ISSN PRINT 2319 1775 Online 2320 7876

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Handling Shadows in Diseased Maize Leaf Images Using Image Processing Techniques

Ms. Mohana Priya. C[1]*,

[1]*Asst Professor, Department of Computer Applications, Tiruppur Kumaran College for Women, SR Nagar,Tirupur-641687,Tamilnadu,India Email: mohanapriya.cmp@gmail.com,

Dr. P.R. Tamilselvi[2]

[2]Asst Professor, Department of Computer Science, Government Arts and Science College, Komarapalayam -638183, Tamilnadu, India. Email: selvipr2003@gmail.com

***Corresponding Author:** Ms. Mohana Priya. C

*Asst Professor, Department of Computer Applications, Tiruppur Kumaran College for Women, SR Nagar,Tirupur-641687,Tamilnadu,India Email: mohanapriya.cmp@gmail.com,

Abstract

The maize leaf is normally affected by Cerpospora, Common Rust, Northern Leaf blight diseases. Shadows in maize leaf disturb the disease detection. This Study aims at removing shadows in disease affected maize plant. The mean shift segmentation is used to detect shadows by applying Y channel information in YcbCrcolor space and HSI color space information. The detected Shadows are removed by processing in HSV color space and area is restored by histogram matching Techniques. No training model is needed to be applied in this study. After the shadow detection has been reached, without training can directly remove the shadows. This helps in misclassification of shadows in cerpospora diseased maize leaf as region of interests. The Accuracy, misclassification and Precision values before shadow removal and after shadow removal are 0.2, 0.8, 0.2 and 0.85, 0.15, 1 respectively.

Keywords: Cerpospora, HSV, YCBCR, DPC, SPC, SP, DP

1. INTRODUCTION

In spite of the fact that the shadow in the image is a sort of picture data, it often disturbs image segmentation. So shadow identification and removal have got across the broad consideration. The struggle of removing shadows is how to protect them after removal. It only removes the shadow, and does not change other features of the image in the shadow area. Shadows disturb the disease detection in all kind of plant leafs. Shadows on the leaf images, behind the leaf and on the background may affect the disease detection. The shadows turn out to be a diseased part as a result of segmentation and leads to a wrong prediction as diseased part.

Even under the controlled environment of laboratories, there will be lighting differences that can be the source problems for segmentation [1]. The shadows might be misjudged as diseased chunk and segmentation brings about incorrect estimation of disease. The obscurity in the leaf abandoned as shade might be wrongly diagnosed as an unhealthy part. This is a difficult perspective in disease identification using image processing [2]. An algorithm by fusing group pixels and edge probability maps to generate superpixel blocks to detect and

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remove the shadows for detecting apples in orchards under natural light conditions produced under intense illumination and direct sunlight conditions. The shadow detection results showed that the root mean square error decreased from 7.9% to 6.4%. With the new shadow removal algorithm, the precision, accuracy, specificity, and modified segmentation accuracy were improved by 10, 11, 4.5, and 10.1%, respectively and the average segmentation processing time was 0.59 s [3].

[4] Presents method of detection and recreation of shadows from Very High Spatial Resolution Images (VHSR pictures). Exhibits a compelling unaided strategy for division for recognizing shadows utilizing altered Self Organizing Maps (SOM and MRF). This term MRF is adjusted with SOM segment the shadows without giving trained dataset samples [4]. Then vegetation segmentation is challenging due to shadows and a ground shadow detection and removal method based on color space conversion and multi-level threshold was proposed. The projected ground shadow detection and removal method improves the performance of vegetation segmentation under natural illumination conditions in the field and is feasible for real-time field applications.[5]. Segmentation to select diseased maize leaf functions admirably in well captured pictures. But in pictures with shadows or high illuminated pictures, the shadows are identified as infection. This is the hidden issue to be sorted through [7].

To propel the image segmentation execution of cotton leaves in natural environment, an automatic segmentation model of diseased leaf with active gradient. It is found that the model has the upside of segmentation accuracy and running time when preparing seven sorts of cotton sickness leaves pictures, including uneven lighting, leaf infection spot blur, adhesive diseased leaf, shadow, complex background, unclear diseased leaf edges, and staggered condition [8]

A collection and comparison of chromacity based, physical, Geometry-based and Texture based methods across the categories is compared in terms of quantitative as well as qualitative observations. [9]. The Pixels fitting to moving objects, ghosts, and shadows are treated differently in order to supply an object-based selective update which utilize the color information for both background subtraction and shadow detection to improve object segmentation and background.[10] A specific procedure has its strengths and limitations (e.g., indoor/outdoor only), and are designed for particular data domains (e.g.,colour/monochrome, pixel/transform). A specific algorithm is ideal for a specific application and may perform efficiently without modification. Still, due to the complex nature of many environments, adaptive and/or hybrid forms of existing approaches may best be able to meet the needs of dynamically changing conditions [11]. Proposed outcome using Gaussian Mixture method is performed and shows that the method is accurate, reliable and efficient. But, Background subtraction on the two videos and after Background subtraction shadows are also detected as moving object which causes false detection of foreground object. [12]. The heavy noises reduce the correctness of the subregion matching in the step of shadow removal, which cause the unnatural shadow

removal result. The details in shadow regions are lost, it is difficult for the method to regain the features in the shadow removed results. Third, computational cost is currently a computational bottleneck to our algorithm.[13]. Though the proposed algorithm using on the

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process of histogram Fitting and line seed filling algorithm has more adaptability and better effect it has some limitations as does not apply to specially enhanced images and transition area extraction is not ideal[14]. A deep learning CNN-based methodology for identifying shadows in images was applied. The CNN consequently extracts features from the input image and uses them to identify shadows.[15]. Bidimensional Empirical Mode Decomposition (BEMD) is used for an automatic and data-driven approach for shadow detection and elimination. This proposed method remains the best in terms of shadow removal quality and is slow in comparison with the other approaches[16]. This study involves a detailed process of identifying and removing the shadows in cerpospora diseased maize plants. Many researches are ongoing about disease detection in agricultural leaf and fruits. A challenging aspect in disease detection is shadows which may be treated as diseased chunk in a leaf or a plant. Figure 1 shows a detailed view of this study which takes a cerpospora affected shadowed RGB maize leaf as input. This RGB is converted to a YCBCR image.

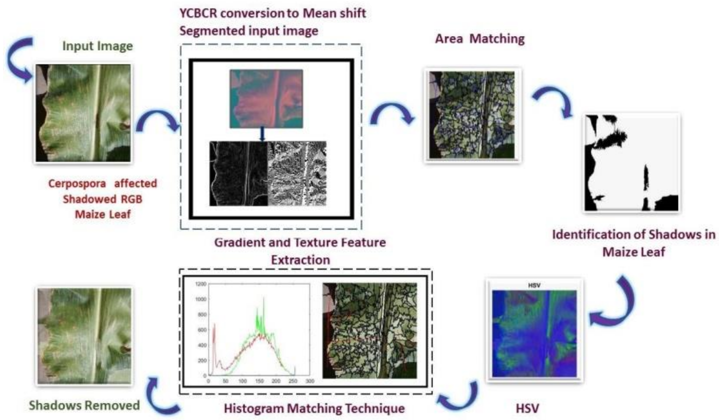

Figure 1: Identification and Removal of Shadows in cerpospora affected diseased Maize Leaf

The gradient, texture and distant features are extracted. The area matching algorithm is applied to detect the shadow. The detected shadow area, Input image and its corresponding HSV converted image are supplied and along with the histogram matching technique the shadows are removed in the input image. The diseased part alone remains in the cerpospora diseased maize leaf.

2. MATERIALS AND METHODS

Shadow detection has been reached, no training is required, and can directly detect.

DATASET

Cerpospora disease affected maize leafs are collected from github[6]. Shadowed images in this huge dataset are utilized for this study.

2.1.2. AREA MATCHING COMPUTATION

Since the color, saturation, and different attributes will change depending upon whether there is a shadow in the zone, the objective searches for the two materials. The features used for region matching are the two shadow invariant features Gradient features Texture features

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The gradient change of the gradient feature map is almost independent of whether it is a shadow area. The likeliness of gradients between domains is stronger. In order to extract this feature, calculate a histogram of the gradient value of each area of the graph. The Manhattan distance between the two regions histograms is calculated for measuring the similarity between the two regions. The texture feature map shows that texture features are almost independent of shadows. The similarity between regions is measured by calculating the Manhattan distance of the two region histograms. So as to guarantee local consistency, the distance between points in two areas is added as the judgment area phase.

The similarity between regions i; j is calculated as Eq (1).

$Di, = Dgradient\ i,j + Dtexture\ i,j + Ddistance\ i,j$--(1)

The Shadow removal process is shown in Figure 2 for a sample of three shadowed cerpospora diseased leaf images.

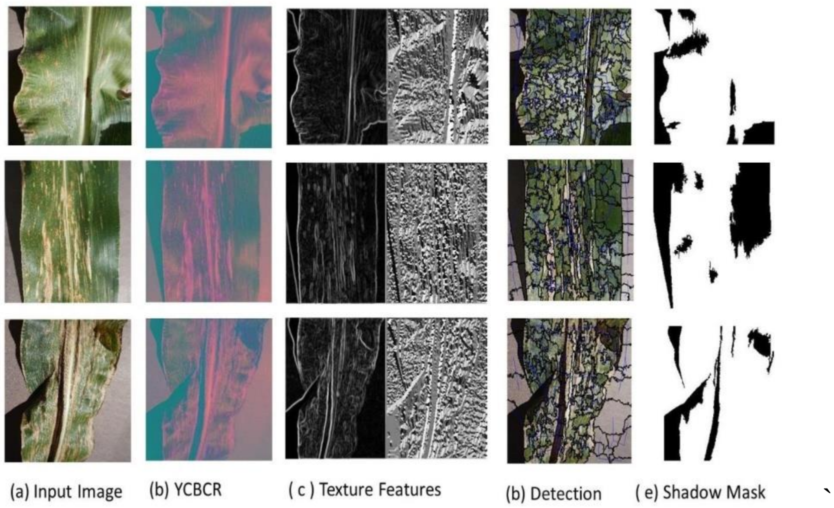

Figure 2: Shadow Detection Process

Initially the RGB to YCBCR conversion is made and along with extraction of gradient magnitude and gradient direction gmag and gdir texture features. The Area Matching process is applied to the resultant image to detect the shadow and obtain the shadow mask as shown in the figure 2.

2.1.3. FEATURE SELECTION

YCbCrcolor space Y channel information transforms the original image from RGB color space to YCbCr color space. In YCbCr , Y is the luma component of the color which speaks about the brightness of the color which implies the light intensity of the color. The human eye is more sensitive to the Y component. Cb and Cr is the blue component and red component identified with the chroma component and speaks about the actual color of the pixel and are less sensitive to the human eyes.

$$Y = \left(\frac{77}{256}\right) R + \left(\frac{150}{256}\right) G + \frac{29}{256} (B)$$

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$$C_b = -\left(\frac{44}{256}\right) - \left(\frac{87}{256}\right) G + \left(\frac{131}{256}\right) B + 128$$

$$C_r = \left(\frac{131}{256}\right) - \left(\frac{110}{256}\right) G - \left(\frac{21}{256}\right) B + 128$$

Y: Luminance; Cb: Chrominance-Blue; and Cr: Chrominance-Red.

When the value of a pixel on the Y channel of YCbCr space is larger than the whole picture and when the average value of the Y channel is 60%, the pixel can be directly considered as being in the shadow. Take the average value in the area Si and record the feature as Yi. HSI color space information can be extracted by transforming the original image from RGB space to HSI space. H S I channels are extracted from
RGB as,

H
$\theta \quad if\ B \circ G$

$= \{with \quad 360 - \theta \qquad if \quad B > G$

$$= cos^{-1} \left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G^2)+(R-B)(G-B)]^{1/2}} \right.$$

$$S = S = 1 - \frac{3}{(R+G+B)} [\min (R,,B)]$$

$$I = \frac{1}{3} (R + G + B)$$

Using mean shift segmentation each area of cerpospora affected maize leaf is marked as Si, the middle is marked as Ci, and total of n blocks are used. Difference between the Si, Sj is calculated as per Eq(1) and Di, j is noted with the utmost match for each region. For all Ri, 1<i<n, use k means clustering to calculate C shadow and Clit corresponding to standard std shadow, to calculate the confidence that belongs to c shadow and Clit.

For each area Si, Refusei represents whether it is forbidden from other areas since it is a shadow area and initialized to 0.
If Yi < 60% *mean(Y image),then labeli =shadow

The values of hue H are normalized to the interval [0; 1] by dividing all the values by 360 to get H_e; I_e extract Eq (2) for each pixel. Take the average of the area Si and record the feature as Ri.

$R \quad H^{(x,y)}$ ---------------------(2)

The parameter settings for shadow detection are mainly in Si; Sj is full of Eq (3), consider that the label attribute of Ri;
Rj is opposite, and set Refusej = 1;

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$R^{i-Cshadow} \cancel{- Rj-Cshadow} > 3$ ------------(3)
$Stdshadow^{Std}shadow$

when Si; Sj is full of Eq (4), consider that the label attributes of Ri; Rj are the same, and set labelj = 0.

$\frac{\min(H_i, H_j)}{\max(H_i, H_j)} + \frac{\min(Y_i, Y_j)}{\max(Y_i, Y_j)} + \frac{\min(R_i, R_j)}{\max(R_i, R_j)} > 2.5$--------------(4)

2.2. REMOVING SHADOWS

The shadow removal is mainly performed in the HSV color space. Degree adjustment, through the histogram matching algorithm, removes the shadow on the shadow area Si, while minimizing the impact of the operation on other features. Consider using Sj to highlight Si. Shadow removal process is illustrated in Figure 3. The Histogram Matching (Histogram Specification) Technique is applied to remove the identified shadow. The Process is explained with the algorithm and cerpospora affected maize leaf images.

$x,y = \frac{}{I_e(x,y)}$

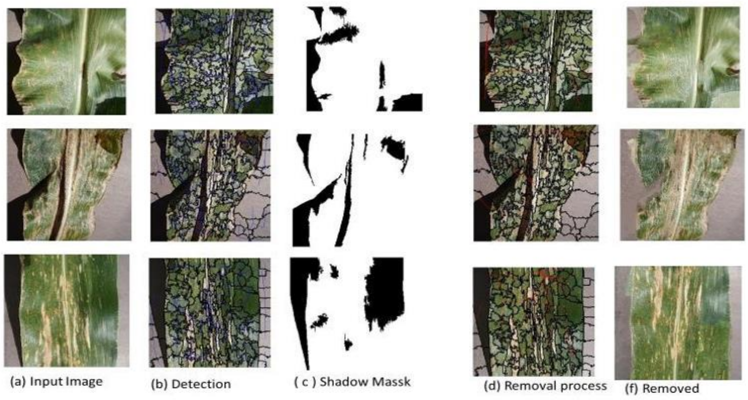

Figure 3: Shadow Removal Process

2.2.1 HISTOGRAM MATCHING

Alteration of an input shadowed maize image so that $_k = T(r_k) = (L-1)\sum^{k}_{j=0} p_r(r_j)$ its histogram matches a specified shadow mask histogram and produces a shadow free maize leaf image is the $_k$ underlying perception of histogram matching technique. This method is used to generate a $= \frac{(L-1)}{MN} \sum n_j \quad k = 0,1,2,\dots\dots\dots L-1$ shadow removed image that has a specified shadow mask $j=0$ histogram given by the transformation function,

Let $p_z(z)$ is the specified shadow mask PDF, which is going to be the PDF of the output image. Then,

$$(Z_q) = (L-1)\sum_{j=0}^{q} p_z(z_i) = S_k$$

Let the feature of region Si be Featurei, given the template histogram HistT. In the case that the distribution of Featurei between each other is the most variable, the overall offset conforms to the distribution of the template T. The approach is as follows.

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i) The histogram Histi of Featurei with the same number of stripes as Template T is calculated.

Desired Value $Z_{q,}$

$Zq = G{-}1(Sk)$

This will give value of z for each value of s, by performing mapping of s to z.

The cumulative histogram Acci; AccT for Histi; HistT respectively are calculated.

3) For each strip p of Acci, calculate the stripe number q with the largest difference in Acct; Move each stripe p to the position of q as a whole

2.2.2. ALGORITHM DESIGN

1) Calculate the shadow detection result and then convert the input image to HSV space.
2) Repeat steps 3) -5) for each shaded area Shadei
3) For area Shadei, find that Sj is full labelj = 1 and Di; j is the largest, and use Sj to brighten Shadei
4) For each channel H; S; I of the HSV color space, calculate the histogram HistH; j; HistS; j; HistI; j
5) Using HistH; j; HistS; j; HistI; j as the template for the histogram matching, adjust the three features of Shadei 6)Again Convert the image to RGB space
7) Calculate the intersection boundary between all the shadow areas and the shadow area in the figure, and then smooth all the boundaries.

The Figure 4 demonstrates the Histogram Matching indicates the non-shadow area in the image. This is matched Technique. The red peak indicates shadow affected input with the input red peak and produces the green peak. The maize histogram. The green peak indicates the shadow green peak in the histogram indicates the shadow removed removed histogram. The small blue peak nearing 255 maize leaf.

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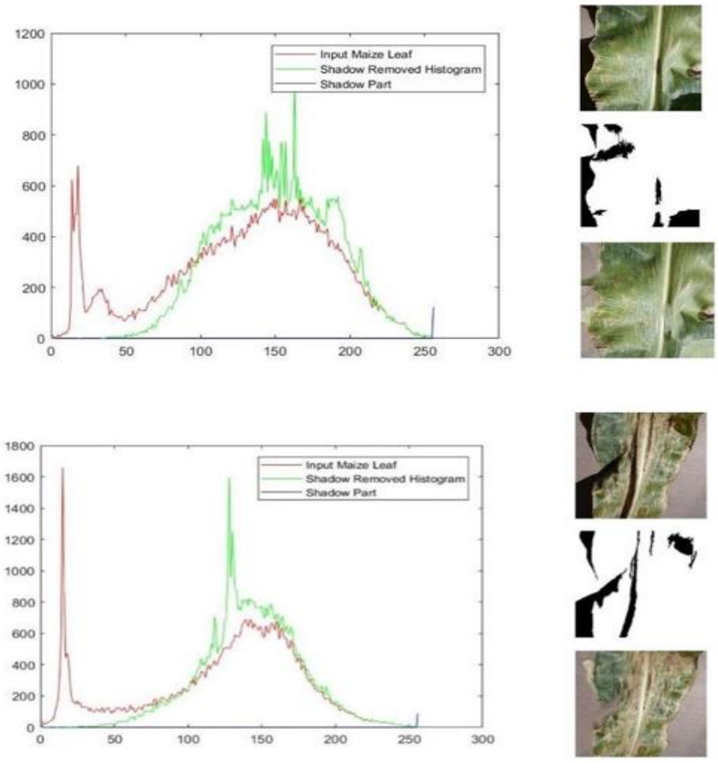
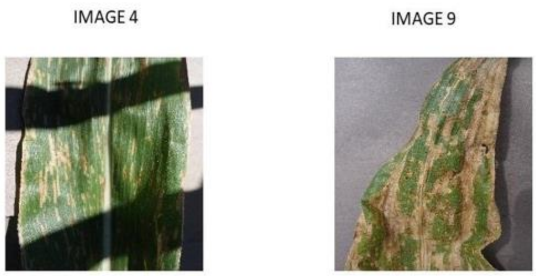


Figure 4. Histogram Matching Technique

3. RESULTS AND DISCUSSION

Around 10 cerpospora diseased shadow images are analyzed. The Total Pixel Count (TPC), Shadow Pixel Count (SPC), Shadow Percentage (SP), Diseased Pixel Count (DPC), Diseased Percentage (DP) are calculated.

Figure 5 shows, Image 4 is with a heavy shadow percentage with a pixel count 0f 23250 and a shadow percentage of 35.48. Image 10 is with heavy disease percentage with 38356-pixel count and a diseased percentage of 58.53



SPC	SP	DPC	DP
23250	35.48	10302	15.72

SPC	SP	DPC	DP
632	0.96	25445	38.83

Figure 5. High SPC and DPC Values.

Only in Image 4 the SPC values are very high than other images meaning shadows are dark and deep in this image. In Image9 the SPC values are very less with the percentage of 0.96 alone than a very high DPC with the disease percentage of 38.83. Table 1 lists all the pixel

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count of shadow and its disease, along with its percentage. Shadows can be dark and light shadows. Dark Shadows can be misclassified as disease whereas light shadows don't affect much in disease classification. Image 9 doesn't produce a false negative even before shadow removal as the shadowed area is very less

.

	TPC	SPC	SP(%)	DPC	DP(%)
IMAGE1	196608	6802	10.38	9710	14.82
IMAGE2	196608	5700	8.70	21152	32.28
IMAGE3	196608	3703	5.65	8807	13.44
IMAGE4	196608	23250	35.48	10302	15.72
IMAGE5	196608	5008	7.64	13404	20.45
IMAGE6	196608	4975	7.59	12726	19.42
IMAGE7	196608	13549	20.67	14123	21.55
IMAGE8	196608	9708	14.81	15075	23.0
IMAGE9	196608	**632**	**0.96**	25445	38.83
IMAGE10	196608	7329	11.18	38356	58.53

Table 1. Disease and Shadow Severity Analysis

Figure 6 display the analysis chart of SPC and DPC values Figure 7 displays chart of SPC and DPC values after the before shadow removal. Image 9 and 10 has a huge DPC shadow removal process. DPC values are brought down to values indicating severity of Cerpospora disease in it. a range as shadows are removed and variation in chart can
be observed

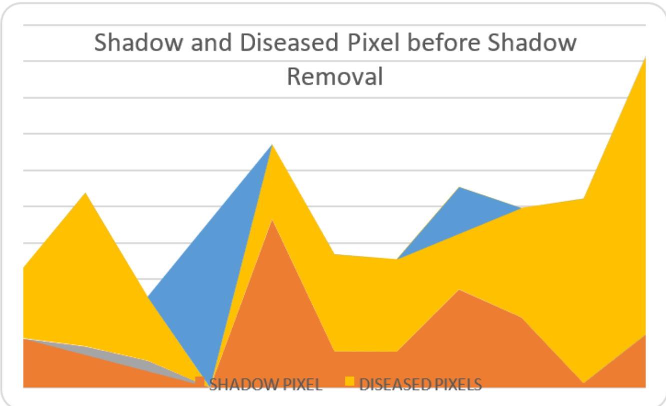

Figure 6. SPC and DPC before Shadow Removal

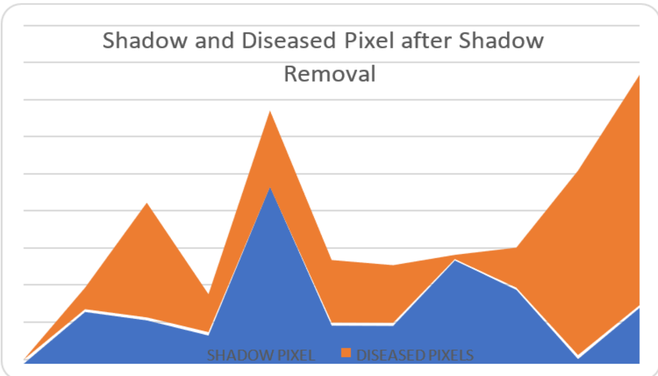

Figure7. SPC and DPC after Shadow Removal

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3.1 PERFORMANCE MEASURE

How many of the positively segmented pixels are relevant is indicated by Precision. Precision denotes the ability to reduce the number of false-positives. Recall specifies how fine segmentation performs in detecting the shadow and thus relates to the power to correctly detect leaf pixels that belong to the shadow region (true-positive). Specificity, states how the segmentation algorithm performs in eluding false-positive error, which also indicates the ability to correctly detect non-shadow pixels that belong to leaf (true- negative) [5]. Accuracy is normally used as a single illustrative performance indicator in the literature. But, this measure has a problem if there is a significant inequality between vegetation and background [5]. Recall or sensitivity (true positive rate, TPR) and missing rate (false negative rate, FNR) are the rates at which shadow regions are correctly and incorrectly segmented, respectively, while the true negative rate (TNR) and false positive rate (FPR) are the rates at which the non- shadow regions are correctly and incorrectly segmented, respectively. The Vital indicators of feature extraction correctness were Accuracy and relative segmentation area error (RSAE). Also, accuracy has a problem when a significant imbalance exists between the target and background. Yet, when the image contains a small number of targets, the segmentation will lead to a high FP value along with a biased BA value. Authors propose the use of Modified Segmentation Accuracy (MSA), which was calculated as the harmonic mean between the BA and RSAE and MSA value provides a better indication than both BA and RSAE

when a significant imbalance occurs.[3]. For the images before shadow removal the rate of Accuracy, misclassification, Precision and Sensitivity were compared with those after shadow removal to measure the progress in the performance improvement.

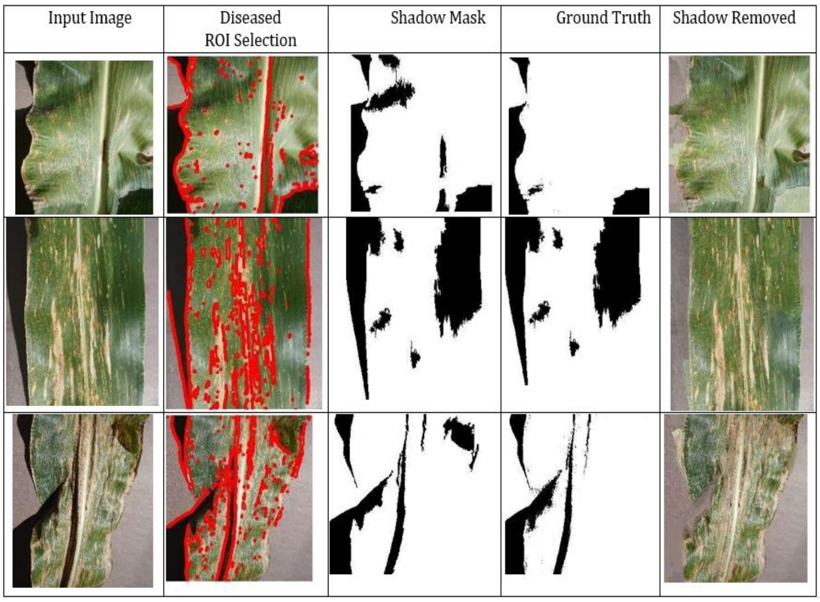

Table 1: Tabulation of Diseased ROI , Shadow mask, Ground Truth and shadow removed image.

Earlier the Shadow removal the accuracy of disease detection is 0.2 if collection of all diseased images were shadowed and diseased but this value drastically increases to 0.85 by

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maintaining all the collection of images as diseased and shadowed. With the Precision the ratio of the correctly detected and removed shadows to all the shadow images are identified. Prior to Shadow removal the Precision of disease detection is 0.2 but this value drastically increases to 1. Before Shadow removal the misclassification of disease detection is 0.8 as the number of actually shadowed regions were misclassified as diseased regions of cerpospora diseased maize leaf but this value drastically reduces to 0.15 as the shadows were removed. This reduces the rate of misclassification drastically. There were some losses of true positive pixels (actual diseased leaf which is not shadow) as a result of shadow removal process. This slighter loss occurs when shadow removal was applied to Cerpospora leaf images without shadows. The False negative value should be reduced as the problem with foreground and background shadow detection in area matching. The lesser value of RSAE (Reduced Segmentation Accuracy Error) [3] also justifies the minor deviation of shadow images from the ground truth images.

The average segmentation processing time of this study is 1.5 seconds which is to be reduced further.

ACCURACY

The ratio of the correctly labeled shadows in maize leaf to the whole pool of leaf images

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

Before Shadow removal the accuracy of disease detection is 0.2 but this value drastically increases to 0.85. This Study results with the Accuracy of 0.85

PRECISION

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

The Precision is the ratio of the correctly detected and removed shadows to all the shadow images. Before Shadow removal the Precision of disease detection is 0.2 but this value drastically increases to 1

This Study results with the precision of 1.

MISCLASSIFICATION

The misclassification is the number of non-shadow regions detected and removed as shadow region.

$$Misclassification = \frac{FP+FN}{TP+TN+FP+FN}$$

In other terms,

Misclassification=1-Accuracy

Before Shadow removal the misclassification of disease detection is 0.8 but this value drastically reduces to 0.15.

The misclassification of this work is 0.15 .

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COMPUTING TIME

The average segmentation processing time of this study is 1.5 seconds and the average segmentation processing time of [3] is 0.59. The Processing time should be increased which is a drawback. The False negative value should be reduced as the problem with foreground and background shadow detection in area matching and this is the further perspective to be studied on. . The Figure 8 shows the rate of accuracy, misclassification, Precision and sensitivity before and after shadow removal.

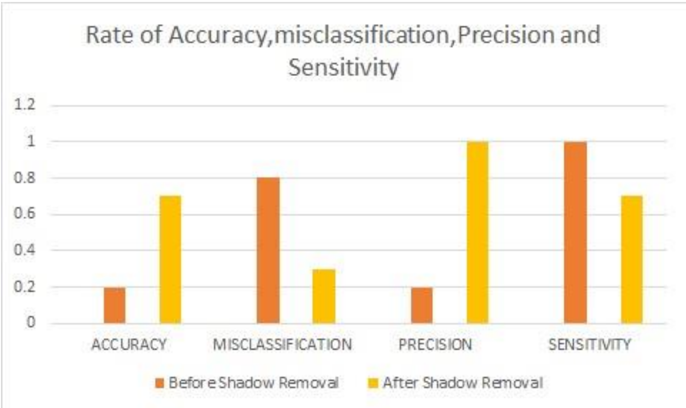

Figure 8. Rate of Accuracy, misclassification, Precision and Sensitivity before and after shadow removal

RSAE- RELATIVE SEGMENTATION ACCURACY ERROR

$$S_r$$
$$, if \ \ S_r < S_G$$

$$RSAE= S_G$$
$$S\_G \text{ , } if \ Sr > SG$$
$$\{S_r$$

The Smallest RSAE is preferred and from the Table 2 it can be concluded that RSAE of shadow region is 8.4 and bright region can be ignored as we don't have bright images related to Sunlight.

	RSAE (Shadow Region)	RSAE (Bright Region)	RSAE (All Region)
Weiyue Xu	10.3	4.5	6.4
Finlayson et al. (ECCV 2002)	25.3	8.5	14.0
Khan et all. (CVPR 2014)	16.2	6.4	8.9
(ours)	8.4	-	4.5

Table 2: Comparison of RSAE between the Proposed and the Previous Work.(Small RSAE is preferred) [3]

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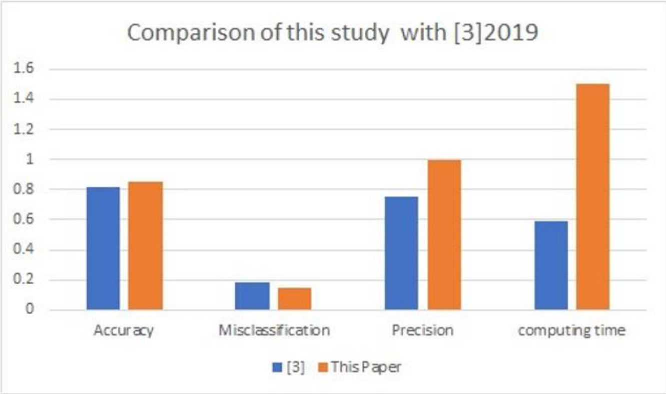

4. CONCLUSION

One of the Primary pitfalls in agricultural plant leaf disease detection is shadow detection and removal. This paper analyzes 10 cerpospora affected maize leaf which is disturbed by shadow. The shadows disturbing disease detection are identified and removed. The DPC which counts SPC as diseased are detached. This enhances the study of disease detection process. Detecting Shadows and removing them were challenging aspects in image processing. In this paper by Using Area matching algorithm image shadow detection is achieved and without any training can directly able to remove the shadows. This helps in misclassification of shadows in cerpospora diseased maize leaf as region of interests. The Accuracy, misclassification and Precision values before shadow removal and after shadow removal are 0.2, 0.8, 0.2 and 0.85, 0.15, 1 respectively. The average segmentation processing time is 1.5 seconds which can be reduced in further perspective. The False negative value is 1.5 in shadow removal which occurs in misclassification of pixels and should be dealt with. One of the Primary pitfalls in agricultural plant leaf disease detection is shadow detection and removal. This paper analyzes 10 cerpospora affected maize leaf which is disturbed by shadow. The shadows disturbing disease detection are identified and removed. The DPC which counts SPC as diseased are detached. This enhances the study of disease detection process.

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ISSN PRINT 2319 1775 Online 2320 7876

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AUTHORS PROFILE

Ms.C. Mohanapriya, received her MSc(CT) in Kongu Engineering College, Perundurai. She has completed her M.Phil in Mother Teresa Womens University, Kodaikanal. She is `currently working as an Asst. Professor in Tiruppur Kumaran College for Women, Tirupur. She is pursuing her Ph.D in Periyar University, Salem.

Dr. P.R. Tamilselvi, received the M.Sc and M.Phil Computer Science from Bharathiar University. She has completed Ph.D from Anna University, Chennai. She has guided 20 M.Phil scholars from various universities. She has presented and published many papers in national and international conferences and journals. She has organized many seminars, workshops and conferences. Currently she is working as an Assistant Professor at Government Arts and Science College, Komarapalayam. Her area of research interest is Medical Imaging.