FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 564-571 | e-ISSN: 2347-470X

Directional Shape Feature Extraction Using Modified Line Filter Technique for Weed Classification

Seri Mastura Mustaza[1], Mohd Faisal Ibrahim[2], Mohd Hairi Mohd Zaman[3], Noraishikin Zulkarnain[4], Nasharuddin Zainal[5] and Mohd Marzuki Mustafa[6]

[1]Department of Electric, Electronic and Systems Engineering, Faculty of Engineering and Built Environment, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, Malaysia; [1]seri.mastura@ukm.edu.my, [2]faisal.ibrahim@ukm.edu.my, [3]hairizaman@ukm.edu.my, [4]shikinzulkarnain@ukm.edu.my, [5]nasharuddin@ukm.edu.my, [6] marzuki@ukm.edu.my

*__Correspondence:__ Seri Mastura Mustaza; Email: seri.mastura@ukm.edu.my

ABSTRACT- Precision agriculture is gaining attention as it employs modern technologies and intelligence for automation in agricultural practices. In the area of weed management, automation is advantageous to select the appropriate herbicide and manage the amount used, which consequently reduced the cost and minimizes the environmental impact. Selective spraying using a sprayer boom can be implemented using automatic detection of weed type. This paper presents a weed classification method based on a modified line filter image analysis technique that can effectively detect the morphological differences, mainly directional shape features, between two types of weeds. After the result for binary classification has been verified, a third dataset is introduced which is mixed leaves which consists of an approximately balanced amount of broadleaves and narrow leaves. The weed images were pre-processed using the adaptive histogram method and difference of Gaussian to improve the image contrast and delineate the edges of the weed. The images were then processed using the proposed modified line filter feature extraction technique. The filter is based on the evaluation of pixel response that corresponds to the pre-defined lines at different orientations from 0° to 360°. The pixel strength of each line was compared to determine the overall response of the filter. The proposed method achieved around 97% classification, superior compared to previously reported methods such as Gabor wavelet as well as a combination of Gabor and Gradient Field Distribution (GFD).

Keywords: Weed classification, precision agriculture, line filter, image processing.

ARTICLE INFORMATION

Author(s): Seri Mastura Mustaza, Mohd Faisal Ibrahim, Mohd. Hairi Mohd Zaman, Noraishikin Zulkarnain, Nasharuddin Zainal and Mohd Marzuki Mustafa

Received: 30/04/2022; **Accepted**: 06/07/2022; **Published**: 07/09/2022
e-ISSN: 2347-470X;
Paper Id: IJEER22AAN001;
Citation: 10.37391/IJEER.100326
Webpage-link:
https://ijeer.forexjournal.co.in/archive/volume-10/ijeer-100326.html

crossref member
CROSSREF.ORG
THE CITATION LINKING BACKBONE

Publisher's Note: FOREX Publication stays neutral with regard to Jurisdictional claims in Published maps and institutional affiliations.

1. INTRODUCTION

Weeds are undesired plants that compete against productive crops for space, water, and soil nutrients, and can potentially cause yield losses. Weed control is an important aspect of farming and agriculture. Efficacious weed management has many advantages which include safety and path clearance for drivers and workers of the plantation, reduced natural resources to undesired weeds as well as decreased the alternative hosts for insect pests and diseases. [1]. Each year, farmers and plantation companies spend a lot of money on weed management as failure to adequately control weeds will affect the growth of crops and lead to reduce in product quality. In current practice across plantations, the methods used to manage the growth and spread of weeds are either mechanical, chemical (herbicides), or a combination of both. The most common practice in plantations for weed management is the use of chemical herbicides [2]. However, the continued reliance on chemicals as a weed control strategy can lead to adverse environmental impacts if not managed carefully. Precision agriculture employs modern information technologies for decision-making and operations in the management of crop production.

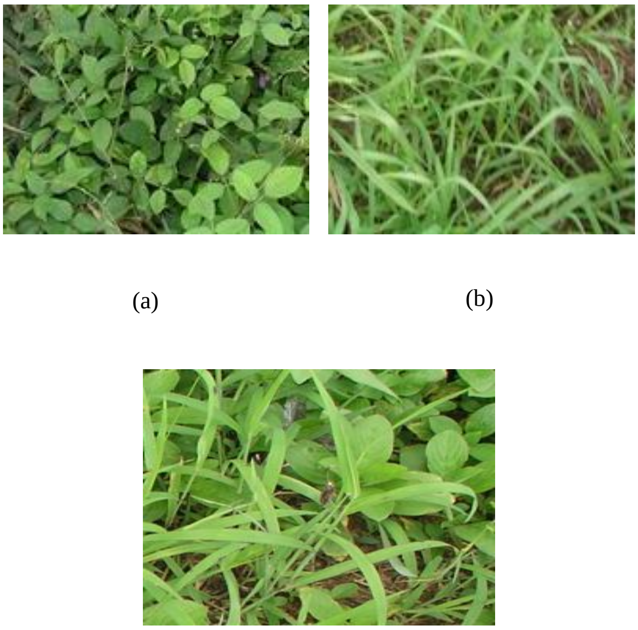
Precision agriculture offers the assurance of enhanced productivity, increased profitability, reduced production costs with optimal use of resources, as well as enhanced sustainability [3]. One of the approaches to precision agriculture is to integrate multi-spectral and multimodal data acquisition devices within the currently used tractor [4] or all-terrain vehicles (ATV) for crop monitoring, field damage identification as well as capturing the growth of weeds. Specific to weed management, these data acquisition devices can be mounted on a sprayer boom tractor or ATV to be used as an accurate classification system of crops and weeds. The devices provide the decision-making information for the sprayer boom to perform selective herbicide spraying. A more cost-effective and sustainable approach to weed management can be achieved by harnessing an adequate and correct amount of chemicals based on the type and density of weed at the specific site. However, these data acquisition devices are still facing adaptation challenges to obtain the desired accuracy and timeliness to deliver the required information [5].

There are diverse species of weeds within certain plantations, but for the purpose of chemical weed treatment, it is sufficient to distinguish between the two shapes of weeds, i.e. broad and narrow leaves. [3]. By observing the two types of weeds, it is evident that the robust and reliable technique for classification is based on the directional shape property of the images. In the past, methods that have been employed to extract the directional shape feature are Gabor transform, gray level co-occurrence matrix (GLCM), Gray level gradient co-occurrence matrix (GGCM), local binary pattern (LBP) as well as Histogram of Oriented Gradient (HOG). The Gabor filter is a special class of bandpass filter whereby it can be customized to reveal a specific frequency content in a particular direction within a localized region of an image, and the remaining sub-information is filtered out by tuning the filter's parameter such as frequency, orientation, aspect ratio, and bandwidth. The work in [6] and [7] applied this filter for weed classification in maize fields and palm oil plantations, specifically. Most studies however employed the Gabor filter in conjunction with other methods such as the GLCM, GGCM, and LBP [8]. Chen et al. tested these filters independently as well as fused them together to observe the classification accuracy among all of them for the classification between corn seedlings and weeds [9]. Specific to this application a fusion between GGCM, LBP and HOG give the best classification accuracy. Chaki & Bhattacharya combined the Gabor filter with GLCM to discriminate between 31 classes of leaves and obtained an accuracy of 92.5% [10] and Tang et. al. used an improved algorithm of LBP and GLCM to classify fresh tea in the production line with an accuracy of 94.8% [11].

Although there have been various well-established techniques to solve the weed classification problem, it is evident from the literature that the best solution is by fusing multiple techniques. There is no single technique that is best to suit the problem. Many studies have relied on machine learning [12], [13] for the purpose of weed detection or classification, but the machine learning strategy still uses a series of image-processing techniques [14] as part of its pre-processing stage, to extract the shallow features of weeds and before sending the images to a classifier for detection. Therefore, this study aims at developing an improved image processing technique based on the directional shape feature, in order to classify between two types of weeds, namely broadleaves and narrow leaves. These attributes were considered as they are the major distinguishing feature between the two types of weeds. This proposed filter is a modified line filter technique from the line filter proposed in [15] [16]. The filter consists of pre-defined lines at different orientations from 0 to 360°. The method presents in this study considered and mapped all pixels within the window to the nearest angled line, as opposed to the previous studies whereby only pixels along the configured line within the window were considered. The proposed method is more robust as it ensures that every pixel that corresponds to the weed leaves is captured. The pixel strength of each line was computed and compared to determine the overall response of the filter. This study go a step further and utilized the proposed method to classify three types of datasets, by introducing a mixed leaves dataset. The mixed leaves dataset consists of images that are approximately balanced amounts of broadleaves and narrow leaves. The remainder of the paper is organized as follows. *Section II* describes the dataset used for this study, and *Section III* describes the overall classification process, which includes the pre-processing steps and the proposed image processing method. *Section IV* discusses the classification results. Finally, *Section V* concludes the paper.

2. DATASET

The colored digital images of weeds used in this study were obtained from a palm oil plantation in Selangor, Malaysia, and captured under natural lighting conditions on a sunny day. The images were captured from approximately 1.5m height with a camera viewing angle of 45°. This height and angle are chosen based on the current height and design of the sprayer boom tractor available in the palm oil plantation in Malaysia. The two dominant weeds on the plantation are the broadleaf weeds, as well as the narrow grass weeds. *Figure 1* shows the sample images used in this study. Three types of datasets were used consisting of a total of 516 images which are 172 narrow leaves, 172 broadleaves, and 172 mixed weeds. A mixed weeds image is defined as having approximately 50% broadleaves and narrow leaves, or 40% broadleaves 60% narrow leaves, or 60%



(a) (b) (c)

Figure 1: Weed dataset from palm oil plantation (a) broadleaves weed, (b) narrow weed and (c) mixed weeds

broadleaves 40% narrow leaves. All images captured were resized to 120 x 160 pixels before being processed.

3. METHODOLOGY

3.1 Pre-Processing

The images were subjected to pre-processing stages to improve image contrast, delineate the edges and enhance the features of interest. The pre-processing steps employed aim to improve the extraction of relevant features useful for proposed image processing techniques.

FOREX Publication
Open Access | Rapid and quality publishing
International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 564-571 | e-ISSN: 2347-470X

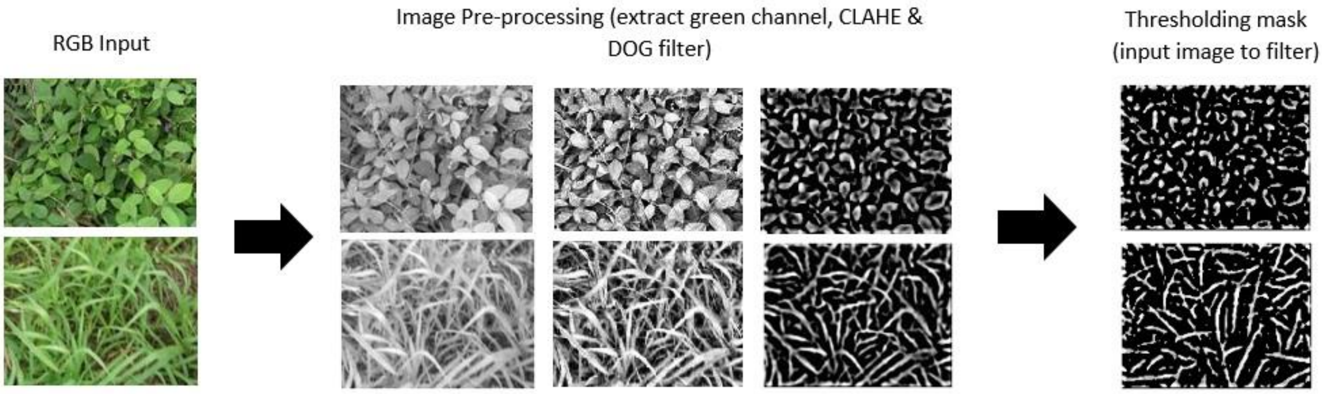


Figure 2: Block diagram and output of the image pre–processing steps.

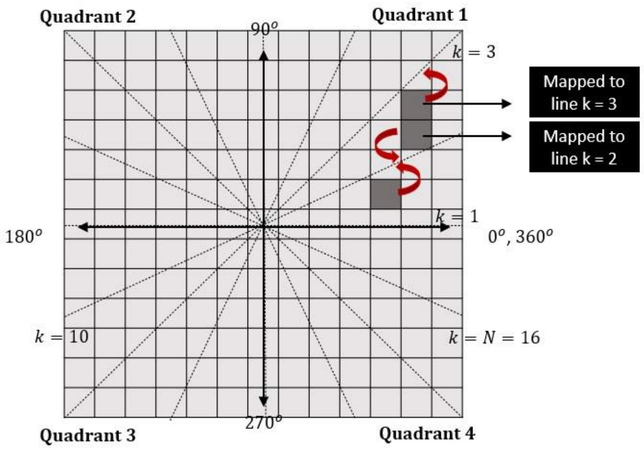


Figure 3: Example of filter window with N = 16 lines

The green channel of the images was first extracted by removing the red and blue components since weeds in general have a greater green intensity compared to red and blue. The excess green (ExG) and modified excess green (MExG) [17] color indices were attempted, as these color indices were usually employed when dealing with weeds and crop images. However, it yielded an inferior result compared to just using the green channel, because the output images if ExG were applied do not clearly retain the feature of interest that differentiate between the two types of weeds, which is the directional shape feature. Next, the contrast of the images was enhanced using the Contrast Limited Adaptive Histogram Equalization (CLAHE) method, a technique based on histogram modifications. This filter changes the distribution of gray scale value in the images to derive an image with a histogram of a more uniform spread for each block of the image. Afterward, the Difference of Gaussians (DoG) was utilized to increase the visibility of edges [18]. This step lessens the amount of data to be processed and improves computation time since the redundant and less relevant information was disregarded. The DoG filter is obtained by subtracting two Gaussian kernels with different standard deviations as in *equation (1)*.

$$F(x,y) = DoG * f(x,y) = (G_{\sigma_1} - G_{\sigma_2}) * f(x,y) \qquad (1)$$

where G_σ is a Gaussian kernel with standard deviation σ, and $\sigma_1 > \sigma_2$. Proper selection of sigmas and convolution between customized DoG filter and the input ExG image results in image representation suitable for the technique proposed for this study. Other edge detection filters such as Canny and Sobel edge detectors were also tested to delineate the edges of the weed, but outcomes were poorer compared to the DOG filter. The leaf's morphological shape feature is absent if these three filters were to be applied, hence unsuitable to be utilized for this weed classification algorithm. The images are then normalized, and a mask is created for image thresholding to only process the pixel value above the fixed threshold, remove the noise in the image, and improve the speed of computation. The pre-processed images at every step and the final input image fed into the proposed filter are shown in *figure 2*.

3.2 Image Processing

Shape features can play an important role in image analysis for weed classification. The method introduced in this study is built upon the difference in the spatial feature of the two weed categories, which are the elongated rectangularity of the narrow leaves versus the circularity of a broadleaves weed.

Processing of the image starts by selecting a square window within the pre-processed image. The lines at different orientations from 0 to 360°, all equally spaced and centered around the center pixels of the window, are first determined and placed within the window as in *figure 3*. In contrast to the line filter used by Azzopardi et al. and Ricci et al [15], [16], whereby only selected pixels that fall along the pre-determined lines were considered for processing, in this proposed modified line filter, all the pixels within the window will be processed.

FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 564-571 | e-ISSN: 2347-470X

The previous studies were not robust as it only caters to strictly straight edges. Weeds in nature are not strictly straight, therefore, to ensure every pixel intensity is captured, all pixels within the window are mapped to the nearest line (refer to *fig. 3*) and considered for processing. Intensity array, I(d,k), for each pixel, *d* distance away of every line is obtained based on the pixel values of all the pixels that have been mapped to the corresponding line, as in *equation (2),*

$$\begin{aligned} \boldsymbol{I}(d,1) &= [I(1,1) \quad I(2,1)\ldots \quad I(d,1)] \\ \boldsymbol{I}(d,2) &= [I(1,2) \quad I(2,2)\ldots \quad I(d,2)] \\ &\vdots \\ &\vdots \\ \boldsymbol{I}(d,k) &= [I(1,k) \quad I(2,k)\ldots \quad I(d,k)] \end{aligned} \tag{2}$$

where k is the number of lines $0,1,\ldots,N$ and d is the distance from the center pixel of the window and $\boldsymbol{I}(d,k)$ is the corresponding array intensity value of the line k with d distance away from the center pixel.

As mentioned earlier, this technique is designed by taking into consideration the different nature and shape of the type of weeds. The overall array intensities for each line, $\boldsymbol{p}(k)$, are calculated using *equation (3).*

The narrow leaves weed has a higher tendency to contain full array intensity values along the lines, as well as its mirroring line at the opposite angle, compared to the broadleaves weed. Considering this fact, therefore, each line within the window and its corresponding pair, which is the opposite line reflected across a mirror line of the pair, is folded onto one another by taking the array product of the pixel intensities between the two lines as in *equation (4).*

$$\boldsymbol{p}(k) = \prod_{i=0}^{d} \boldsymbol{I}(i,k) \tag{3}$$

$$\boldsymbol{p}(N) = \prod_{k=1}^{N} \boldsymbol{p}(k) \cdot \boldsymbol{p}(k + {}^{N}/_{2}) \tag{4}$$

It is adequate to only consider the first and second quadrant since the 90º line and the 270º line, or the 45º line and the 225º line will refer to the same weed inclination.

Each array output from *equation (4)* for each line is then multiplied by the pixel value of the center pixel (r,c), as in *equation (5)* and the maximum value among this product is used as the pixel value of the center pixel of the window.

$$p(i,j) = \max[I(r,c) \cdot \boldsymbol{p}(N)] \tag{5}$$

The flowchart for the image processing procedure is shown in *figure 4.*

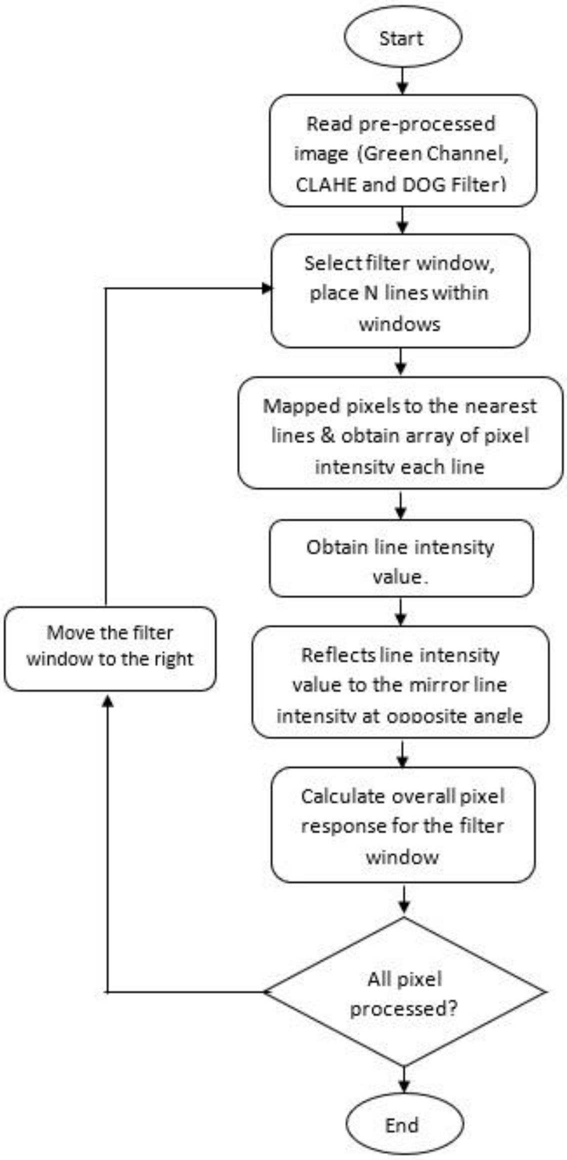


Figure 4: Flowchart of the image processing procedure using modified line filter technique

3.3 Classification

Once all the pixels have been processed, the total pixel response of the processed image is calculated as follows:

$$P(i,j) = \sum_{i=0}^{R} \sum_{j=0}^{C} p(i,j) \tag{6}$$

900 images consisting of 300 broadleaves weeds, 300 narrow leaves weeds and 300 mixed leaves weeds were used as training images to determine the appropriate classification threshold based on the value of $P(i,j)$. In the initial phase of this study, the proposed technique was used to classify between broadleaves and narrow leaves only, to tune the window size for feature extraction steps. Multilayer perception neural network (MLPNN) is used as classifier after the mixed leaves dataset was introduced. The inputs to the classifier were the features extracted from the proposed image processing technique and

the output were the weed class i.e: broadleaves, narrow leaves and mixed leaves. The input data were applied to the input layers, propagates through the hidden layers and the output layers. In this study, the network has 50 hidden layers. The remaining images were subjected to classification after the model has been trained.

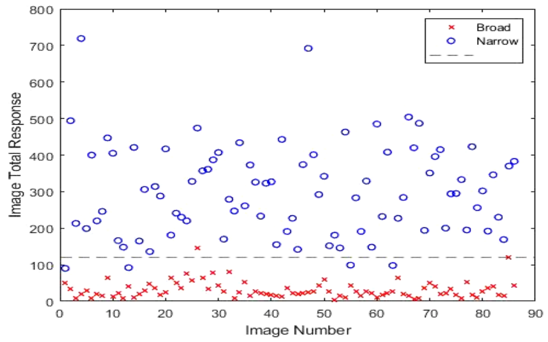
The algorithm of the entire procedure starting from the pre-processing stage to image processing and classification is shown in *Table 1*.

Table 1: Algorithm of the proposed modified line filter

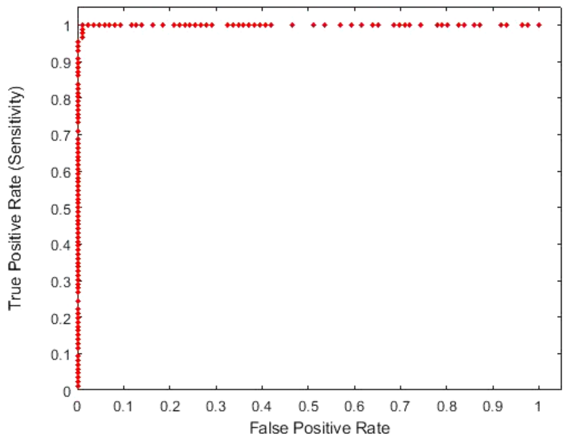
Algorithm 1
1. **Input:** RGB image
2. Extract the green channel
3. Pre-Processing: CLAHE and DOG
4. R x C ← size of the image
5. r x c ← size of the kernel
6. **for** i,j in range R
7. **for** j in range C
8. Select window. Place N line on kernel (Fig. 3)
9. **for** m in range r
10. **for** n in range c
11. Map all pixels to the nearest line
12. end for
13. end for
14. **for** x in range N
15. Pixel response for all lines Eqn. 2
16. end for
17. Calculate array product Eqn. 3 & 4
18. Move to the next window
19. end for
20. end for
21. Calculate total pixel response Eqn. 5
22. Classification

4. RESULTS AND DISCUSSION

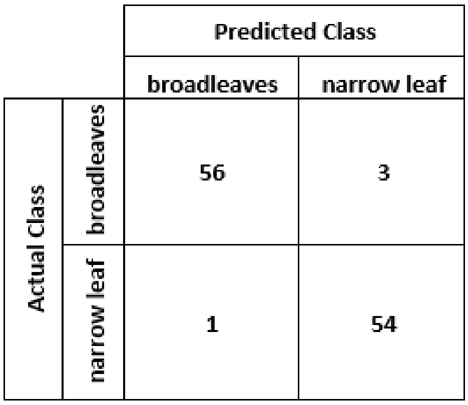
The weed classification in this study involves labeling the weeds to either grasses or narrow leaves broadleaves or mixed leaves categories. 516 images consisting of 172 narrow leaves, 172 broadleaves weeds and 172 mixed of narrow and broadleaves were utilized to test the effectiveness of the proposed image processing technique. 70% of each dataset was used for training and the remaining 30% was used for testing and validation, equally.



(a)



(b)



(c)

Figure 5: Two-class classification result (a) Scatter plot of the classification, (b) ROC Curve, (c) confusion matrix

During processing, the weed image is inputted into the system and subjected to pre-processing stages. Once the contrast and edges have been enhanced, the images were fed to the proposed filter to extract the directional feature of the weeds, as explained in *Section 3*. The classification is based on value from *Equation (5)*. As previously explained, for the purposed of tuning the window size for the filter, the classification was carried out between two class i.e., broadleaves and narrow leaves. As the intended application of this technique is for the sprayer boom system for the weed control system in a palm oil plantation, appropriate window size needs to be determined first based on the height of the mounted camera on the sprayer boom tractor. The window size plays an important role to provide optimum classification accuracy between the two types of weeds.

Table 2: Effect of window size on the accuracy of classification

Window Size	**Broadleaves Accuracy**	**Narrow leaves Accuracy**
7×7	83.7%	91.8%
11×11	90.6%	94.2%
19×19	97.7%	96.5%
21×21	96.5%	94.2%

FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 564-571 | e-ISSN: 2347-470X

Four window sizes were tested which are 7×7, 11×11, 19×19 and 21×21. The result is tabulated in *Table 2*. Poorer performance was observed for window sizes that are too small because the output of *Equation (4)* for some of the broadleaves weed would be similar to narrow leaves resulting in misclassification. The window size needs to be large enough to just capture the elongation and rectangularity of the narrow leaves when the lines are folded to one another according to *Equation (4)* and isolating the narrow leaf feature.

Table 3: Classification Accuracy and Comparison with the previously reported method

Class	Classification Accuracy	Gabor Wavelet	Gabor & GFD
Broadleaves	97.7 %	87.7%	93%
Narrow leaves	96.5%	81.1%	92%

The 19×19 window for two-class classification result was also compared to a previously reported method, which is the Gabor Filter [20] and a combination of the Gabor filter and Gradient Field Distribution (GFD) method based on the work by Ishak et. al [3] as shown in *Table 3*. The accuracy of the proposed algorithm is superior compared to previously reported methods. The scatter plot of the pixel response and the receiving operating characteristic (ROC) curve was also plotted as illustrated in *Figure 4*. ROC is one of the widely used performance indicators in binary classifiers and the closer a ROC curve approaches the top-left corner at point (0,1), the better the performance of the algorithm [15]. For the algorithm proposed in this study, the curve almost approaches the (0,1) point (refer to *Figure 4(b)*) which implies that the method proposed in this study is reliable to classify between broadleaf and narrow leaf. After the window size has been determined, another dataset, which is mixed leaves was introduced. This test is important because the weeds in the plantation can also be a mixed between broad and narrow.

Introducing the mixed leaves dataset causes the classification problem to be a multiclass classification. The same image processing method was used as detailed out in *Section 3.2* and MLPNN was utilized as a classifier. The performance of the multiclass classification was measured through the accuracy, precision, recall and F1-score which can be obtained using *Equation (7)* [19].

$$\begin{gathered} Accuracy = \frac{T_P + T_N}{P + N} \\ Precision = \frac{T_P}{T_P + F_p} \\ Recall = \frac{T_N}{T_N + F_p} \\ F1 - score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \end{gathered} \tag{7}$$

T_P, T_N, P and N are performance parameters which are true positive, true negative, total positive, and total negative, respectively. For binary or two-class classification, these values are easy to calculate. However, for multiclass classification, each of this parameter need to be calculate for each class. Using broadleaves class as an example, T_P indicates the number of records when broadleaves are correctly detected, T_N indicates the number of records when the other classes are detected correctly, P is total positive which is $T_P + F_N$ and N is total negative equivalent to $T_N + F_P$. F_N and F_P are false positive and false negative values for each class, respectively. The four performance parameters were calculated for each class using the values found within the confusion matrix in *Figure 6*.

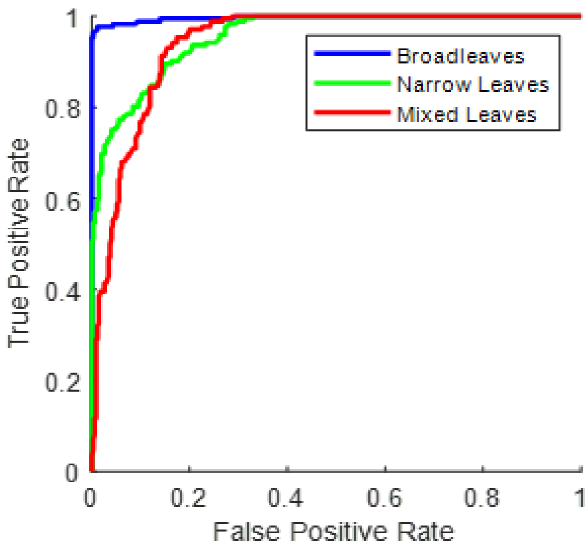
Table 4: Accuracy, Precision, Recall and F1-score for the multiclass classification

Class	Accuracy	Precision	Recall	F1-score
Broadleaves	0.99	0.99	0.98	0.98
Narrow leaves	0.92	0.93	0.81	0.87
Mixed leaves	0.91	0.82	0.94	0.87

Based on the four performance indicators in *Table 4*, the proposed technique is superior in predicting the broadleaves category. This is reflected by the high values of all four performance indicators for the broadleaves class. The dataset used for this study is balanced where each class contain the same number of images. Therefore, the accuracy value is a good indicator to measure the overall performance of the data. The overall performance for the classification is good based on the accuracy value, and superior compared to the previously reported methods. The accuracy drops slightly from 96% (Table 3) to 92% in predicting narrow leaves after the mixed dataset was introduced for multiclass classification. Referring to *Figure 6(b)*, there were numbers of mixed images that were incorrectly classified as narrow and vice versa. One of the main reasons for this misclassification is, the algorithm was designed to extract the shape of the narrow weed leaves and the mixed dataset contain the narrow leaves. The mixed leaves images that were incorrectly misclassified as narrow leaves were those that contained dominantly narrow leaves images as opposed to broadleaves. The narrow leaves images that were misclassified were images that contain sparse amounts of narrow leaves. There is always a trade-off between precision and recall value as can be seen for the narrow leaves and mixed leaves class. The F1-scores were obtained which is the harmonic average between the precision and recall. The F1-score for broadleaves, narrow leaves and mixed leaves are 0.98, 0.87 and 0.87, respectively. The ROC for this multiclass classification is shown in *figure 6(a)*. The ROC curve reflects the performance indicator in *table 4* where all three classes approached the top left corner indication good classification performance, with the broadleaves class curve is the closest to the top left corner indication the highest classification performance among the three classes.

FOREX Publication
Open Access | Rapid and quality publishing

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 564-571 | e-ISSN: 2347-470X



(a)

		Predicted Class		
		Broadleaves	Narrow Leaves	Mixed Leaves
Actual Class	Broadleaves	168	0	4
	Narrow Leaves	0	139	33
	Mixed Leaves	1	9	162

(b)

Figure 6: Multiclass classification result (a) ROC Curve and (b) confusion matrix

5. CONCLUSION

In this study, a method for extracting the directional shape feature of weed has been proposed for the weed classification task. A dataset obtained from a local palm oil plantation was used to test the algorithm. The proposed technique was designed based on a line filter method. This modified line filter technique is aimed to be applied to a sprayer boom system, therefore, tuning and testing of the window size used for the classification were also performed. The result obtained demonstrates that the proposed technique is highly reliable and can be used to classify between broadleaves and narrow leaves weeds with an accuracy of over 97% with the appropriate size of the window was used. The performance of the classification slightly reduced after mixed leaves dataset were introduced as a third class in the classification but still highly reliable and superior compared to previously reported methods. This algorithm can be implemented in an automated weed management system for precision agriculture. Ongoing work is currently being carried out to increase the number of images in the dataset so that testing of the algorithm could be validated for various lighting conditions and weed density. The algorithm also will be further improved accordingly to increase the performance and robustness of the technique.

ACKNOWLEDGEMENT

The work described in this paper is supported by the Research University project grant from Universiti Kebangsaan Malaysia (UKM) under grant agreement GGPM-2019-060.

REFERENCES

[1] D. Slaughter, D. Giles, D. Downey, K. Gillis, R. Zarghami, and et.al., “Intelligent herbicide application system for reduced herbicide vegetation control phase ii - commercialization,” California Department of Transportation - Division of Research and Innovation, Tech. Rep. CA08-0279, Dec. 2008.

[2] R. B. Mohamad, W. Wibawa, M. G. Mohayidin, A. B.Puteh, A. S. Juraimi, Y. Awang, and M. B. M. Lassim, “Management of mixed weeds in young oil-palm plantation with selected broad-spectrum herbicides,” Pertanika J. Trop. Agric. Sci, vol. 33, no. 2, pp. 193–203, 2010.

[3] A. J. Ishak, A. Hussain, and M. M. Mustafa, “Weed image classification using Gabor wavelet and gradient field distribution,” Computers and Electronics in Agriculture, vol. 66, no. 2009, pp. 53–61, Dec. 2008.

[4] X. P. Burgos-Artizzu, A. Ribeiro, M. Guijarro, and G. Pajares, “Real-time image processing for crop/weed discrimination in maize fields,” Computers and Electronics in Agriculture, vol. 75, no. 2, pp. 337–346, 2011. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0168169910002620

[5] R. R. Shamshiri, I. A. Hameed, S. K. Balasundram, D. Ahmad, C. Weltzien, and M. Yamin, Fundamental Research on Unmanned Aerial Vehicles to Support Precision Agriculture in Oil Palm Plantations. Intech Open, Nov. 2018.

[6] G. N., L. L. R., and T. Anurada, “Weed classification in maize field using Gabor filter,” International Journal of Innovative Research in Science, Engineering and Technology, vol. 6, no. 4, pp. 2347–6710, 2017.

[7] M. A. and M. M., “Development of a real-time site sprayer system for specific weeds using Gabor wavelets and neural networks model,” in Malaysia Science and Technology Congress, Apr. 2005, pp. 406–413.

[8] Z. Wu, Y. Chen, B. Zhao, X. Kang, and Y. Ding, “Review of weed detection methods based on computer vision,” Sensors, vol. 21, no. 11, p. 3647, May 2021.

[9] Y. Chen, Z. Wu, B. Zhao, C. Fan, and S. Shi, “Weed and corn seedling detection in the field based on multi-feature fusion and support vector machine,” Sensors, vol. 21, no. 1, p. 212, Jan. 2021.

[10] J. Chaki, R. Parekh, and S. Bhattacharya, “Plant leaf recognition using texture and shape features with neural classifiers,” Pattern Recognition Letters, vol. 58, pp. 61–68, 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S0167865515000586

[11] Z. Tang, Y. Su, M. J. Er, F. Qi, L. Zhang, and J. Zhou, “A local binary pattern-based texture descriptors for classification of tea leaves,” Neurocomput., vol. 168, no. C, p. 10111023, Nov. 2015. [Online]. Available: https://doi.org/10.1016/j.neucom.2015.05.024

[12] J. Behmann, A. Mahlein, and T. Rumpf, “A review of advanced machine learning methods for the detection of biotic stress in precision crop protection,” Precision Agriculture, vol. 16, p. 239260, 2015.

[13] P. Lottes, M. Hoeferlin, S. Sander, M. Mter, P. Schulze, and L. C. Stachniss, “An effective classification system for separating sugar beets and weeds for precision farming applications,” in 2016 IEEE International Conference on Robotics and Automation (ICRA), 2016, pp. 5157–5163.

International Journal of
Electrical and Electronics Research (IJEER)
Research Article | Volume 10, Issue 3 | Pages 564-571 | e-ISSN: 2347-470X

[14] M.Thanjaivadivel, R.Suguna. Leaf Disease Prediction Using Fast Enhanced Learning Method International Journal of Engineering Trends and Technology, vol. 69 no. 9, pp. 34-44

[15] G. Azzopardi, N. Strisciuglio, M. Vento, and N. Petkov, “Trainable cosfire filters for vessel delineation with application to retinal images,” Medical Image Analysis, vol. 19, no. 1, pp. 46–57, 2015. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1361841514001364

[16] E. Ricci and R. Perfetti, “Retinal blood vessel segmentation using line operators and support vector classification,” IEEE Transactions on Medical Imaging, vol. 26, no. 10, pp. 1357–1365, 2007.

[17] L. Tang, L. Tian, and B. L. Steward, “Classification of broadleaf and grass weeds using Gabor wavelets and an artificial neural network,” American Society of Agricultural and Biological Engineers, vol. 46, no. 4, p. 12471254, 2003.

[18] F. Akram, M. Garcia, and D. Puig, “Active contours driven by the difference of Gaussians,” Sci Rep, vol. 7, p. 14984, 2017.

[19] N. Islam, M. M. Rashid, S. Wibowo, C.-Y. Xu, A. Morshed, S. A. Wasimi, S. Moore, and S. M. Rahman, “Early weed detection using image processing and machine learning techniques in an Australian chili farm,” Agriculture, vol. 11, no. 5, p. 387, Apr. 2021.

[20] M. H. M. Zaman, S. M. Mustaza, M. F. Ibrahim, M. A. Zulkifley and M. M. Mustafa, "Weed Classification Based on Statistical Features from Gabor Transform Magnitude," 2021 International Conference on Decision Aid Sciences and Application (DASA), 2021, pp. 147-151