# Comparative Analysis of Segmentation Methods for Wheat Canopy Extraction

Ankita Gupta[1*], Dr. Lakhwinder Kaur[1], Dr. Gurmeet Kaur[2]

[1] Dept. of Computer Science and Engineering , Punjabi University , Patiala, India

[2] Dept. of Electronics and Communication Engineering , Punjabi University, Patiala, India

*Corresponding author

doi: https://doi.org/10.21467/proceedings.114.7

## Abstract

Global food demand is expected to be doubled by 2050, while natural resources are continuously under threat due to unpredictable climatic changes. This challenge can be tackled by increasing the yield of the crops and by reducing abiotic stresses such as water stress. Research shows that due to water stress the morphology and the structure of plant's canopy changes. The first step in building early water stress detection system is to extract accurate area where photosynthetic activities of the plant are occurring. In this research work, comparative analysis of seven different segmentation algorithms viz., convolution gradient-based, watershed, mean-shift, k-means, Global static thresholding, Otsu thresholding and hybrid approach (combination of Global Static thresholding with k-means) has been analyzed in order to identify the most probable area of canopy where maximum photosynthetic signals can be captured. The comparison is done in terms of IoU metric. The comparative results indicate that the most appropriate method for wheat canopy segmentation is a hybrid approach, which achieves IoU score of 59.8 and its runner up algorithm is Global Static Thresholding with an IoU score 53.8.

**Keywords:** Segmentation, Wheat Canopy, Thresholding.

## 1 Introduction

There is an urgent need for innovation in agriculture [1][2]. Advances in the field of "high-throughput plant phenotyping" will aid in the identification of stress in the plants [3]. According to the latest reports on the drought situation in India the states of Andhra Pradesh, Bihar, Gujarat, Jharkhand, Karnataka, Maharashtra, parts of the North-East, Rajasthan, Tamil Nadu, and Telangana are badly impacted due to deficit monsoon rains this year [4]. In Punjab, India's condition is on the verge of getting worse due to exacerbating groundwater extraction [5].

A plant may undergo two kinds of stress; Biotic stress and Abiotic stress. Biotic stress is caused by living organisms such as viruses, bacteria, parasites, fungi, etc. It reduces the plant's photosynthetic efficiency, water intake, etc [6]. In India, it is estimated that around 10% to 20% of yield is lost due to biotic stress. Abiotic stress is caused by non-living elements such as humidity, light, water, nutrients, etc which in turn reduces plant yield [7]. Annually over 42% of the crop yield is lost due to abiotic stress. In India 67% of the area is rain-dependent for irrigation [8], thus drought stress is the most leading agricultural development concern that needs to be resolved by technology.

The process of studying various physical and biological traits as they change concerning the gene mutation and environmental influences is called "Plant Phenomics**"** [9][5]. Measurements regarding the various plant parameters such as yield, colours of leaves, height, stem size, chlorophyll content, photosynthesis activity, transpiration rate, no. of grains per spike, leaf area, spike length, and other parameters [10][11] are computed using computer vision technologies. Such computer vision technologies can help to diagnose and map stress under which plant is undergoing [12][13]. But the biggest challenge in this context is the accuracy in capturing the fluorescence in the canopy as it changes when the plant is subjected to water stress.



Proceedings DOI: 10.21467/proceedings.114; Series: AIJR Proceedings; ISSN: 2582-3922; ISBN: 978-81-947843-8-8

Research shows that as the relative water content (RWC) of the plant decreases, there is a reduction in the chlorophyll content consequently the plant canopy size reduces [14]. This can be detected using non-destructive and non-invasive methods such as morphological feature analysis, which act as an indicator of stress identification in plants [15]. The issue with these methods was that they require expensive and sophisticated instrumentation to track absorption, emittance, and reflectance of the plants. High-Throughput plant Phenotyping is a technique that also helps to track the photosynthetic related activity in plants using image processing functions by measuring re-emittance of light (chlorophyll fluorescence)[16][17][18].

There are five ways to understand the current research in the context of the wheat plant's water stress detection. The first method focuses on the computation of wheat plant's biomass [19]. The second group of methods works on the estimation canopy (vegetative index) using aerial imaging. The third group of methods focuses on measurements and calculations of various parts of the wheat plant such as counting the number of wheat grains, ears, and kernels, etc. [20] [21] [22]. The fourth method focuses on constructing estimation models of wheat production. All these methods require image processing operations and statistical methods enriched with machine learning algorithms [23]. Otsu method of segmentation has been preferably used by many authors which gives a high percentage of accuracy with a confidence level of 95% [24]. Hyper-spectral imaging has been used to process the wheat images for analyzing the canopy's water content, growth level of the plant using reflectance values. Segmentation of green color vegetation from the image is used at an accuracy level of 90% with minimal misclassification. Few researchers are using machine learning models for automation and prediction such a CNN (accuracy =~ 99%) and the error rate of 11.73%, K-means accuracy >90%) for counting and classification of wheat ears [25]. The fifth important category of research revolves around the estimation of pigment volumes and information about the chlorophyll fluorescence.

Limited work has been found in the context of developing models for estimating stress. The live plant material is splitting the light into three phenomena viz., absorption, emittance, the reflection of light. Due to which correct estimation of parameters under observation needs careful calibration and measurements. The image of the wheat canopy holds information regarding the volume of pigments active inside the plant material [10][22][6]. From which inferences can be drawn about the status of nutritional water stress and health of the plant. Hence, the current work presented in this paper is about the accurate isolation of the plant canopy from wheat images, which contains the information related to the amount of light processed by the plant. The main contributions of the work are as follows:

1. In this research work, comparative analysis of seven different segmentation algorithms for extraction of wheat canopy has been performed. According to the best of author's knowledge such analysis has not been undertaken in the literature.
2. Implementation of new hybrid algorithm (Global Static Thresholding with k-means) for extraction of wheat canopy.
3. This work will be useful to automate the process of detecting water stress in the wheat plants.

## 2 Materials and Methods

The main material used for this research work is chlorophyll fluorescence images. The images were sourced from the public repository of (594X2) images of control and water stress captured for the period of 60 days [26]. Initial observations show that all three channels (R, G, and B) of the control as well as stressed wheat crop images have approximately an equal amount of information and pixels intensity level distribution. It is evident from minimum and maximum mean intensity values of the wheat canopy images. The intensities (standard deviation) can be characterized into three ranges. The first range starts from 0.345 to 0.355. The difference is only of 0.010 which implies that the range is very tight and small. The second range of intensities that can estimated from the images begins from 0.71 and ends at 0.73. the difference is again of 0.02. The third range of intensity starts from 2.99 and ends at 8.89 the difference is 5.9. From all these values it is clear that these ranges are not continuous in nature and are discrete. Secondly all these values shows that the difference between the background and foreground pixels is very narrow which implies that the segmentation algorithm will find hard to separate foreground and background. When histograms of the images were computed, then it was observed that an increase in the number of pixels from right to left happens [27]. The histograms are tailing towards the right and have peak levels on the left side. It is a well-known fact that some signal is absorbed, emitted, and reflected in the environment. The next section discusses the approaches applied to segment and accurately isolate the canopy cover of the wheat plant that will be useful for making fully automatic systems for the detection of water stress in the wheat plants. The set of biochemical and physical traits of the plant undergoes many changes under various environmental conditions. Hence, the first step required after the acquisition of the wheat crop images is the extraction of canopy.

The wheat canopy segmentation is the key task that is required before we need to find a relationship between the various kinds of image-based attributes for identifying relationships between variables for detecting stress such as water scarcity. Segmentation is also required in case there is a need to automate the process of detecting stresses in plants. The automation can be done with the help of machine learning or deep learning models. Contemporary image processing text books shows that there are mainly six types of segmentation approaches viz., Thresholding (static, adaptive, automatic), Pixel Clustering (Kmeans, Otsu etc.,), Convolution Filters (Canny, sobel etc.,), Region based segmentation (Watershed etc.), machine learning based segmentations methods (ANN, Nero-Fuzzy etc.,), and Deep learning (CNN) based approaches. Finding and constructing an appropriate segmentation algorithm approach is a challenging work as it requires some degree of experience and empirical experimentation. Additionally, pre-processing and intermediate steps that argument accurately segment processes are also needed to be carefully selected or constructed. Hence, hybrid approaches or combinational approaches may be required to achieve objectives of segmentation. In this research work, we explore all the seven types of approaches for identifying most accurate approach for segmenting the wheat plant canopy images.

Table I Presents a summary of the different methods used for segmentation in this research work.

TABLE I. DESCRIPTION OF SEGMENTATION ALGORITHMS

| S.no | Algorithm Used | Description |
|---|---|---|
| 1 | Global static Thresholding (GST) | Segment with multirange fixed threshold. |
| 2 | Global Automatic Otsu Thresholding (GAT) | Segment with automatic threshold. |
| 3 | K-means based on set of mean values | Create the group pixels that capture maximum canopy area. |
| 4 | Watershed | Transforms the image into various segments as if image is topographical surface. The pixels with highest gradient magnitude intensity (GMI) are separated from local intensity minimum (LIM). Pixels draining to a common minimum form a ROI area. |
| 5 | Mean-shift | This pixel clustering algorithm iteratively shifts the pixels in such a manner that the pixel values become close to mod (highest density of data points). |
| 6 | Convolution gradient Filter | Uses various edge detection operators for canopy extraction. |
| 7 | Hybrid Segmentation Approaches | Hybrid combination approach to extract ROI wheat canopy from the image. |

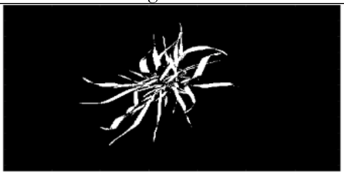
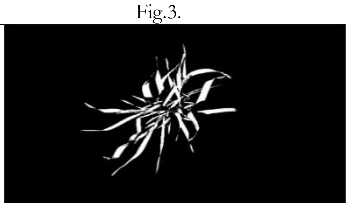
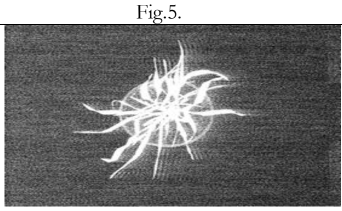
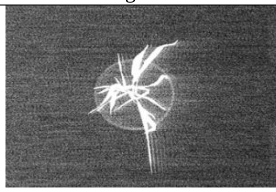
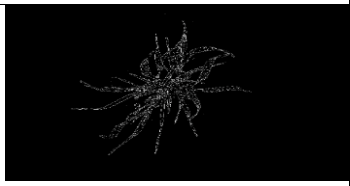
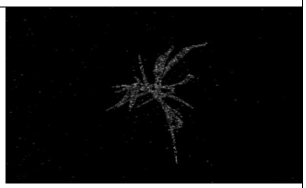
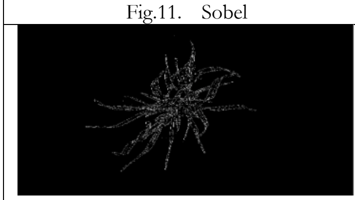
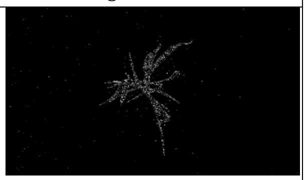
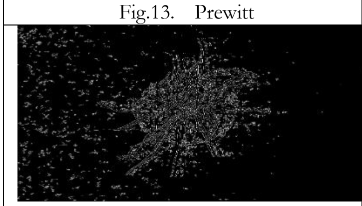
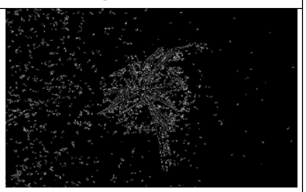
# 3 Results and Discussion

## 3.1 Qualitative Results

For qualitative comparison, this section shows the output images of various approaches considered for wheat segmentation. The control as well as drought input images has been input to seven segmentation algorithms as shown in (Fig.1. and Fig.2.) in Table II. Table II demonstrate the output images for both under control and drought. The first method applied for the segmentation of the canopy was global static thresholding (GST). A multi-range threshold between (16<Threshold >11) has been found experimentally by hit and trial to achieve satisfactory segmentation. but there was an opportunity to improve the segmentation output as shown in Table II. It can be also observed that a good number of pixels from the output images were either misplaced or missing. This leads to inaccurate segmentation (see Fig. 3, 4) resultant images of fixed values between (16<Threshold >11) of the image. The second method applied was the Otsu thresholding method. This method is based on finding the region based on the variation of the pixels in the full image. It was found that the Otsu method of thresholding was able to separate dark pixels from the brighter ones in images that had low visibility of the wheat plant canopy in the image. But, in the images that had the high intensity of pixels the Otsu algorithm gave unwanted pixels in the output. This can be observed in Fig. (5, 6). The output of the k-means shows that it has a lot of noise in the image which can be further improved as shown in Fig. (7,8) if low-intensity pixels are removed beforehand. The mean-shift and watershed algorithms did not give satisfactory output. The output of the mean-shift algorithm was almost white and blank. The visual analysis of the watershed's output images shows that it is not useful for the wheat canopy segmentation as shown in (Fig. **(**9,10)). Multiple Convolution gradient-based filters have been used by many researchers in the context of identifying the boundaries of the objects. The performance of three edge detection methods has been analyzed and it was found that none of the edge methods works well. The output of the Sobel operator resulted in non-smooth edges as shown in Fig. (11,12). The boundaries were broken into smaller regions. A similar outcome in the case of the Prewitt operator application, the edges were distorted and had no proper form as shown in (Fig. (13,14). The Canny operator's application leads to a noisy image as shown in Fig. (15, 16). For the persuasion of the aims of the research, the hybridization strategy was adopted as described in Table II (Fig. 17, 18).

The accuracy of the segmented object in the case of the wheat canopy is the maximum area of photosynthetic activity. Technically, there is a beginning of the photosynthetic activity and a point at which the photosynthetic activity fully happens. The calculations regarding the difference between the photosynthesis activities between the initial stage and current state can be tracked [28]. The beginning of photosynthesis activity is denoted by the variable 'fo' which is referred to as the point of minimum fluorescence and 'fm' is a variable that defines the point where fluorescence signal attains its maximum value called maximum fluorescence. The difference between these two values defines the "Maximum Area of Canopy". The resultant image matrix 'unit' was logical. Now, the logical values in the above images were replaced with pixel values from the first image as shown in (Fig. 19. and Fig. 20) in Table III, for both controlled, water-stressed, and from the twenty-fourth image as shown in (Fig. (21,22). The output of this step leads to the generation of two images 'fo' (image with minimum fluorescence) and 'fm' (image with maximum fluorescence) for controlled, water-stressed respectively for all the plants for a particular day [22]. The next step was to compute the 'fv' variable fluorescence image matrix; this is obtained by subtracting (Fo-Fm). The ratio of fv/fm as per theoretical and empirical evaluations proved to be a robust indicator for chlorophyll Fluorescence evaluation for a particular day as shown in Table III (see Fig. 23, 24).

TABLE II: COMPARITIVE VIEW OF THE SEGMENTATION ALGORITHMS

| Algorithm | Control | Drought |
|---|---|---|
| Input image without any algorithmic computation |  Fig.1. |  Fig.2. |
| Global static thresholding (fixed Value) |  Fig.3. |  Fig.4. |
| Global Automatic Thresholding (Otsu) |  Fig.5. |  Fig.6. |
| K-means based on 4 mean value |  Fig.7. |  Fig.8. |
| Watershed |  Fig.9. |  Fig.10. |
| Meanshift | Unsatisfactory Results | Unsatisfactory Results |
| Convolution Gradient Based Filters |  Fig.11. Sobel |  Fig.12. Sobel |
| |  Fig.13. Prewitt |  Fig.14. Prewitt |
| |  Fig.15. Canny |  Fig.16. Canny |


Proceedings DOI: 10.21467/proceedings.114
Series: AIJR Proceedings
ISBN: 978-81-947843-8-8
ISSN: 2582-3922

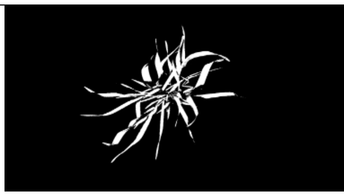
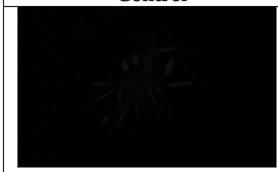
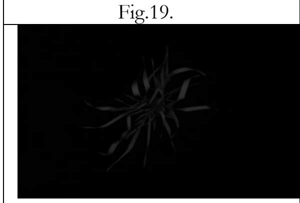
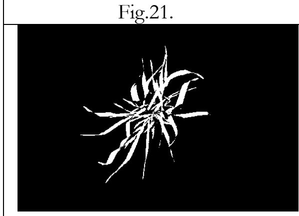
| | | |
|---|---|---|
| Hybrid Segmentation Algorithm |  Fig.17. |  Fig.18. |

TABLE III: SEGMENTED CANOPY(MAXIMIZED)

| Control | Drought |
|---|---|
|  Fig.19. |  Fig.20. |
|  Fig.21. |  Fig.22. |
|  Fig.23. |  Fig.24. |

### 3.2 Quantitative Results

For quantitative evaluation of the segmentation algorithms, the following procedure was followed:
Using a random sampling method, mutually exclusive sets of images were created. The minimum sample size was 25 and the maximum was 100.

1. The Ground Truth images were decided by visual inspection and a separate set of such images were created for running evaluations.
2. The intersection (IoU) between the target (Valid Segmented image) and predicted (Segmented image by different algorithms) was computed using Eq. (1)
3. IOU = target $\cap$ prediction / target $\cup$ prediction (1)
4. The IOU value is computed and average values for sample evaluation were found. Table. IV presents the IoU values of the algorithms that are competing with each other in terms of accuracy for wheat canopy extraction. Algorithms such as mean-shift, watershed, Sobel, canny, and Prewitt were ignored as visually it was abundantly clear the segmented output was not satisfactory. A threshold of 0.5 was considered for considering an image as correctly segmented and four evaluations were done against the ground truth/valid segmented image set.

TABLE IV: PERFORMACE COMPARISON OF SEGMENTATION ALGORITHMS IN TERMS OF IOU SCORE

| | | Sample Size | | | | |
|---|---|---|---|---|---|---|
| ***S.No*** | ***Method*** | 25 | 50 | 75 | 100 | ***Average IoU Score*** |
| 1 | Global Static Thresholding (Fixed-Value) | 20 | 40 | 67 | 88 | 53.8 |
| 2 | Global thresholding (Otsu) | 19 | 33 | 60 | 76 | 47 |
| 3 | K-means | 22 | 46 | 70 | 92 | 50 |
| 4 | Hybrid Segmentation Algorithm | 24 | 48 | 72 | 95 | 59.8 |

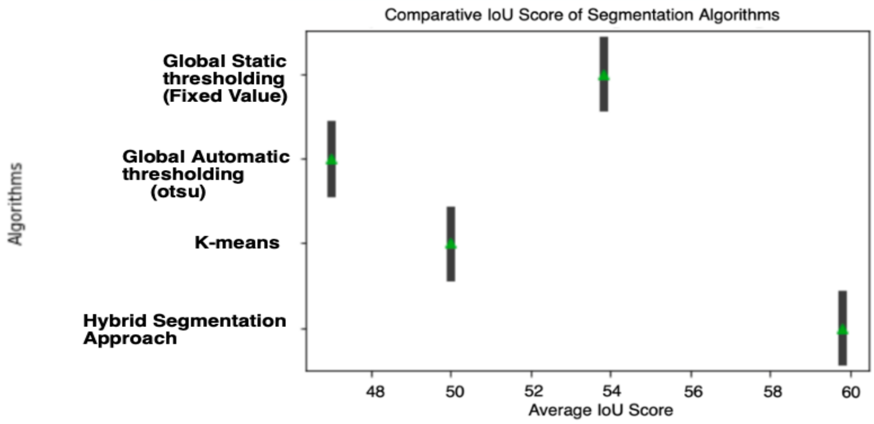



Fig.25. Performance Comparison of Segmentation Algorithms

It can be observed from the boxplot (Fig. (25)) that the hybrid segmentation method has the maximum IOU score. This means that this hybrid algorithm gives a maximum number of valid segmented images as per the ground truth set of images. In each mutually exclusive random sample of evaluations, the number of correctly segmented images is highest. For maintaining reproducibility of work, the code and output is available at [29].

## 4 Conclusion

This work compares the performance of seven segmentation approaches to find the most suitable algorithm that can be useful to track the morphology of wheat canopy. It was found that the direct application of classical algorithms such as k-means, Otsu etc., does not yield satisfactory areas of interest nor did these approaches grouped the pixels correctly to get maximum area of photosynthetic activity. Also, the watershed and mean-shift algorithms are not found to be useful. The visual inspection of the output images as well as the quantitative evaluation of the rest five segmentation algorithms, shows that the hybrid algorithm (K-means in combination with the Global Static Thresholding) is best for capturing the full area of the canopy of the wheat. This is apparent from the IoU score values also. For future directions, it is suggested that this work can be extended to automate the process of water stress detection in wheat crop.

## References


[1] POPULATION REFERENCE BUREAU, "2019 World Population Data Sheet," *2019 World Popul. Data Sheet*, 2019.

[2] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Front. Plant Sci.*, vol. 7, no. 1419, pp. 1–10, 2016.

[3] A. Chawade, J. Van Ham, H. Blomquist, O. Bagge, E. Alexandersson, and R. Ortiz, "High-throughput field-phenotyping tools for plant breeding and precision agriculture," *Agronomy*. 2019.

[4] X. Zhang, R. Obringer, C. Wei, N. Chen, and D. Niyogi, "Droughts in India from 1981 to 2013 and Implications to Wheat Production," *Sci. Rep.*, vol. 44552, no. 7, pp. 1–12, 2017.




Proceedings DOI: 10.21467/proceedings.114
Series: AIJR Proceedings
ISBN: 978-81-947843-8-8
ISSN: 2582-3922

[5] V. Mishra, A. Asoka, K. Vatta, and U. Lall, "Groundwater Depletion and Associated CO 2 Emissions in India," *Earth's Futur.*, 2018.

[6] A. K. Singh, B. Ganapathysubramanian, S. Sarkar, and A. Singh, "Deep Learning for Plant Stress Phenotyping: Trends and Future Perspectives," *Trends in Plant Science*. 2018.

[7] S. Ghosal, D. Blystone, A. K. Singh, B. Ganapathysubramanian, A. Singh, and S. Sarkar, "An explainable deep machine vision framework for plant stress phenotyping," *Proc. Natl. Acad. Sci. U. S. A.*, 2018.

[8] S. India, "Report Drought Status In India," 2018.

[9] N. P. Thao and L. S. Phan Tran, "Enhancement of Plant Productivity in the Post-Genomics Era," *Curr. Genomics*, 2016.

[10] A. F. Sid'ko, I. Y. Botvich, T. I. Pisman, and A. P. Shevyrnogov, "Estimation of chlorophyll content and yield of wheat crops from reflectance spectra obtained by ground-based remote measurements," *F. Crop. Res.*, 2017.

[11] S. Y. S. Lisar, R. Motafakkerazad, M. M., and I. M. M. Rahm, "Water Stress in Plants: Causes, Effects and Responses," *Water Stress*, pp. 1–15, 2012.

[12] L. Li, Q. Zhang, and D. Huang, "A review of imaging techniques for plant phenotyping," *Sensors (Switzerland)*, vol. 14, no. 11, pp. 20078–20111, 2014.

[13] A. Singh, B. Ganapathysubramanian, A. K. Singh, and S. Sarkar, "Machine Learning for High-Throughput Stress Phenotyping in Plants," *Trends Plant Sci.*, vol. 21, no. 2, pp. 110–124, 2016.

[14] S. Grzesiak, N. Hordyńska, P. Szczyrek, M. T. Grzesiak, A. Noga, and M. Szechyńska-Hebda, "Variation among wheat (Triticum easativum L.) genotypes in response to the drought stress: I–selection approaches," *J. Plant Interact.*, vol. 14, no. 1, pp. 30–44, 2019.

[15] P. Soille, "Morphological image analysis applied to crop field mapping," *Image Vis. Comput.*, 2000.

[16] H. M. Kalaji *et al.*, "Frequently asked questions about chlorophyll fluorescence, the sequel," *Photosynthesis Research*. 2017.

[17] S. Bhugra, N. Agarwal, S. Yadav, S. Banerjee, S. Chaudhury, and B. Lall, "Extraction of Phenotypic Traits for Drought Stress Study Using Hyperspectral Images," in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*, 2017, vol. 10597 LNCS, pp. 608–614.

[18] H. M. Kalaji *et al.*, "Erratum to: Frequently asked questions about chlorophyll fluorescence, the sequel," *Photosynth. Res.*, 2017.

[19] M. O. Hunter, M. Keller, D. Victoria, and D. C. Morton, "Tree height and tropical forest biomass estimation," *Biogeosciences*, 2013.

[20] A. Haghshenas and Y. Emam, "Green-gradient based canopy segmentation: A multipurpose image mining technique with potential use in crop phenotyping and canopy studies," *bioRxiv*, 2019.

[21] J. A. Fernandez-Gallego, S. C. Kefauver, N. A. Gutiérrez, M. T. Nieto-Taladriz, and J. L. Araus, "Wheat ear counting in-field conditions: High throughput and low-cost approach using RGB images," *Plant Methods*, 2018.

[22] B. L. Shrestha, Y. M. Kang, D. Yu, and O. D. Baik, "A two-camera machine vision approach to separating and identifying laboratory sprouted wheat kernels," *Biosyst. Eng.*, 2016.

[23] T. Liu, W. Wu, W. Chen, C. Sun, X. Zhu, and W. Guo, "Automated image-processing for counting seedlings in a wheat field," *Precis. Agric.*, 2016.

[24] 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*, 2017.

[25] Z. Liu, W. Huang, and L. Wang, "Field wheat ear counting automatically based on improved K-means clustering algorithm," *Nongye Gongcheng Xuebao/Transactions Chinese Soc. Agric. Eng.*, 2019.

[26] Sukhjit Sandhu, "Plant Stress Analysis Based on Chlorophyll Fluorescence and Image Processing." Mendeley, Delhi, p. 01, 2019.

[27] S. Arivazhagan, R. N. Shebiah, S. Ananthi, and S. Vishnu Varthini, "Detection of unhealthy region of plant leaves and classification of plant leaf diseases using texture features," *Agric. Eng. Int. CIGR J.*, vol. 15, no. 1, pp. 211–217, 2013.

[28] M. Reynolds *et al.*, "Breeder friendly phenotyping," *Plant Science*. 2020.

[29] A. Gupta, "Maximization of Wheat Canopy Segmentation Using EBTK Algorithm." Mendeley Data, p. 11, 2020.