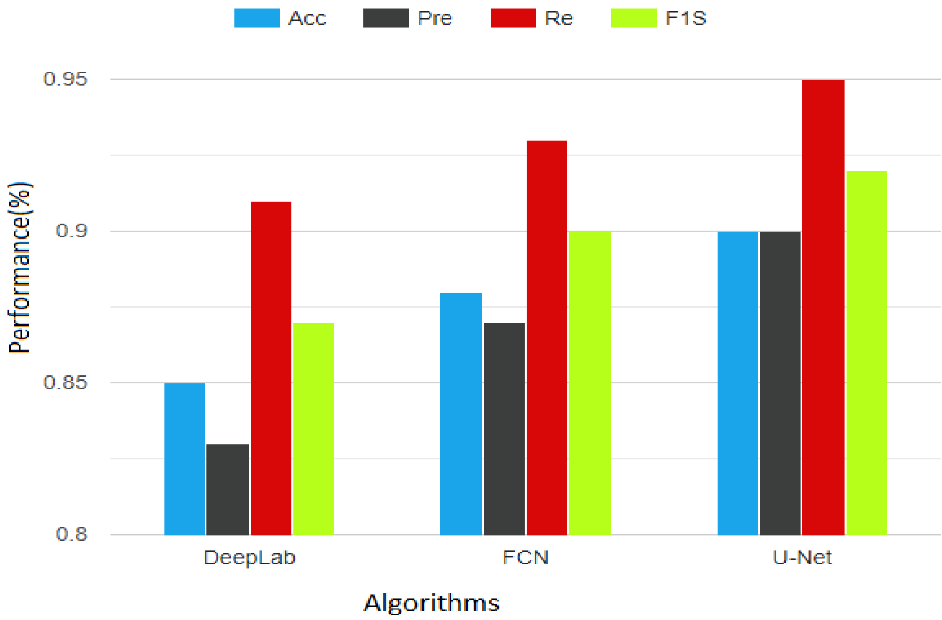

Figure 5: Performance of Algorithms based on obtained count values

7. CONCLUSION

The DooderNet is implemented by combining with RESNET50 as a pre-trained model and classification model Fully Convolutional Network (FCN). The transfer learning is used to transfer the features of the RESNET50 based on the weighted vectors present in the pre-trained model. The potential of deep learning models, specifically U-Net, DeepLab, and FCN, in accurately identifying and segmenting Cuscuta species. The high accuracy achieved by the U-Net model suggests that it is a promising tool for agricultural practitioners seeking to improve pest management strategies. Future research could focus on integrating these models into automated systems for real-time monitoring and intervention, ultimately contributing to increased black gram yield and sustainability in agriculture.

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