STRATEGIES FOR PIXEL CLUSTERING FOR EXTRACTION OF PHOTOSYNTHETIC ACTIVITY AREA IN WHEAT CANOPY

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ABSTRACT

In order to develop automated systems that detect nitrogen stress in wheat images, segmentation must first be completed. Hence, in this research work, the focus is to develop an improved method of wheat canopy segmentation. When compared to the methods that have been used in the past, the new strategy has the advantage of being more straightforward as it involves a hybridation strategy that is sequential in nature. In terms of IOU accuracy, it was discovered that the combination of Ostu and K Mean (k=2) algorithms is the best approach to get the photosynthetic activity area from the image of the wheat canopy. All of the information has been tested against objective and subjective evaluation methods to ensure that it is accurate and reliable.

Keywords: *Wheat Research, Pixel Clustering, wheatCanopy, Chlorophyll Fluorescence, Photosynthesis*

Introduction

Agronomists use imaging technology to detect and analyse stress in the field and in the lab [1]–[3]. Stress affects plants at all stages of development. Each stage requires a different imaging modality [4-6] , depending on the plant's tissue stress. This method does not provide information regarding the plant's internal functioning, such as the amount of photosynthetic activity occurring within the plant, and is therefore not advised. They are coupled to metabolomics to improve morphological imaging. It uses internal functionality testing to accomplish reagent-based early detection. PET quantitative time-dynamic imaging techniques can detect changes in the plant's functional behaviour as a result[7], [8]of inputs to its vascular system. Most crop breeding programmes use chlorophyll fluorescence image analysis to discriminate between nitrogen deficiency tolerance in crops, drought resistant, and controlled crops. examining how mutation affects efficiency [9–11] . A machine learning algorithm with PSII can identify important stress factors. This modality can capture the impacts of climatic fluctuation on the photosynthetic activity of the plant. Imaging-based fluorescence imaging will be a significant tool for understanding damage development and response in crops. Under stress, structure and physiology have a big impact on GPP. The results of the experiment imply that solar induced fluorescence (SIF) is a good estimation metric for GPP [12], [13] . While phenotyping in wheat has been studied for several years, there are still lagunas in the existing domain when it comes to diagnosing water stress in the plant. Several challenges related to the use of intelligence-based technologies and subdomains in agriculture need to be addressed in order to improve food security in the country.

The literacy level of Indian farmers is exceedingly low, making it difficult to bridge the gap between technological improvement and farmer adoption of new technology [14]. Agriculturalists are the least motivated to digitise their businesses and improve their farming procedures. Rural locations have less connectivity than urban areas, making the deployment of sensor-based systems problematic.

The machines' classification and prediction abilities differ based on the country's climate and geography. Most complicated technologies are more expensive and need more computational power, energy, and time. A highly adaptive paradigm is urgently required, not only for the wealthy but also for the majority of farmers. It is a well known fact that machine learning is the future of agriculture [15–17] , but we must help farmers use it effectively. Developing an approach that can bridge the gap between the lab and the field while being cost-effective is critical to overcoming the issues listed above.

Using phenomics and chlorophyll fluorescence in plant studies can help comprehend and model plant stressors (both biotic and abiotic) [18–20]. The development of machine learning models based on wheat plant images for stress detection is a difficult task. This is because determining the best feature to map the ground truth is difficult. It is possible to create machine learning models that accurately map the actual condition of nitrogen stress on an Indian wheat variety crop by quantifying stress variables. This is done by quantifying stress features. More importantly, a reliable solution must overcome several challenges and technological hurdles. The next section gives information and analysis from contemporary literature regarding the use of unsupervised machine learning and image processing methods in the context of plant research.

Literature Review

Clustering algorithms have been frequently used in the segmentation of the objects that are embodied in an image [21] . They provide an easy and simple way to get the region of interest from the whole image. They are extremely useful in the images that have somewhat bimodal kind Histograph properties. However, in complex scenarios such as landscape also they have been used with great success. In this section, a review of the clustering methods that are currently used in the field of image processing for segmentation or otherwise argumentation of some pre or post process in image processing is discussed.

The clustering is an unsupervised learning algorithm which is applied to get the clusters of the pixels of an image [22], [23].It can be applied to find the groups of similar pixels in the image.It is the most important tool for the segmentation of an image.There are different algorithms that are used for clustering.Some of them are used for the classification of an image and some others for the segmentation of an image. The clustering algorithms can be classified on the basis of their application to the images and their working.The algorithms can be classified into two classes namely, algorithms for clustering images and algorithms for clustering pixels embodied in the images.

The algorithms that are used to cluster the images are known as the image clustering algorithms.The algorithms are used to segment the objects of an image.They are also used to find the cluster of the images that have similar properties.These algorithms are also used extensively used in the segmentation of the objects semantical located in image. K-means and SOM algorithms are extensively used for organising images in image based content retrieval systems [24], [25]. In case of k-means clustering. It is typically used to cluster the images. based on similarity of features to a given number of classes chosen by the user. The centroids of the clusters are calculatedwith given starting points. The algorithm starts iteration from the starting data points and finds the clusters in the full dataset image. The self-organising map is another clustering algorithm that is used to cluster the images datasets. It is a hybrid clustering algorithm. It uses the nearest neighbourhood, the probability and the gradient information of the image.The self-organising map consists of a twodimensional grid of neurons.Each neuron represents a cluster. The neurons in the grid are connected to the neurons of the grid which are in a distance of less than 2. It has the various properties. It has two natal neurons with weights 1,0 on its edges of the grid which can be considered as a whole or dead neuron. The neurons on the two sides of the grid are connected to the pixels on their left and the right according to the data on the edges of the grid. If the grid has m number of neurons, then it has m^2 number of weights 1,0. Many researchers are using fuzzy logic to organise the image files and even clustering the pixels [23], [26]. Fuzzy logic is used to cluster the pixels of an image. It has good speed in terms of finding clusters and organising the images and has been considered for many purposes quite efficient. It has been also used for clustering the objects of an image with help clustering similar pixels using appropriate metrics for finding fuzzy similarities. The clustering of the pixels with fuzzy logic is similar to the clustering of the pixels with k-means clustering. The fuzzy clustering can be calculated in different forms.In the positive fuzzy clustering, we choose the size of the clusters and then the input and output fuzzy sets are set up. In negative fuzzy clustering we choose the size of the clusters and then the input and output fuzzy sets are defined by the class label. In the grey-fuzzy clustering the same method is used in the positive and negative fuzzy clustering.In order to have the object of the image in the clusters,it is necessary to choose the input and output fuzzy sets that fit the object that is in the clusters of the image. It should also be noted that fuzzy clustering works similarly to k-means clustering. In fuzzy logic, the algorithmallows for the inclusion of different domains of attributes in the clustering process. So, as one or two domains of attributes can beassociated with the range of values of another domain, clustering will be performed accordingly using the variation from one domain to another domain and the centroid of the final clusters.

Community Detection in images is a new topic of research in the field of image processing [27], [28]. A community is an aggregation of objects or entities with interdependence that are different and with common external interactions. Based on our experience this method is extensively used in physical and social networks. In community detection , an image or set of images is treated as a mathematical object with its inherent structure. The difference between this method and the rest of the clustering methods is the formalism and their scope. It consists of the intrinsic features of objects or the concept of intrinsic features like symmetry, existence of external interactions and their influence on an entity. The community detection is further sub categorised into spectral clustering and label-based community detection .

Colour based Clustering

As contemporary literature shows that there are multiple ways followed by previous researchers on how to cluster the images [29], it is important to note that images may be two dimensional, three dimensional or multidimensional. In simple words the images may be grey, binary, colour or an image of multiple spectrums. Technically, when images are captured based on a specific spectrum of the light the image will possess different kinds of the properties, for example the images captured in the spectrum of visible light will have different colour, texture and statistical properties as compared to infra-red spectrum of the light. In context of the problem undertaken here, properties of chlorophyll fluorescence (CF) are critical.

Properties of chlorophyll fluorescence (CF) Images of chlorophyll fluorescence are generally acquired with a Miniature Pulse-Amplitude Modulated fluorometer (MINI-PAM, Walz, Germany) as previously described (Wüstefeld et al., [@B69]; Yang et al., [@B72]). The fluorescence intensity of dark-adapted leaves was measured at a low light intensity of 0.04 μmol photons m^−2^ s^−1^. Other parameters such as temperature are important when the specific study is initiated. For example, The authors did all the experiments on wheat plants when the temperature was 5°C, and the leaves were dark adapted for 15 min before the measurements. The leaf chlorophyll content and the concentration of chlorophyll *a* and *b* (Chl *a* and Chl *b*) were determined by a spectrophotometer (UV-2450, Shimadzu, Japan) according to the method of Lichtenthaler ([@B37]). The maximum quantum efficiency of photosystem II (*F*~v~/*F*~m~) and the effective quantum yield of photosystem II (Φ~PSII~) were measured according to Yang et al. ([@B72]). The light-saturated rate of photosynthesis (*P*~max~) was determined by fitting the data to the light response curve of net photosynthesis with the least squares method. In such studies importance of the colour properties of the plant parts such as root or canopy become critical. The separation (segmentation) of the region of interest (ROI) such as the canopy of the plant where the maximum photosynthetic activity is important. Hence,

The coloured pixels of the image or objects are technically assigned to specific colours such as the red, green and blue in RGB colour space. Pixels with close colour similarity belong to the same classes. The methodology allows the flexibility to run some pre or post image processing algorithm for the classification of the image based on the pixel classification performed using these colours for the segmentation of objects or colour regions. The [30] article reviews the colour segmentation methods. The structure of the plant body has structure and the structure generally can sub-structures. If the researchers are serious about finding the clusters of information in different parts or sub-part of the plant then Linkage and Dendrogram based Clustering is useful according to[31] . Dendrogram based Clustering is based on graphs and trees that has been used to identify and classify some significant patterns in the fields like Fractals, texture, objects, etc. Although linkage is classified into divisive, divisive and agglomerative approaches this approach is highly suitable for image segmentation because the clustering is directly correlated to the correlation matrix .

Algorithms that are based on Super Pixel Clustering uses global neighbourhood information to recognise pixels from the same object to organise the pixels in a photo or other image [32]. The clustering process then attempts to match the pixels to those from the same object. These algorithms work very well for objects that are not moving and are not too far away from the camera. Super pixel algorithms are not suitable for use with panoramas, landscapes, or images where the camera has a wide angle. These algorithms work very well for objects that are not moving and are not too far away from the camera. These algorithms are not suitable for use with images with moving objects or very far away objects. The algorithm divides each of the pixels in the image into 9 classes based on their global characteristics. These algorithms are very popular in image manipulation software. Super pixel algorithms are not suitable for use with images where the pixel values of objects are not as distinguishable from each other as in the case of skin tone and large patches of sky. It is also not suitable for use with images with many small objects (such as traffic signals). An algorithm that determines the optimal number of super pixels is the uniform segmentation algorithm, which has a goal of balancing the workload needed for clustering and the quality of the result. Since the goal is to generate super pixels, the ideal solution to this problem is to use no super pixels. As the number of super pixels increases, the quality of the result decreases. The worst-case scenario is a super pixel for every pixel. There are two basic types of superpixel clustering algorithms, namely Point-based and Voxel-based. The point based is the one in which the image is first divided into a grid, and each pixel is checked against the other pixels. In the voxel approach, the image is divided into 3D voxels. A voxel is the smallest cube of space that can be indexed. However, multiple experiments show that this type of algorithm is very computationally intensive. Another, related approach is known as 'Picking'. Grids are chosen that divide the image into equal squares and then checked to see if they contain any pixels of interest. If the square contains a pixel of interest, the square is grouped with the others that contain that pixel. If the square contains a pixel of no interest, then it is left out of the grid and will not be grouped with other squares. In case of Multi-level thresholding , the image is thresholded at multiple levels. All pixels that are less than the threshold are set to zero, all pixels that are greater than the threshold are set to one, and all pixels that are between 0 and the threshold are set to half-way between zero and one. Pixels that are neither greater than the threshold nor less than the threshold are unchanged. At each level, pixels that are below the threshold are removed, and all pixels that are above the threshold are added. This algorithm may result in a large number of small disconnected objects, and it does not always yield the best results for images that have moving objects, and it requires a high degree of algorithm debugging. Some of the researchers also use a technique in which the pixels are segmented into connected regions by using image statistics such as connected component analysis, Jaccard index, or max flow/min cut. Any pixels that have a weak signal or a value that falls below a threshold are disregarded, and any pixels that have a weak signal or a value that exceeds a threshold are combined. In multi-level strategy, the image is processed at multiple levels. Further in this approach the pixels are segmented into connected regions by using thresholding functions. Each pixel has a probability that it belongs to a particular connected region. The threshold used to split an object is chosen by looking at the probabilities of each pixel that belong to a given region, and the threshold is chosen to equal the probability that it belongs to the desired object. Each region is labelled accordingly. The result of using this method is that the regions are very close together, so if there is a mixture of areas of different object pixel values, this method tends to separate them into separate regions. Another method of using this is to use multiple thresholds that make different regions [33], [34] . The results tend to have different problems, such as overlapping or overly-dense regions.

Following the completion of the study of the contemporary literature survey, it has become obvious that the k-means algorithm and its variants are the most often used and extensively tested algorithms for the segmentation of the wheat canopy in the world [35] . The author has developed a system that makes use of a combination of curve fitting methods as well as a modified version of the k-means clustering algorithm that searches for clusters based on initial values taken from histograms [36]. The fundamental disadvantage of employing curve fitting-based equations is that they are completely reliant on the data from which they are formed, which is not always the case. This means that the segmentation work has been confirmed for photos associated with drought stress [36] rather than images associated with nitrogen stress. As a result, the goal of this study endeavour is to develop highly generalised algorithms that are capable of working under a variety of stressors while also being capable of working with a variety of wheat types. In a nutshell, this work is an exploratory voyage to find ways to combine known algorithms with a novel technique for pixel clustering in order to improve performance. The next section explains each step taken. The paper ends with a conclusion and future directions. Results and Discussion are also mentioned before the conclusion section.

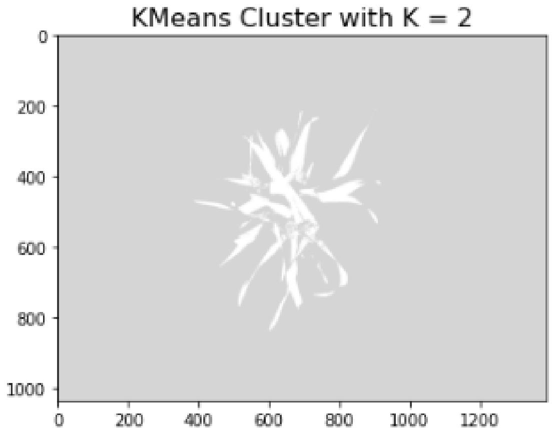
Methodology

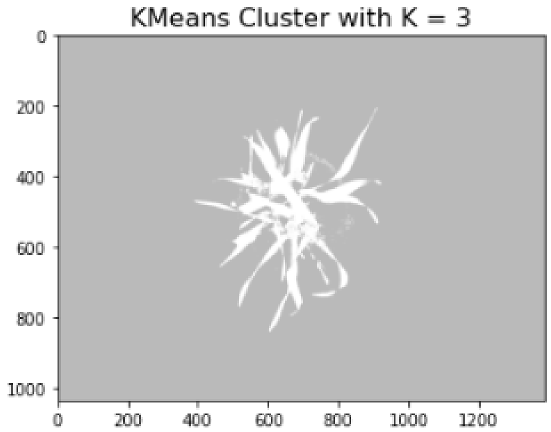
Here, we will describe the parameters of the dataset and how several clustering algorithms were examined in order to choose the optimum pipeline of approaches for detecting nitrogen deficiency in the wheat plant canopy, as well as the results of the evaluation. The following are the characteristics of the dataset that was used in this investigation.

Data Set

Images of the PBW550 wheat variety images were collected from [Sandhu, Sukhjit (2019), “Plant Stress Analysis Based on Chlorophyll Fluorescence and Image Processing”, Mendeley Data, V2, doi: 10.17632/jnjd835ncg.2].

In this section, the outcome of the segmentation algorithms are given. The results incorporate the results from the previous authors and implementation of a new sequential hybridization approach of pixel clustering of the wheat canopy. The literature survey gives copious evidence the most frequently used algorithm for pixel clustering is k-means and [Ref] has worked on the hybridization of the kmean using curve fitting method. For a preliminary analysis, application of the kmean algorithm was done and it was found to be inadequate for the said purpose.However, this process allowed us to identify the value of ‘k’ or the number of clusters that are required to produce best possible results.





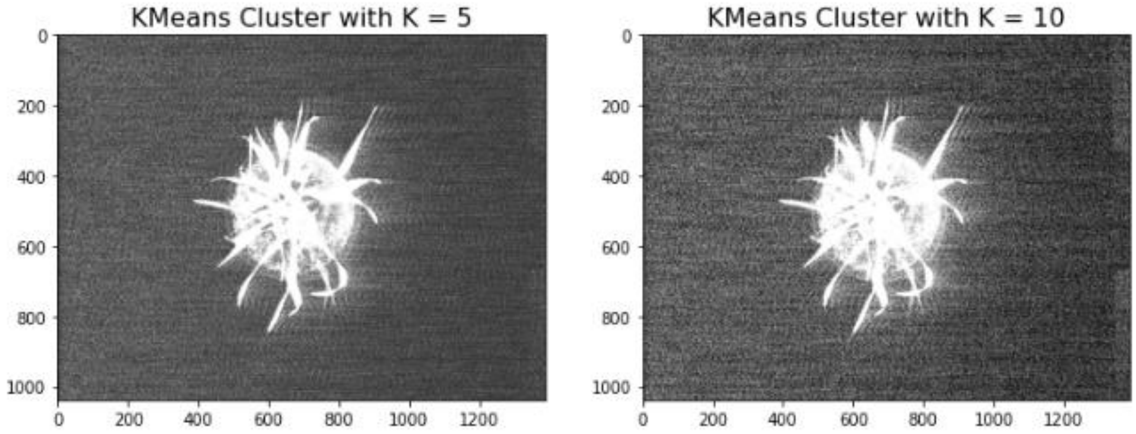
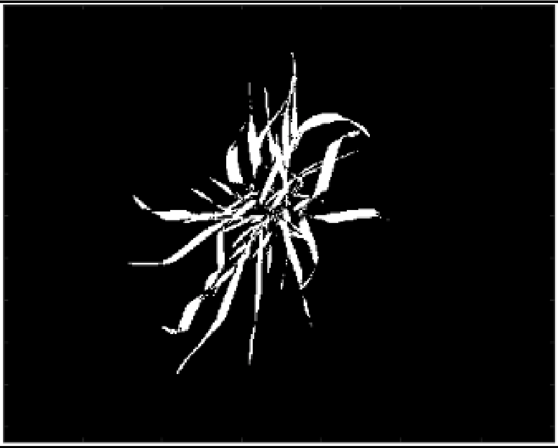
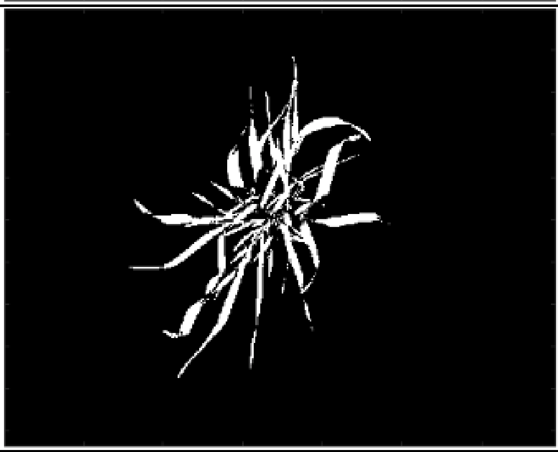


Figure 1: Selection of Number of Clusters 'K'

It can plainly be seen (Figure 1) that when the value of K is 2, the algorithm produces the best possible result. In other instances, it may be noted that either a portion of the pot is visible in the segmented image or a significant portion of the pot is visible in the segmented image. If we need to use the hybridization approach, the value of K = 2 produces the best segmented image in this situation. After the implementation of the previous authors work, other methods of clustering were implemented and Table 1 gives the output of all the algorithms implemented.

Pixel Clustering Method	**Segmented Region of Photosynthetic Activity**	**Description**
Multi-Range Thresholding		Large number of pixels are missing photosynthetic activity.
ISO-Data		Missing some pixel of the photosynthetic activity in the wheat canopy

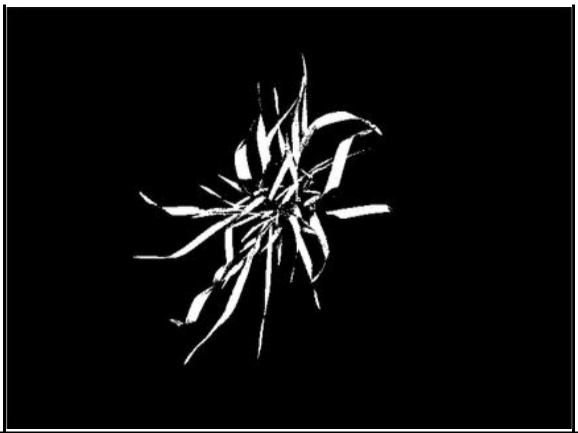
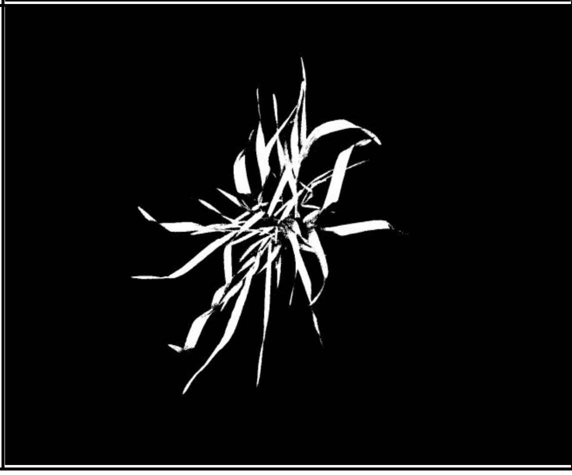
Ostu		Results better than ISO and multi-range thresholding
Combinational (Ostu+Kmeans)		Most Accuracy in Capturing photosynthetic area of the canopy

Table 1: Segmentation Results of Wheat Canopy

Clearly, the combination of the otsu algorithm and the kmean is giving best segmentation results. Other variants of k-means such as kmean++, kmedian ,k-medoids were also implemented and found to give inadequate results , especially in terms of the time they take in clustering pixels of each image. Taking clues from the previous work, convolution filters were avoided and methods such as multi-range manual thresholding were applied. Extensive experimentation helped us to go for an automated method of computing thresholding, hence 'Otsu' and ISO Data methods were applied but again it was found to miss pixels having information on photosynthetic activity. But, its combination with k means (with k-value of 2) works really well as it can be observed from Table 1.

The purpose of this research work is to support the detection of the nitrogen deficiency in the wheat plant by observing changes in the shape of the wheat canopy. As mentioned earlier, accurate segmentation of the wheat canopy having information on the photosynthetic activity is the main logic around which this work resolves. From previous work, we get hints that the k mean clustering method is the best method for this purpose but requires some degree of improvisation for it to work with specific data. The outcome from this work demonstrates and confirms the previous works in this context and at the same time this work overcomes the limitation of the previous work. In this next section, validation of the work is done using IoU metric.

S.No	Algorithm	Sample Sizes			Average IoU Score
		100	200	300	
1	CFit[36]	86	170	192	224
2	Proposed Method	98	182	289	189.6

Table 2: Objective Evaluation of the segmentation algorithms

Evaluation of the Segmentation Results

This section provides an explanation of the evaluation process that was used to validate the segmentation results. The objective evaluation method of the IoU measure has been described in the preceding section, and it does not require the participation of domain experts in the field of agronomics. However, in this section, we will discuss how to do a subjective evaluation of the segmentation method using a random sample. When it came to the subjective evaluation, a unipolar discrete five-grade scale was used. Using two domain experts, it was decided that the images should be evaluated on the basis of the quality of the segmented images, which is defined as how accurately the segmentation algorithm is able to capture photosynthetic area and whether or not the segmentation algorithm added any new level of information to the images. The evaluation sheet from the process is summarised in Table 3.

Wheat Canopy Segmentation Algorithm Subjective Evaluation				
Methods	Factors	Judge 1 Score	Judge 2 Score	Average Score
CKfit[36]	Information Gain	8.9	9	8.95
	Photosynthetic Area	7.9	8.8	8.35
Proposed Method	Information Gain	9	9.5	9.25
	Photosynthetic Area	9	9	9

Table 3: Evaluation of Segmentation Algorithm

In terms of the quality of the segmentation of the wheat canopy area, the subjective evaluation follows a similar pattern to the objective evaluation.

Conclusions and Future Directions

It can be observed from this study that clustering is an effective strategy for building systems of detection as in the use case of "wheat canopy ". The process of segmenting wheat photos must be accomplished before automated algorithms may be developed to detect nitrogen stress in wheat photographs. In order to improve the method of wheat canopy segmentation, the goal of this study work is to produce a more accurate method. When compared to previous ways, the new strategy has the advantage of being more straightforward because it involves a hybridation strategy that is sequential in nature, as opposed to the methods that have been employed previously. In terms of IOU accuracy, it has been revealed that the combination of Ostu and K Mean (k=2) algorithms is the most accurate method for determining the photosynthetic activity area from a picture of the wheat canopy, according to the researchers. For the purpose of ensuring that the information provided is accurate and dependable, it has been subjected to a variety of objective and subjective review procedures.As the process is computationally intensive and time consuming as per nature, the processes mentioned in the section will surely attract the researchers to understand the approach and utilise this in their work.

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