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Customized Semantic Segmentation for Enhanced Disease Detection of Maize Leaf Images

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Abstract
Maize leaf images are affected by various diseases. Though many image processing techniques are available to identify diseased segment of a diseased maize leaf image proper methodology to segment every chunk in the leaf as disease, shadow, healthy and background using a single methodology is still in search of. So, a single line of attack is availed using Semantic Segmentation for diseased maize Leaf images through which every pixel in an image is equated to a class. Initially multiple classes in the maize leaf images are Labeled and trained. ImagedataStore and PixelLabelDatastore are used to distinguish original images and trained images. With different classes defined and trained using the Semanticseg model and later applying semantic segmentation to the diseased maize leaf images they are segmented into various classes such as healthy, diseased, shadow and background. The shadows and background are difficult to handle and with this segmentation the exact pixel count of various classes are displayed. The output of semantic segmentation is a maize Leaf image where each pixel is equated to a particular class whereas in normal CNN the output is not an image but a class.

I. INTRODUCTION

Leaf images gathered from a farm to detect and analyze diseased chunk are difficult and troublesome due to the following factors which are Lack of Lightening Effects, Complex/Busy background, Images with shadows, overlapping of leafs, Exposure to Sunlight. etc. and if any one of the conditions exists in the diseased images then the detection may mislead. Later testing the diseased Leaf images with segmentation the infected parts can be identified. In Each and every state due to some kind of image condition, shape variations or overlapped leafs diseased part may lead to a wrong decision. [1]

Authors employ the WG-MARNet with the design for the classification of maize leaf diseases. To reduce image noise at the input side and to construct a high and low frequency multi-channel network structure, a wavelet threshold-guided bilateral filtering (WT-GBF) algorithm is proposed to be integrated into the network structure based on the features of maize diseases. [3].

Supervised machine learning techniques Naive Bayes (NB), Decision Tree (DT), K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Random Forest (RF) for maize plant disease detection was implemented with the help of the images of the plant. These techniques are analyzed and compared in order to select the finest model with the highest accuracy for plant disease prediction and the RF algorithm results with the highest accuracy of 79.23% as compared to the rest of the classification techniques. These trained models will be used by the farmers for the early detection and classification of the new image diseases as a preventive measure. [4]

The authors [5] used discrete Wavelet Transform, PCA-Principal Component Analysis and GLCM Grey Level Co-occurrence Matrix are used to obtain and reveal the features of the leaf samples and then the extracted features are classified using machine learning approaches such as SVM-Support Vector Machine, CNN- Convolutional Neural Network and K-Nearest Neighbor (K-NN).Based on VGG and ResNet, the two-channel Convolutional Neural Network was constructed. The maize leaf diseases data set has been preprocessed and the structure and characteristics of AlexNet, VGG and ResNet are introduced and then b y adjusting the parameters of the two-channel Convolutional Neural Network , the accuracy of identifying the maize leaf disease type in the validation set can reach 98.33%, while the VGG model can reach 93.33% The results on three types of maize leaf diseases show that the two-channel Convolutional Neural Network has a improved accomplishment than the single AlexNet model.[6]

Authors presented a robust deep learning (DL)-based approach namely ResNet-34-based Faster-RCNN for tomato plant leaf disease classification which includes three basic steps. Generate the annotations of the suspected images to specify the region of interest (RoI) and next step, authors introduced ResNet-34 along with Convolutional Block

Attention Module (CBAM) as a feature extractor module of Faster-RCNN to extract the deep key points. Finally, the calculated features are utilized for the Faster-RCNN model training to locate and categorize the numerous tomato plant leaf anomalies. Authors tested the presented work on an accessible standard database, the PlantVillageKaggle dataset. Obtained the mAP and accuracy values of 0.981, and 99.97% respectively along with the test time of 0.23 s. The proposed method shows a low-cost solution to tomato leaf disease classification which is robust to several image transformations like the variations in the size, color, and orientation of the leaf diseased portion. Also the framework can locate the affected plant leaves under the occurrence of blurring, noise, chrominance, and brightness variations. [7]

14-DCNN model was designed and trained to detect 42 leaf diseases in 16 plants through leaf images where the data augmentation and hyperparameter optimization techniques were used to enhance the performance of the 14-DCNN in this research. Here three augmentation techniques were used to enhance the dataset size to 147,500 images which are NST, DCGAN, and BIM. The class size, including original and augmented images, of the dataset, was 2500 images. This model pulled of a classification accuracy of 99.9655%, a precision value of 99.7999%, a recall value of 99.7966%, and an F1 score of 99.7968% on the training dataset [8]

To detect the disease in tomato leaf a deep learning-based approach is discussed for the disease detection and classification where a Convolution Neural Network based approach is applied. Here three convolution and three max pooling layers followed by 2 fully connected layer. The experimental results show the efficacy of the proposed model over pre-trained model i.e. VGG16, InceptionV3 and MobileNet. The classification accuracy varies from 76% to 100% with respect to classes and average accuracy of the proposed model is 91.2%. [9]

Maize leaf RGB images are converted to HSV color space and then using color filtering Technique non-green color pixels are filtered out and a threshold mask is applied for segmenting out disease affected regions ROI which is extracted from the original image and their Entropy, Mean and IDM values of around 50 leafs are extracted and compared.[10]

II. MATERIALS AND METHODS

A deep learning semantic segmentation algorithm equates a label with every pixel in an image, enabling the distinction of various pixel clusters representing different image categories. Diseased maize leaves are initially separated using integrated color filtering and threshold masking. However, shadows pose a challenge, as they can be mistakenly diagnosed as diseases. To address this issue, shadows are removed using histogram matching techniques. In this paper, the concept of semantic segmentation, implemented through deep learning, is used to segment disease-affected areas, healthy regions, shadows, and background areas, each represented with different colors.

Figure 1 depicts the block diagram illustrating the application of semantic segmentation to diseased maize leaf images. The process involves passing an input image through several layers, which consist of the following: an "Image Input Layer," a "Convolution Layer," a "ReLU Layer," and a "Max Pooling Layer." In this context, the input is an image, and the output is also an image. However, the key distinction lies in the fact that each pixel in the output image corresponds to a specific class, whereas in a typical CNN, the output represents a class label. In semantic segmentation, the output is a maize leaf image, and every pixel within this image is assigned to a particular class.

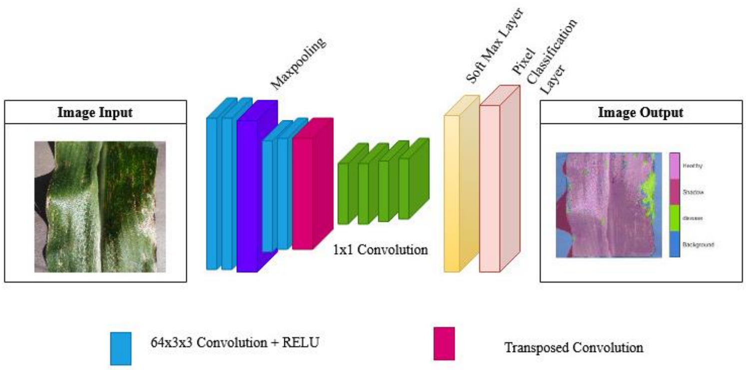

Figure 1: Semantic segmentation of diseased Maize Leaf Images
Source: Authors, (2023).

II.1.LABEL MULTIPLE CLASSES IN AN IMAGE

Huge amounts of datasets enable more rapid and accurate mapping to a particular input. By making little changes to an image, such as translation, cropping, or alteration, new, unique images are created. Be using the Image Labeler, Video Labeler, or Ground Truth Labeler tools can manually label pixels and export label data for training. The image Labeler application can be used to label scene labels and rectangular regions of interest (ROIs) for image categorization. Figure 2 depicts the way of defining the Scene Labels using the Image Labeler App.

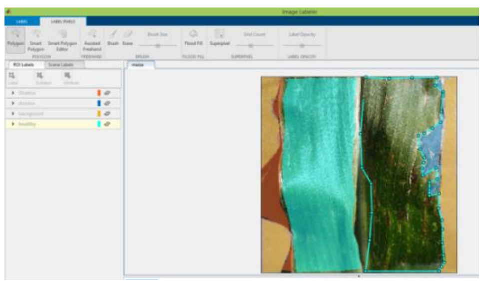

Figure 2: Image Labeler defining Scene Labels
Source: Authors, (2023).

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Matlab 2021a is used for applying this Semantic Segmentation technique. Initially Ground truth images must be labeled and if done manually will be a time consuming process if the image count is in thousands or millions. Every pixel is associated with a label in semantic segmentation Each and every pixel is classified under a class which are Healthy, Shadow, Disease and background. By using Pixel Label data store, every pixel is grouped under various classes and every pixel is segmented separately using the semantic segmentation with deep Learning. The Images are Labeled using image Classifier App. Load the images in Image Labeler App. Once labeled, export them to the Pixel Label data store. Though it's a time consuming process it's to be used if pertained models are not used.

II.2. CREATE IMAGE DATASTORE FOR ORIGINAL IMAGES AND LABELLED IMAGES

Once done with ground truth Labelling create image data store which contains original images. To create a segNet,the two datastores are needed,

- ImagedataStore which contains original Images
- PixelLabel Datastore which Contains Labelled Images.

Declare Classes:

Classes =[“Healthy”
“Shadow”
“Disease”
“background”]

II. 3. CREATE A PIXEL LABEL DATASTORE

A pixel label datastore is created. Initially the image data store is prepared, classes declared and next is to prepare pixel Label datastore. pixel,LabelIds and classes are analyzed.

II. 4. TRAINING SEMANTIC SEGMENTATION NETWORK

The image data store and pixel data store are analyzed. A collection of pixel Labeled images containing the ground truth images combined with images from Image data store containing original images for training the semantic segmentation.

1. Create a semantic segmentation Network
2 .Train the Network
3. Segment the images into pixel Categories.
4. Assess the accuracy of the Network.

Training on single CPU.
Initializing input data normalization.

Epoch	Iteration	Time Elapsed (hh:mm:ss)	Mini-batch Accuracy	Mini-batch Loss	Base Learning Rate
1	1	00:00:00	15.96%	7.8819	0.0010
50	50	00:00:28	85.48%	0.4690	0.0010
100	100	00:00:56	91.05%	0.3230	0.0010
150	150	00:01:25	92.53%	0.2567	0.0010
200	200	00:01:57	93.63%	0.2147	0.0010

Figure 3(a): Training of Semantic Segmentation Network
Source: Authors, (2023).

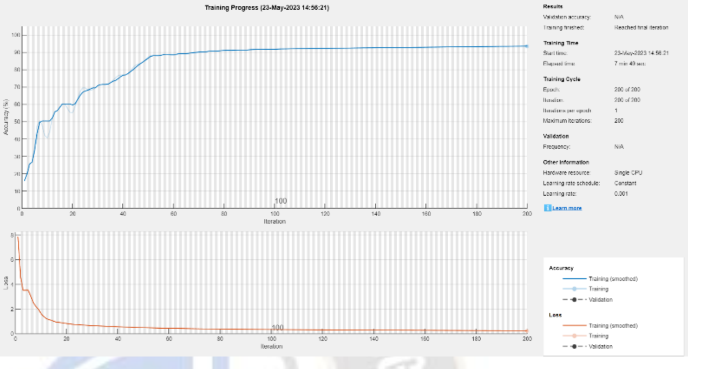

Figure 3(b): Progress of Training
Source: Authors, (2023).

Figure 3(a) shows the Training data using the Semantic Segmentation and 3(b) shows its progress... The Epoch value is set to 200 and it can be noted that and as the time elapsed for each iteration the mini-batch Accuracy increases and mini batch Loss decreases. The Model is trained using 60% of the shadowed images from the dataset. The rest of the images are split evenly in 20% and 20% for validation and testing respectively. The semantic segmentation network architectures such as SegNet, fully convolutional networks (FCN), or U-Net can be used and here SegNet is used.

The Table 1 shows the Pixel count distribution of diseased maize leaf later than applying semantic segmentation. The diseased pixel count is 3779 and shadowed pixel count is 1576 and background area covers 2832 and healthy count is 49149 which clearly depicts the distribution of various classes of pixel in a diseased image and can easily conclude and analyze the severity disease and doesn't ned to confuse by various factors like shadow, background and illumination which disturb the disease detection can be handled easily. Authors [2] tried to remove shadows and restore area in diseased maize leaf images by using Mean shift segmentation histogram matching techniques. Here by using semantic segmentation the removing shadows and restoring process can be skipped and instead exact pixel count of various categories or classes of image can be obtained and this deep learning methodology outperforms all existing methods.

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Table 1: Pixel Count Distribution of diseased Maize leaf following Semantic Segmentation

Name	PixelCount	ImagePixel Count	ClassWeights
Disease	3779	65536	5.1723
Shadow	1576	65536	36.3807
Background	2832	65536	20.2458
Healthy	49149	65536	1.1666

Source: Authors, (2023).

Figure 4 shows the bar chart of variety of classes of semantic segmentation such as disease, shadow, background and healthy. The chart clearly depicts frequency of healthy part of the image is higher than diseased part. The background pixel is slightly higher than the shadowed region of the image.

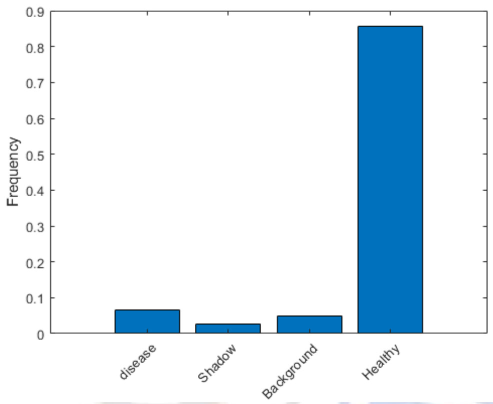

Figure 4: Bar chart of various classes of a Maize leaf image
Source: Authors, (2023).

III. RESULTS AND DISCUSSIONS

III.1 ACCURACY

The percentage of correctly identified pixels for each class is determined with the help of Accuracy and to know how properly each class correctly identifies pixels.Accuracy is the ratio of rightly classified pixels to the total number of pixels in that class, according to the ground truth.

Accuracy score = TP / (TP + FN)

TP is the number of true positives and FN is the number of false negatives.

For the aggregate data set, Mean Accuracy is the average Accuracy of all classes in all images.For each image, Mean Accuracy is the average Accuracy of all classes in that particular image. The class accuracy is a simple metric analogous to global accuracy, but it can be misleading. For example, labeling all pixels "healthy" gives a perfect score for the "healthy" class (although not for the other classes).So we use class accuracy in conjunction with IoU for a more complete evaluation of segmentation results. Table 2 depicts the Accuracy values of the four classes. The Healthy and shadow classes have a high accuracy of 0.94103 and 0.93088 respectively which means these classes are segmented well. The disease class has an Accuracy of 0.91117 and background class has an accuracy of 0.74014 which confirms that these classes have some False Negative values .The True Positive values are higher in healthy class and False positive values are higher in Background Class. The Global Accuracy is 0.91827

Table 2: Accuracy, Iou And Meanbfscore Metric Evaluation For Classes

	Accuracy	IoU	MeanBFScore
Background	0.74014	0.47319	0.77212
Disease	0.91117	0.43331	0.37617
Shadow	0.94103	0.80465	0.75991
Healthy	0.93088	0.92456	0.39661

Source: Authors, (2023).

III.2 IOU METRIC

Jaccard similarity coefficient which is called as Intersection over union (IoU), is the most frequently used metric. for a statistical accuracy measurement that penalizes false positives. IOU is the ratio of accurately classified pixels to the total number of ground truth and predicted pixels in that class.

IOU score = TP / (TP + FP + FN)

In Figure 5 it can be noted that when the results of segmented output image is compared with the expected ground truth stored in the pixeldatastore the green and magenta regions highlight areas where the segmentation results differ from the expected ground truth. It can be noted that the semantic segmentation results overlap well for classes such as background and healthy whereas objects like small disease areas and small shadow areas are not as accurate. The quantity of overlap per class can be measured using the intersection-over-union (IOU) metric, also known as the Jaccard index. Using the jaccard function to measure IOU. The IoU metric confirms the visual results. Healthy and Shadow classes have high IoU scores such as 0.92456 and 0.80465, while classes such as disease and background have low scores such as 0.43331 and 0.47319. Some of the smaller disease areas in the image are overlapped with background classes and the shadow regions are background misclassified pixels are denoted by green color pixels.The lower IOU values of these classes also confirms with the same. The Mean IOU obtained is 0.65893

Figure5: Comparison of Semantic Segmented Image With Groundtruth
Source: Authors, (2023).

III.3 GLOBALACCURACY

GlobalAccuracy is the propotion of correctly classified pixels, despite of class, to the total number of pixels. The global accuracy metric can be used if wanted a quick and computationally inexpensive estimate of the percentage of correctly classified pixels. The GlobalAccuracy obtained for this diseased maize Leaf image using semantic segmentation is 0.91827.

Table 3 Semantic Segmentation Evaluation Metrics

GlobalAccuracy	MeanAccuracy	MeanIo	Weighted IoU	MeanBFScore
0.91827	0.88081	0.65893	0.87539	0.57621

Source: Authors, (2023).

III. 4 MEANBFSCORE

The MeanBFscore indicates how well the predicted boundary of each class aligns with the true boundary. The BF score is used if a metric that tends to correlate better with human qualitative assessment. For each image, MeanBFScore is the average BF score of all classes in that particular image. The MeanBFscore acquired for this diseased maize Leaf image using semantic segmentation is 0.57621 as listed in Table 3 and Figure 6 shows the barchart of MeanBFscore for all the classes. The background and shadow classes have MeanBFscore of 0.77212 and 0.75991 respectively.

III.5 WEIGHTED-IOU

Weighted IOU Metric is the Mean IoU of each class, weighted by the number of pixels in that class. This metric can be used if images have disproportionally sized classes, to lower down the impact of errors in the small classes on the aggregate quality score. The WeightedIOU gained for this diseased maize Leaf image using semantic segmentation is 0.87539.

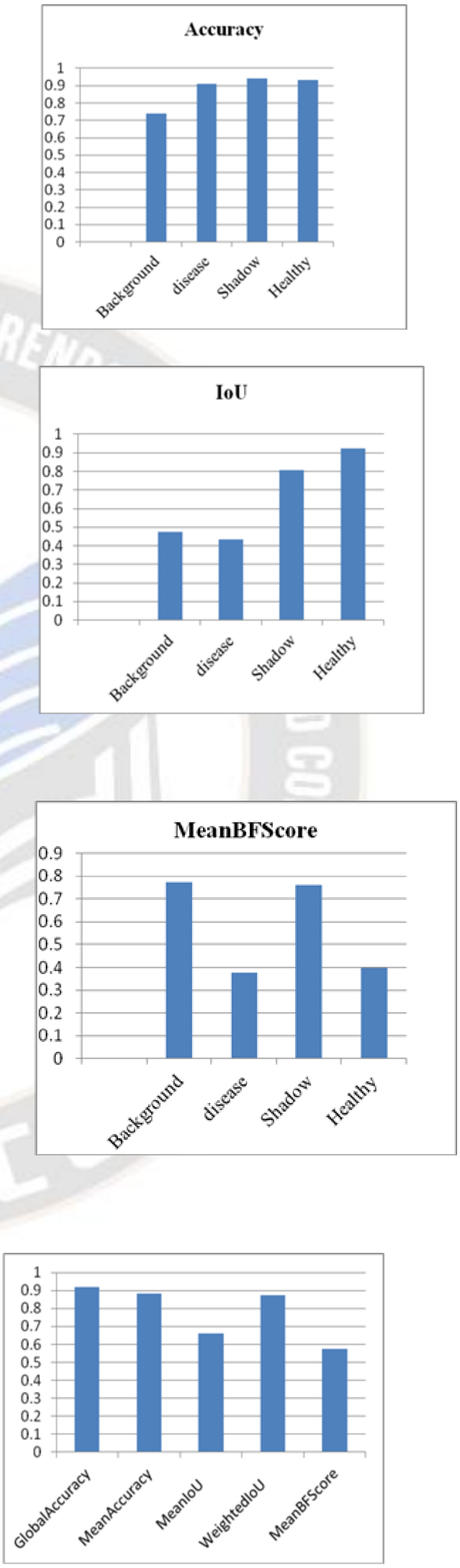

Figure 6: Evaluation Metrics of Semantic Segmented Image
Source: Authors, (2023)

In this evaluation of a semantic segmentation algorithm applied to diseased maize leaf images, multiple performance metrics were utilized. Global Accuracy, with a score of 0.91827, provides a quick assessment of pixel-level classification accuracy, while the MeanBF Score, specifically designed to align with human qualitative assessment, yielded a Mean BF Score of 0.57621. This metric was further broken down for individual classes, revealing Mean BF Scores of 0.77212 for the background class and 0.75991 for the shadow class. Additionally, the Weighted IoU was employed, resulting in a score of 0.87539. This metric is particularly valuable when dealing with images containing imbalanced class sizes. Together, these metrics offer a comprehensive evaluation of the algorithm's performance, encompassing both pixel-level accuracy and boundary alignment, ultimately indicating its effectiveness in distinguishing different categories of pixels in diseased maize leaf images.These metrics provide a comprehensive evaluation of the segmentation algorithm's performance, taking into account both pixel-level accuracy and boundary alignment with the true classes. The reported scores indicate how well the algorithm is distinguishing between different categories of pixels in the diseased maize leaf images.

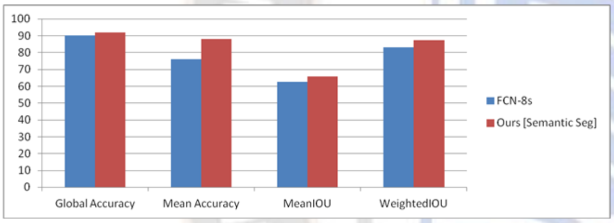

Figure 7. Comparison of Proposed work with [11] FCN
Source: Authors, (2023)

Table 4: Comparison of Semseg with FCN

Metrics	***FCN-8s***	***OurProposed work***
Global Accuracy	90.3	91.8
Mean Accuracy	75.9	88.0
MeanIOU	62.7	65.8
WeightedIOU	83.2	87.5

Source: Authors, (2023)

The evaluation presented in Table 4 and Figure 7 demonstrates that our proposed method surpasses the "FCN-8s" method in all the metrics considered. Specifically, our method achieves superior performance in terms of global accuracy, mean accuracy, mean IoU, and weighted IoU. These results indicate that our approach delivers more precise and dependable semantic segmentation outcomes for the targeted task. These metrics hold substantial importance in assessing the overall quality and efficacy of semantic segmentation models when applied to the detection of maize leaf diseases.

IV. CONCLUSIONS

The challenge of segmenting every component of a maize leaf image, including disease, shadow, healthy, and background, using a single methodology has been addressed through Semantic Segmentation. This approach equates each pixel in the image to a specific class, allowing for fine-grained segmentation. Multiple classes are labeled and trained using techniques like ImagedataStore and PixelLabelDatastore, and the Semanticseg model is employed for training. Subsequently, this trained model is applied to diseased maize leaf images, effectively categorizing them into various classes. Despite the difficulties posed by shadows and background, this methodology accurately quantifies pixel counts for each class. This differs from traditional CNNs, which output a class label rather than an image. The high-performance capabilities of deep learning are well-suited for this pixel-level segmentation task.

However, there are still challenges to address, particularly in dealing with small disease lesions and small shadow areas, where accuracy is lower. These inaccuracies may result from false detections. Therefore, further refinement and focus on improving the detection of small disease lesions are essential areas for future research. Overall, the adoption of deep learning-based Semantic Segmentation represents a significant advancement in the precise identification and classification of different components within maize leaf images, holding promise for enhanced disease detection and agricultural diagnostics.

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