Journal of Soft Computing and Engineering Applications

https://srkpublication.org/

Watershed Crop Weed Segmentation based on Hybrid Equilibrium Optimization and Kapur's Multi-Thresholding

J. Prabakaran[1*], T. Jeffiin Gracewell[2]

[1]*Assistant Professor, Department of Electronics and Communication Engineering, Coimbatore Institute of Engineering and Technology, Tamil Nadu 641109, India*

[2]*Associate Professor, Department of Electronics and Communication Engineering, CSI Institute of Technology, Thovalai, Tamil Nadu 629302, India*

[*]Corresponding author email: prabha.rathi@gmail.com

Abstract: Watershed segmentation is very efficient approach to extract ROI from the pre-processed crop weed image. To enhance this Watershed crop weed Segmentation, in this work hybrid algorithm is proposed. The proposed Watershed crop weed Segmentation executes the hybrid algorithm based on the Equilibrium Optimization (EO) and Kapur's multi-thresholding. In this manuscript, extracting the ROI of the image from crop weed database, Ground Truth (GT) with the qualified assessment and the similarity values are recorded. At last, the execution is performed on the MATLAB software. The experimental outcome portrays that the proposed system performs better based on Dice, Jaccard, Specificity, Sensitivity, Accuracy and Precision. The proposed WSS-EO algorithm provides higher performance for Jaccard 6.74%, and 10.46%, Dice 4.54%, and 3.37%, Sensitivity 7.69% and 11.36 %, Specificity 10.11%, and 22.2%, Accuracy 4.44%, and 16.04% and Precision 15.18%, and 5.81% compared with existing compared with Real Time Semantic Segmentation (RTSS) and PixelWise Segmentation (PWS) methods respectively.

Keywords: *Crop weed, watershed segmentation, multi thresholding, Kapur's entropy, region of interest*.

1. INTRODUCTION

Agriculture is the main activity that sustains human life by the sustainability and development is assumed the key element of civilization on general. Therefore, the major challenges are facing the agricultural area [1, 2]. To achieve them, good monitoring of crop variable is essential. This information involves the plant growth have accurate information on plant. Precision agriculture is the senor information system and challenges the technologies are enhanced by the robotics and optimize the productivity [3]. In this technology that is a computer vision is applied to the various crop weed agriculture development such as quality of product detection and crop monitoring, production and crop disease identification [4, 5]. In computer vision is to analyze the plant image is the critical and essential step to the segmentation of plant, then separating the plant materials in the region of interest (ROI) from background [6].

In this Smart cultivation are continuously supervised by the plants using the dedicated procedure for monitoring the cultivation [7]. In agriculture to monitor the weed, image assisted procedure s are normally employed in crop diseases and damage in crop due to insects [8]. High resolution cameras or autonomous robots are used to monitor the agricultural field. Generally the various images are collected and related these images are processed on central monitoring station to need the decision of healthy cultures [9, 10]. This watershed crop weed segmentation to enhance the ROI from the crop weed image is generally implemented by the Kapur's multi-threshold. This multilevel threshold is implemented by the Kapur Entropy in threshold of grayscale and RGB images. In this paper, different threshold values are executed in preprocessing step and the result is considered for matching the ROI extraction. The threshold value of crop image is adjusted randomly by the WSS-EO until the maximum value.

The major contribution of this manuscript are mentioned as follows,

- In this manuscript, Watershed crop weed Segmentation executes the hybrid algorithm based on the Equilibrium Optimization (EO) and Kapur's multi-thresholding system for enhancing the crop weed image and mining process to remove the Region of Interest (ROI)
- For realizing the improved result of the procedure is developed by equilibrium optimization algorithm is assumed to examine the multiple threshold tasks.
- Subsequently, the ROI is extracted as text image, Ground Truth (GT) is run with the qualified assessment and the similarity values are recorded.
- Then the performance of the equilibrium optimization algorithm is authenticated with well-known heuristic procedure like spider monkey optimization algorithm (SMO), bat algorithm (BA) and firefly algorithm (FA), respectively.
- At last, execution is performed on MATLAB software. The experiment portrays that the proposed method has better results.

The rest of this manuscript are summarized below, the literature survey is suggested on section 2. Section 3 presented the proposed system. Result and discussion is suggested on section 4 and at last section 5 concludes the manuscript.

2. LITERATURE REVIEW

Some of the recent literatures related to crop weed segmentation through various approaches which are explained as follows,

In 2016, Hamuda et al [11] have presented a study of image processing systems for extraction and segmentation of plants on field. This paper introduces three approaches for comparison that are color index, threshold, and learning approaches are the segmentation-based approaches. In general performance, the color index method has few restrictions while the light is strong or poor, thus threshold optimization is required for targeting a last segmentation. Moreover, it is only appropriate for problems wherever the dominant plant color was green.

In 2015, Zhihua et al [12] has presented an image segmentation system to cotton mite disease depends on area threshold and color characteristics. This paper introduces a RGB channel normalization that was not used prior to transformation. After that, the threshold is set and used for discriminating values that exceed 0-225 range. According to this work, it performs well with lighting problem and computation complexity.

In 2017, Yu et al [13] have introduced an image analysis line for automated classification of light conditions of images and quantification of wheat canopy coverage time series at field phenotyping. In this, the machine learning mechanism is classified into three steps that are, lighting classification, segmentation and post-processing. The main disadvantage of the introduced work is that it was only tested with wheat data set that had orange and red foliage color. Moreover, the pre-processing and post-processing operations do not facilitate applications of this strategy for real-time operations.

In 2018, Bosilj et al [14] have presented the morphology of the connected attribute for segmentation and unified classification of vegetation at precision agriculture. In this, the segmented region of pixels depends on SVM and NDVI was suggested and used at two data sets: onion and sugar beet. Each image is segmented and neighborhood information was acquired by maximum tree hierarchy mechanism. Then the drawback that overcomes the global threshold method likes poor performance in uneven lighting conditions. This system exhibits rough segmentation at the edges of plants that does not use in the data set through a high background feature.

In 2016, Yu et al [15] has presented the image-based automatic detection technology of two dangerous growth steps of maize. In this manuscript, the affinity propagation mechanism supports group pixels to maximize the similarity colors on every class. Then the Hue-Intensity was used to judge the consideration of the distributed parameters. This paper produces the performance measure based on accuracy was 96. 68%.

In 2014, Haug and Ostermann et al [16] have described the weed field image data set for evaluation of machine vision-based precision agriculture operations. According to the evaluation measurement were fear, it was worth noting that there is presently a trouble to compare the segmentation process. There was no standard measure of precision among diverse strategies. In this, the data set represents the lighting environment of image acquisition on crop segmentation.

In 2016, Bai et al [17] have described the segmentation of vegetation robust to lighting variations depends on grouping and morphology modeling. In this particle swarm optimization (PSO) clustering of k-means and morphology modeling on color space of CIE laboratory were discussed. This has been divided into two methods that were offline learning and online targeting. In this segmentation, the result of the color model was applied. The accuracy of the model was 88.1 and 91.7 for rice and cotton.

In 2014, Guerrero et al [18] have presented the Support vector machines for the recognition of crops or weeds on corn fields. This paper introduces a color space transformation as RGB to CIE for utilizing the central pixel neighborhood information for classifying the SVM across pixels. In this experiment, the foliage segmentation approach focuses on single pixel devoid of assuming its neighbors, and then investigates contextualized information on diverse crop species with machine learning strategies.

3. PROPOSED METHOD FOR WATERSHED CROP WEED SEGMENTATION BASED ON HYBRID EQUILIBRIUM OPTIMIZATION (EO) AND KAPUR'S MULTI-THRESHOLDING

In this section a hybrid process depends on Equilibrium Optimization (EO) [19] and Kapur's multi-threshold for weed segmentation-based extraction from watershed crops is discussed. In Crop / Weed Field Image Dataset (CWFID), the image segment is used for watershed crop weed segmentation. When the crop / weed field image data set (CWFID) includes RGB scale image dimension at 1296 x 966 pixels, mainly, when the crop weed image equilibrium optimization guided Kapur's multi-threshold is used by preprocessing technique and the watershed algorithm is based on the post processing. Figure 1 shows that the crop wed valuation procedure for the equilibrium optimization and Kapur's multi thresholding approach.

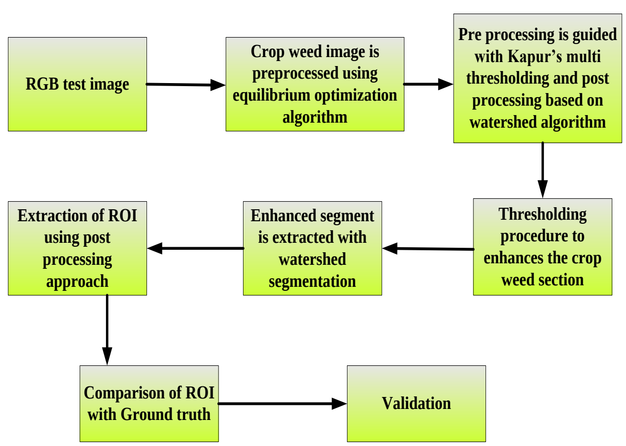

Figure 1: Block diagram for proposed Water Shed crop weed Segmentation method

The crop wed segment enhances the thresholding procedure and eliminate the back ground region is possible according to the chosen threshold. In the watershed crop weed segmentation approach extracted with the enhanced segment, then the segmented ROI is compared to the actual soil image and the image is recorded. Finally the watershed crop weed segmentation based on hybrid equilibrium optimization and Kapur's multi threshold is validated by other existing algorithm like Spider Monkey Optimization (SMO) [20] and BA algorithm [21], Firefly-Algorithm (FA) [22].

In digital camera acquired through the crop and weed images. The sample images are captured in this field and the different times of images are obtained. Additionally, the classification problem is difficult to increase the weed and crop with varying canopy size. Different techniques are used to remove the background image they are threshold, color, edge and watershed crops weed segmentation. In this study, this can use the watershed crop weed segmentation is employed for segmentation operation. The entire segmentation step is performed by binary image, in pre-processing stage, the watershed image is converted to the binary image. In weed and crop classification the input is used to the final segmented image. Weed detection is depends upon their area. Initially the segmented binary image is labeled and assesses the areas of objects. The weed and crop plants are classified based on the threshold value. When binary image is changed by thresholding based on watershed image utilize the below equation (1)

$$h(a,b) = \begin{cases} X, & |H-S| > T and\, |H-P| > T \\ P_h, & otherwise \end{cases} \tag{1}$$

At original image the absolute values of all pixels are calculated. The pixel distance of the gray scale line is the measurement of distance value is higher to threshold (T) and classification of pixel represented X. Where P_h is represented as the pixel classified as background. The number of (T) is equal with threshold based on available image material. The substances are classified by the crop plants and areas of individual objects are computed by equation (2)

$$N(n,m) = \frac{1}{I^n g^m} \sum_{1=1}^{I} \sum_{g=1}^{G} (a_i)^n (b_g)^m E(I,G) \tag{2}$$

In the above equation $E(I,G)$ represents the binary segmented image a_i and b_g are the scaled coordinates then I and G is the binary image. Comparing the threshold value and their area are detected by the weed and crop images. Initially, all images processing method is common to wed detection method, and the watershed crop weed segmentation. The linear combination of the RGB planes is performed with the watershed crop weed segmentation process. Then the threshold value is automatically adjustment in vital to attaining the segmentation to changes the illumination, which occurs due to changing weather frequently, specially that gathering the cloudy days. There are two types of threshold adjustment methods are evaluated that are, Otsu's widely used in Otsu and second one is threshold setting to the mean pixel intensity. In this, to enhance the ROI from the crop weed image is generally implemented by the Kapur's multi-threshold. This multilevel threshold is implemented by the Kapur's Entropy in threshold of grayscale and RGB images.

3.1 Step by step procedure for Watershed crop weed segmentation based hybrid Equilibrium Optimization algorithm (WSS-EO) and Kapur's multi thresholding

In this step Watershed crop weed segmentation based Equilibrium Optimization algorithm are discussed. In this Watershed crop weed segmentation based Equilibrium Optimization is the optimization algorithm stimulated using equilibrium and dynamic states of control volume mass balance model. At equilibrium optimization each solution with its position is act as the search agent. Recently, the equilibrium optimization algorithm is used to get the best answers for the choosen of optimization assignments. The equilibrium optimization algorithm is used to totally search the domain and find the global optimal results. The metaheuristic includes the following advantage effortlessness, independency to the problem, suppleness, and gradient-freenature. In this work water shed segmentation based equilibrium optimization (WSS-EO) is considered to preprocess the CWFID images. Water shed crop weed segmentation is a search procedure to improve the heuristic search presentation. In WSS-EO, the watershed crop weed segmentation is assumed with advanced exploitation facility of the traditional equilibrium optimization. Semi and computerized actions are extracted with the ROI from CWFID representation. In semi-automated method to initiate the removal task may require the assistance of the worker. Therefore, generally choose the picture examination in computerized procedure. In this Watershed crop weed Segmentation to extract ROI from CWFID images. In Water shed segmentation based equilibrium optimization consists of following stages they are, initialization, function evaluation, fitness function, Kapur's entropy, exponential term, generation rate, performance, and validation. Step by step procedure of the watershed crop weed segmentation based on equilibrium optimization algorithm and Kapur's multi-thresholding is discussed below.

Step 1: Initialization

Initialize the initial population M using WSS-EO, C denotes the dimension of search, S represents the size of the random generation (0, 1) and R_i represents the agents of size, $R_{\min j}$ and $R_{\max j}$ represents the upper and lower values and S_i in j way.

$$R_{ij} = R_{\min j} + S(0,1) * (R_{\max j} - R\min j) \quad (3)$$

$$R_{n,ij} = R_{ij} + S(0,1) * (L_{kj} - R_{ij}) + S(-1,1) * (R_{sj} - R_{ij}) \quad (4)$$

When the greedy search revise to implement the location of R based on the finest location.

$$R_{n,ij} = R_{ij} + S(0,1) * (G_j - R_{ij}) + S(0,1) * (R_{ij} - L_{kj}) \quad (5)$$

When equation (4) and (6) represents the learning stages and leader stages of learning and decision making for global leader. Then the WSS-EO displays the preprocessing technique.

Step 2: Function evaluation

In this step watershed crop weed segmentation based equilibrium optimization uses the optimization process to start the initial population. The initial constructions are depends on number of particles and dimensions with random initialization are as follows,

$$D_j^i = D_{\min} + r_i (D_{\max} - D_{\min}) \;\; j = 1,2,\ldots,m \quad (6)$$

where D_j^i the initial is vector of the jth element, and denotes the dimensions of the maximum and minimum value, r_i represents the random vector of the interval (0, 1) and m is the population of the number of elements. Then the elements are evaluated by the fitness function that is determined in step 3. Then overall flow chart of proposed WSS-EQ algorithm is discussed at figure 2

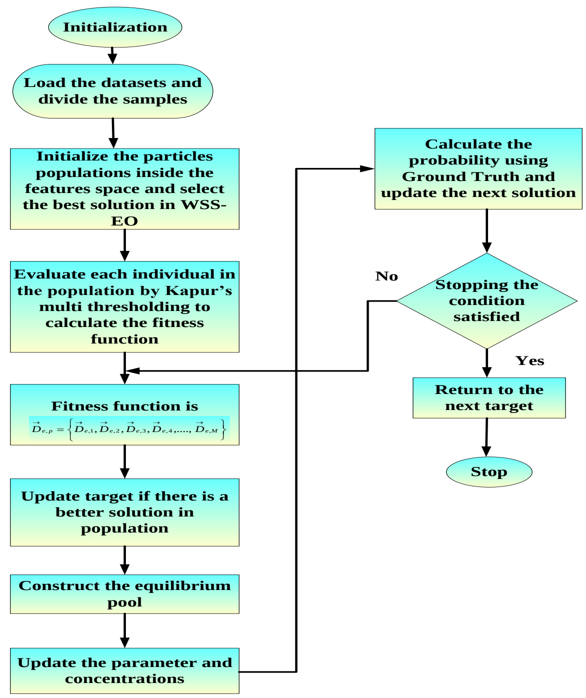

Figure 2: Flow chart for Watershed crop weed Segmentation based hybrid Equilibrium Optimization algorithm (WSS-EO) and Kapur's multi thresholding

Step 3: Fitness function

From the initialized values, the random number of solution is created. The fitness function can be evaluated with each solution as $\vec{D}_{e,p}$. The fitness function of solution is assessed and the objective function is represented in an optimization of Kapur's multi threshold.

$$\vec{D}_{e,p} = \left\{ \vec{D}_{e,1}, \vec{D}_{e,2}, \vec{D}_{e,3}, \vec{D}_{e,4}, \ldots, \vec{D}_{e,M} \right\} \tag{7}$$

The same probability of the random selection among chosen runners in each element will updates the concentration of the iteration. For example, in the first iteration the first element is updated based on the concentration on $\vec{D}_{e,1}$ and the second iteration based on the concentration is $\vec{D}_{e,M}$ till the end of the optimization process.

Step 4: Kapur's entropy

The maximum KE presents the random threshold is recorded from optimal threshold depends on allocated threshold value. KE can be expressed in the equation (3) as given below,

$$E_{EK\max}(th) = \sum_{i=1}^{k} G_I^D \tag{8}$$

Step 5: Exponential term

In the updating rule the main concentration of the next contribution is the exponential term (E) and the equilibrium optimization will support the accurate definition on reasonable balance among exploration and exploitation. Where λ assumed that random vector

$$\vec{E} = f^{-\vec{\lambda}(t-t_0)}$$
(9)

where time t is defined as the iteration of the function it decreases the number of iterations.

$$t = \left(1 - \frac{I}{M}\right)^{\left(a_2 \frac{I}{M}\right)} \tag{10}$$

where I and M implies that maximum number of iterations on current stage, and a_2 is exploitation ability used to manage the constant value. To assurance the convergence of ability in equilibrium optimization algorithm, this study also considers the following equation

$$\vec{t}_0 = \frac{1}{\vec{\lambda}} n(-a_1 g(\vec{s} - 0.5)[1 - e^{-\lambda \vec{t}}]) + t \tag{11}$$

here a_1 denotes that constant value that controls the exploration ability s represents the random vector between 0 and 1. Equation (12) shows that the revised version of equation (E) shows below,

$$\vec{E} = a_1 g(\vec{s} - 0.5)[1 - e^{-\lambda \vec{t}}] \tag{12}$$

Step 6: Generation rate

In this step generation rate is discussed, the generation rate is the most important term in the equilibrium optimization algorithm. The WSS-EO algorithm provides the particular solution in the exploitation phase. In generation rate describes the flexible model in the first order exponential degeneration process is defined as below,

$$\vec{H} = \vec{H}_0\, e^{-k(\vec{t} - t_0)} \tag{13}$$

here $\vec{H}$ represents that initial value and k represents that constant decay. Number of random variable is controlled by the symmetric search pattern, this study assume that the exponential term is previously derived the user. Then the final stage of the generation rate is represent in equation (14)

$$\vec{H} = \vec{H}_0 e^{-\lambda(\vec{t} - t_0)} = \vec{H}_0 \vec{E} \tag{14}$$

Step 7: Performance evaluation

In this step the performance evaluation of the watershed crop weed segmentation based on equilibrium optimization and Kapur's multi-thresholding are discussed. The ROI and GT removal are presented with comparative study of created image evaluation and along with the result of the consultants.

Step 8: Validation

In this step, the importance and throughput of equilibrium optimization technique are validated based on watershed crop weed segmentation. The watershed crop weed segmentation choose the nearness of extracted ROI and GT. Hereafter watershed crop weed segmentation is the representation of the evaluation system in the cultivated fields and used by the inspect of other crop weed images. Then the performance of the WSS-EO is validated contradiction of the existing algorithm like SMO, BA and FA algorithms.

4. RESULT AND DISCUSSION

In this section discussed about simulation performance of proposed Watershed crop weed Segmentation based on Equilibrium Optimization algorithm (WSS-EO) and Kapur's multi-thresholding. The simulation is conducted MATLAB software. This study assumes RGB of size 1296× 966 and Crop/Weed Field Image Dataset (CWFID). Here example of adopted images are discussed and illustrates the crop weed image and their equivalent GT. Here the efficiency of the proposed system Water Shad Segmentation (WSS) was analyzed and compared to Real Time Semantic Segmentation (RTSS) [23] and Pixel Wise Segmentation (PWS) [24] by varying the number of values. The simulation parameters of proposed algorithm are shown on Table 1.

Table 1: Simulation parameter

Parameter	Value
Agent size	40
Exploration dimension	Th
Total number of iteration	2000
Software	MATLAB
RGB size	1296 x 966

4.1 Simulation result of the proposed Water Shad crop weed Segmentation based on hybrid Equilibrium Optimization algorithm (WSS-EO) Kapur's multi thresholding

Figure 3 shows that the implementation of watershed crop weed segmentation based on the Kapur's equilibrium and multiple threshold optimization algorithms.

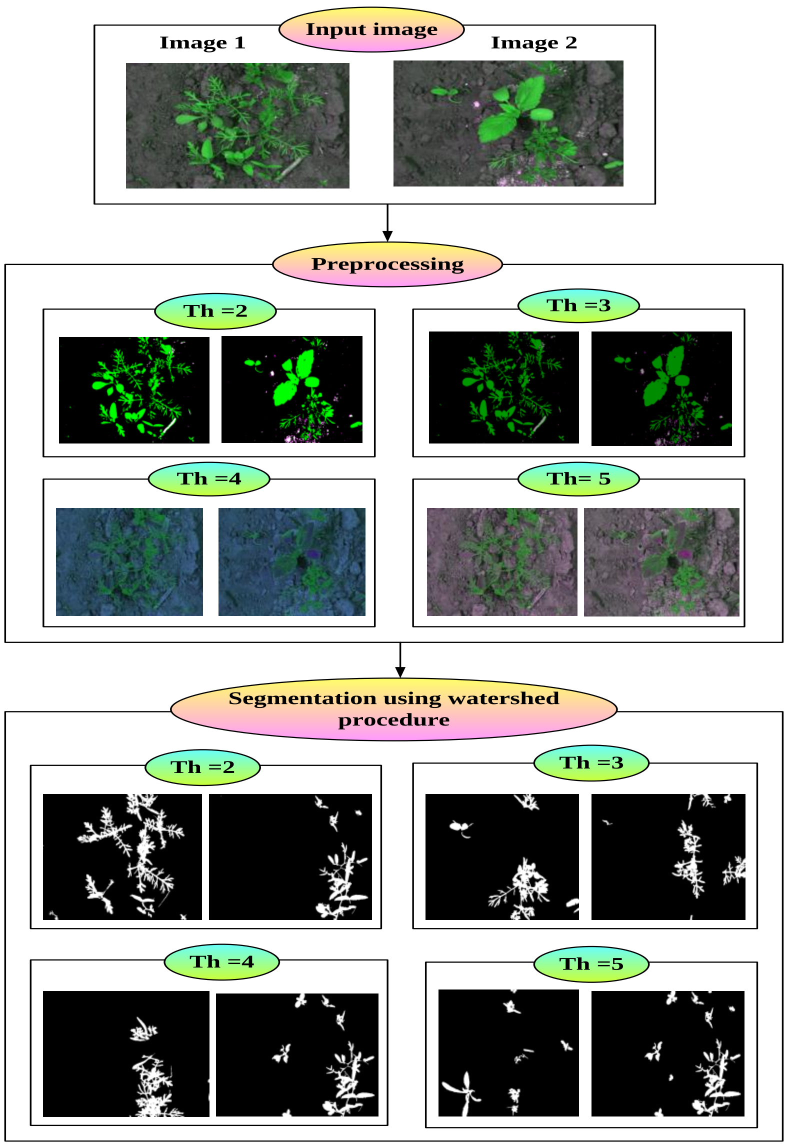

Figure 3: Step involved in the implementation of watershed crop weed segmentation based on hybrid equilibrium optimization and Kapur's entropy

Firstly, watershed crop weed segmentation depends on equilibrium optimization and Kapur's Entropy is implemented based on multiple threshold in CWFID images with the various thresholds (Th) like Th = 2, 3, 4, 5 and crop weed section improvement and background removal is discussed. At first, the image displays the threshold outcome for Th = 2, 3, 4 and 5. Then the outcome of the watershed crop weeds segmentation, the extracted ROI and GT. Then the maximal similarity of the GT image, the WSS-EO and KE with the thresholding value is fixed for the other image available for the CWFID dataset. The extracted ROI image with proposed system, then removing the ROI, the comparison of ROI and GT is executed by watershed crop weed segmentation method. In this proposed watershed crop weed segmentation based on the equilibrium optimization algorithm and Kapur's multi-thresholding is compared with other existing algorithm like SMO, BA and FA algorithm.

4.2 Performance comparison of various methods

Figures 4 and 5 portray that simulation outcome for Kapur's multi-threshold-based hybrid image examination system. In this segment, the various performance metrics such as Jaccard, Dice, Sensitivity, Specificity, Accuracy, and Precision are discussed. Here the performance of proposed Water Shad Segmentation (WSS) system was analyzed and compared to Real Time Semantic Segmentation (RTSS) and Pixel Wise Segmentation (PWS) by varying the number of values.

From figure 4 shows that the performance metrics of Jaccard, Dice, and Sensitivity are discussed. The performance metrics, the proposed WSS shows the Jaccard value is 6.74% higher than the existing Real Time Semantic Segmentation (RTSS) method and 10.46% higher than the Pixel Wise Segmentation (PWS) method respectively. The proposed WSS shows the Dice value is 4.54% higher than the existing Real Time Semantic Segmentation (RTSS) method and 3.37% higher than the Pixel Wise Segmentation (PWS) method respectively. The proposed WSS shows the Sensitivity value is 7.69% higher than the existing Real Time Semantic Segmentation (RTSS) method and 11.36% higher than the Pixel Wise Segmentation (PWS) method respectively.

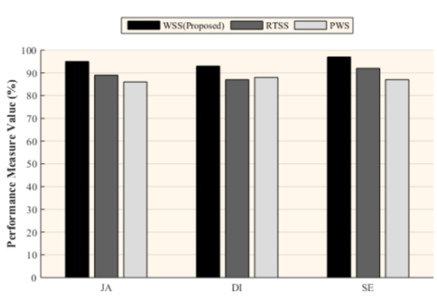

Figure 4: Performance metric of Jaccard Dice and Sensitivity

From figure 5 shows that the performance metrics of Specificity, Accuracy and Precision are discussed. The performance metrics, the proposed WSS shows the Specificity value is 10.11% higher than the existing Real Time Semantic Segmentation (RTSS) method and 22.5% higher than the Pixel Wise Segmentation (PWS) method respectively. The proposed WSS shows the Accuracy value is 4.44% higher than the existing Real Time Semantic Segmentation (RTSS) method and 16.04% higher than the Pixel Wise Segmentation (PWS) method respectively. The proposed WSS shows the Precision value is 15.18% higher than the existing Real Time Semantic Segmentation (RTSS) method and 5.81% higher than the Pixel Wise Segmentation (PWS) method respectively.

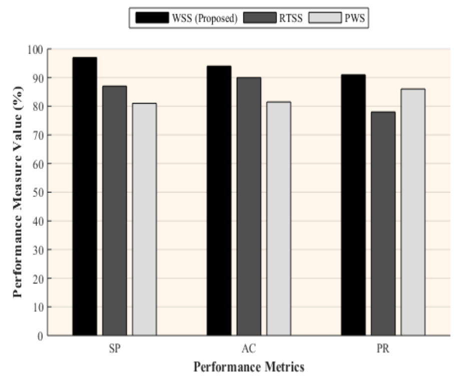

Figure 5: Performance metrics of specificity, Accuracy and Precision

4.3 Performance comparison of various algorithms

Figure 6 and 7 portrays that simulation outcome for Kapur's multi-threshold based hybrid image examination system. In this segment the various performance metrics such as Dice, Jaccard, Specificity, Sensitivity, Accuracy and Precision are analyzed. Here the efficiency of the proposed Water Shad Segmentation method depends Equilibrium Optimization (WSS-EO) algorithm was analyzed and compared with existing Spider Monkey Optimization (SMO), Bat and Firefly-Algorithm.

From figure 6 shows that the performance metrics of Jaccard, Dice, and Sensitivity are discussed. The performance metrics, the proposed WSS-EO shows the Jaccard value is 4.89% higher than the existing Spider Monkey Optimization algorithm (SMO), 8.86% higher than the Bat-Algorithm (BA) and 6.17% higher than the Firefly-Algorithm (FA) respectively. The proposed WSS-EO shows the Dice value is 8.64% higher than the existing Spider Monkey Optimization algorithm (SMO), 11.39% higher than BA and 10% higher than FA respectively. The proposed WSS-EO shows the sensitivity value is 2.22% higher than the existing Spider Monkey Optimization algorithm (SMO), 2.34% higher than theBat-Algorithm

(BA) and 2.22% higher than the Firefly-Algorithm (FA) respectively.

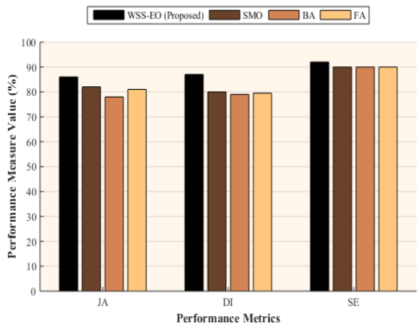

Figure 6: Performance metrics of Jaccard Dice and Sensitivity

From figure 7 portrays that performance metrics of Accuracy, Specificity, and Precision are discussed. A performance metrics, the proposed WSS-EO shows the Specificity value is 2.19% higher than the existing Spider Monkey Optimization algorithm (SMO), 3.33% higher than the Bat-Algorithm (BA) and 2.19% higher than the Firefly-Algorithm (FA) respectively. The proposed WSS-EO shows the Accuracy value is 2.17% higher than the existing Spider Monkey Optimization algorithm (SMO), 4.44% higher than theBat-Algorithm (BA) and 2.17% higher than the Firefly-Algorithm (FA) respectively. The proposed WSS-EO shows the Precision value is 5.1% higher than the existing Spider Monkey Optimization algorithm (SMO), 6.39% higher than the Bat-Algorithm (BA) and 5.1% higher than the Firefly-Algorithm (FA) respectively.

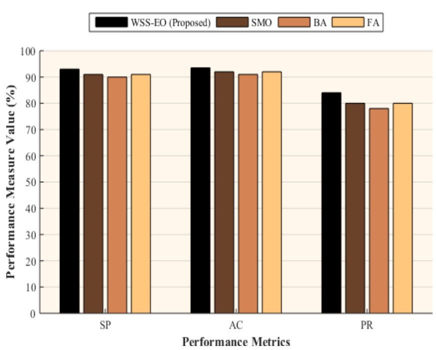

Figure 7: Performance metrics of specificity, Accuracy and Precision

5. CONCLUSION

In this paper, watershed crop weed segmentation based on hybrid Equilibrium Optimization algorithm (WSS-EO) and Kapur's multi-thresholding is examined. Crop/Weed Field Image Dataset (CWFID) are utilized to inspect crop weed in watershed crop weed segmentation based on equilibrium optimization. The dataset containing 60 RGB scale image and the size is 1296 x 966 pixels. The text images are mainly investigated based on different threshold value i.e., Th= 2, 3, 4, and 5. Watershed crop weed segmentation is the very efficient approach for removing the ROI as preprocessed image. The experimental results demonstrate that proposed method performs better based on Dice, Jaccard, Specificity, Sensitivity, Accuracy and Precision. The proposed WSS-EO algorithm provides higher performance for Jaccard 4.89%, 8.86%, and 6.17 %, Dice 8.64%, 11.39%, and 10%, Sensitivity 2.22%, 2.32%, and 2.22%, Specificity 2.19%, 3.33%, and 2.19%, Accuracy 2.17%, 4.44%, and 2.17% and Precision 5.1%, 6.39%, and 5.1% compared with existing SMO, BA and FA respectively.

REFERENCES

[1] J. Rockström, J. Williams, G. Daily, A. Noble, N. Matthews, L. Gordon, H. Wetterstrand, F. DeClerck, M. Shah, P. Steduto, and C. de Fraiture, **Sustainable intensification of agriculture for human prosperity and global sustainability.** *Ambio*, Vol. 46, No. 1, pp.4-17, 2017.
[2] P. Vejan, R. Abdullah, T. Khadiran, S. Ismail, and A. Nasrulhaq Boyce, **Role of plant growth promoting rhizobacteria in agricultural sustainability—a review.** *Molecules*, Vol. 21, No.5, pp.573, 2016.
[3] D.I. Patrício, and R. Rieder, **Computer vision and artificial intelligence in precision agriculture for grain crops: A systematic review.** *Computers and electronics in agriculture*, Vol. 153, pp.69-81, 2018.
[4]Y. Liu, X. Ma, L. Shu, G.P. Hancke, and A.M. **Abu-Mahfouz, From Industry 4.0 to Agriculture 4.0: Current Status, Enabling Technologies, and Research Challenges.** *IEEE Transactions on Industrial Informatics*, 2020.
[5] A. Bakhshipour, A. Jafari, S.M. Nassiri, and D. Zare, **Weed segmentation using texture features extracted from wavelet sub-images**. *Biosystems Engineering*, Vol. 157, pp.1-12, 2017.
[6] P. Lottes, J. Behley, N. Chebrolu, A. Milioto, and C. Stachniss, **Robust joint stem detection and crop-weed classification using image sequences for plant-specific treatment in precision farming.** *Journal of Field Robotics*, Vol. 37, No.1, pp.20-34, 2020.
[7] P. Bosilj, E. Aptoula, T. Duckett, and G. Cielniak, **Transfer learning between crop types for semantic segmentation of crops versus weeds in precision agriculture.** *Journal of Field Robotics*, Vol. 37, No.1, pp.7-19, 2020.
[8] A.I. De Castro, J. Torres-Sánchez, J.M. Peña, F.M. Jiménez-Brenes, O. Csillik, and F. López-Granados, **An automatic random forest-OBIA algorithm for early weed mapping between and within crop rows using UAV imagery.** *Remote Sensing*, Vol. 10, No.2, pp.285, 2018.
[9] W. Strothmann, A. Ruckelshausen, J. Hertzberg, C. Scholz, and F. Langsenkamp, **Plant classification with in-field-labeling for crop/weed discrimination using spectral features and 3d surface features from a multi-**

wavelength laser line profile system. *Computers and Electronics in Agriculture*, Vol.134, pp.79-93, 2017.

[10] X. Zhang, X. Li, B. Zhang, J. Zhou, G. Tian, Y. Xiong, and B. Gu, **Automated robust crop-row detection in maize fields based on position clustering algorithm and shortest path method.** *Computers and electronics in agriculture*, Vol.154, pp.165-175, 2018.

[11] E. Hamuda, M. Glavin, and E. Jones, **A survey of image processing techniques for plant extraction and segmentation in the field.** *Computers and Electronics in Agriculture*, Vol.125, pp.184-199, 2016.

[12] D. Zhihua, W. Huan, S. Yinmao, and W. Yunpeng, **Image Segmentation Method For Cotton Mite Disease Based On Color Features And Area Thresholding.** *Journal of Theoretical & Applied Information Technology*, Vol.48, No.1, 2015.

[13] K. Yu, N. Kirchgessner, C. Grieder, A. Walter, and A. Hund, **An image analysis pipeline for automated classification of imaging light conditions and for quantification of wheat canopy cover time series in field phenotyping.** *Plant Methods*, Vol.13, No.1, pp.15, 2017.

[14] P. Bosilj, T. Duckett, and G. Cielniak, **Connected attribute morphology for unified vegetation segmentation and classification in precision agriculture**. *Computers in industry*, 98, pp.226-240.

[15] Z. Yu, Z. Cao, X. Wu, X. Bai, Y. Qin, W. Zhuo, Y. Xiao, X. Zhang, and H. Xue, **Automatic image-based detection technology for two critical growth stages of maize: Emergence and three-leaf stage**. *Agricultural and forest meteorology*, Vol.174, pp.65-84, 2016.

[16] S. Haug, and J. Ostermann, **A crop/weed field image dataset for the evaluation of computer vision based precision agriculture tasks.** *In European Conference on Computer Vision*, pp. 105-116, 2014.Springer, Cham.

[17] X. Bai, Z. Cao, Y. Wang, Z. Yu, Z. Hu, X. Zhang, and C. Li, **Vegetation segmentation robust to illumination variations based on clustering and morphology modelling.** *Biosystems Engineering*, Vol.125, pp.80-97, 2016.

[18] J.M. Guerrero, G. Pajares, M. Montalvo, J. Romeo, and M. Guijarro, **Support vector machines for crop/weeds identification in maize fields**. *Expert Systems with Applications*, Vol. 39, No.12, pp.11149-11155, 2014.

[19] A. Faramarzi, M. Heidarinejad, B. Stephens, and S. Mirjalili, **Equilibrium optimizer: A novel optimization algorithm.** *Knowledge-Based Systems*, Vol.191, pp.105190, 2020.

[20] V. Rajinikanth, N. Dey, S.C. Satapathy, and K. Kamalanand, **Inspection of crop-weed image database using kapur's entropy and spider monkey optimization.** *In Soft Computing for Problem Solving*, pp. 405-414, 2020.Springer, Singapore.

[21] A. Chakri, R. Khelif, M. Benouaret, and X.S. Yang, **New directional bat algorithm for continuous optimization problems.** *Expert Systems with Applications*, Vol.69, pp.159-175, 2017.

[22] H. Wang, W. Wang, L. Cui, H. Sun, J. Zhao, Y. Wang, and Y. Xue, **A hybrid multi-objective firefly algorithm for big data optimization**. *Applied Soft Computing*, Vol.69, pp.806-815, 2018.

[23] A. Milioto, P. Lottes, and C. Stachniss, **Real-time semantic segmentation of crop and weed for precision agriculture robots leveraging background knowledge in CNNs**. *In 2018 IEEE international conference on robotics and automation (ICRA)*, pp.2229-2235,2018.IEEE.

[24] M. Fawakherji, A. Youssef, D.D. Bloisi, A. Pretto, and D. Nardi, **Crop and Weed Classification Using Pixel-wise Segmentation on Ground and Aerial Images**.