Chapter 10
Research Trends and Systematic Review of Plant Phenotyping

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10.1 Introduction

Agriculture field is very popular for research work. It is essential in terms of food consumption for human needs and maintenance of the ecosystem for which it is required to give abundant attention towards the future challenges. Factors related to crop growth includes some of the major challenges are weather and atmospheric changes, which highly affect the agriculture field. Therefore planning should be in such a way that it assembles the precautions timely and required to develop a low-cost system model. Risks are not defined by the assumption-based approaches; therefore real-time data analysis is highly effective for all the concerns. Image processing is a technique which is based on real-time dataset analysis. The factors used for analyzing real time dataset are mainly time and cost, which are directly proportional to the efforts required for day-to-day analysis by manual observation. Now, this work is defining the challenge for huge dataset with less amount of effort – observation that is based on digitalized world and programming environment. Image processing is the area which has been implemented in plant phenotyping provocation very efficiently. Plant phenotyping is the method to extract the morphological characteristics or physical characteristics of the rice plant which are essential for yield production like height measurement and panicle counts. Rice plant contains tillers, leaf and panicle and panicle is the grain part which directly shows the counts of the panicles for one tiller of a single plant. Classification of inferior panicle count and superior panicle count exhibits an application of yield production and then regular automation is required to assess the quality of the grain part using plant phenotyping. Grain quality depends upon the stage of fertilization,

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which means if the seed is fertilized early, it means they are superior panicles and if later fertilized, they are called inferior panicles. Analysis of morphological characteristics is very important to improve the classification of best rice in terms of rice husk with its color and different shapes. Rice husk or the outer covering of the grain will show the grain quality as well as is useful on the power generation. Rice husk is difficult to use efficiently because of its properties: very hard surface covering, no food nutrition, and presence of very high silicon element; 20 percent of grain weight is attributed to rice husk, which is difficult to use as a biodegradable element [5]. It has been observed that different methods are following the same steps: first is to capture the image and then apply some programming techniques to measure the photographed scene, and after that, calculate the pixel values of the image in inches; afterwards, do the automatic scaling technique, which is setting an absolute scale. Therefore it is very crucial to analyze the rice growth according to its morphological properties. Many researchers have done the experiments based on plant height measurement, tiller counts, analysis of panicle architecture, and so on by using machine learning which is the most recent technique for direct automation. Image property can be enhanced by using the method of thresholding and filtering which are the main parts of the image preprocessing techniques. Regular automation of yield production requires very systematic approach to improve the accuracy in terms of timely observation of plant growth, early disease detection, etc. Error rate calculation of manual detection and direct automation will show the improvement of the technique. Most important factor to make the approach efficient when it should give the low error rate between the manual measurement and direct observation. Image processing is the best technique to take the image-based data for further observation. Image data means it should not be synthetic data. It should be real data for the observation so that it will give the information about the technique which produces less error rate method that is the primary concern because there are lots of methods which are available for digital image processing but unless it is useful for real time data then technique will not become effective. There are different ways to capture the digital images of rice crop; these are by using camera, computer scanning, satellite images, and drone-based images. After data collection, images are analyzed using a software that can easily calculate region of interest (ROI) and pixel value statistics based on user-defined parameters. Improvement of the image-based techniques will be shown by the fast analysis grading of quality of rice varieties which is a crucial point for market rate prediction. Automatic detection is the advantage of the digital-based image analysis because it is of low cost and less time observation. In this work most popular techniques are surveyed for the efficient analysis of the images such as deep learning, machine learning methods like random forest, support vector machines, convolutional neural networks (CNN), etc. Recently deep learning concepts for image processing are very effective for feature extraction; therefore this is a small effort to describe some methods of deep learning algorithms with greater efficiency which are related to rice crop features like panicle, leaf, tiller, root etc., are discussed in Table 10.1 and some selected algorithms are used those are not discussed for the analysis of the plant height, panicle counts and biomass calculation.

Table 10.1 Deep neural network model and its application – gap analysis

S. No.	Paper title	Gap analysis	Methodology used/Description
1	Plant leaf recognition using texture and shape features with neural classifiers [24]	Add some more combination of features other than shape, texture, and color. Using other classifiers like *k*-nearest neighbor, support vector machine, etc.	In this work shape- and texture-based analysis is computed by using Gabor filter and GLCM features. Curvelet features and invariant moments for shape analysis of the leaf
2	Smart farming: Pomegranate disease detection using image processing [25]	Some other combinations of feature like biomass, height, width with other deep neural network classifiers are required to estimate. Training time is slow for SVM	In this work preprocessing and feature extraction are done by using k-mean clustering and then using SVM classifier to classify the different classes of images
3	Plant species classification using deep convolutional neural network [26]	Size of training sample data is very low; therefore accuracy is not achieved. At the same time, SVM is slow for training the data. Feature like biomass is not considered	In this work deep convolutional neural network provides the pixel value calculation; feature extraction will be easy to segment by green pixel value rather than shape-based classification
4	How deep learning extracts and learns leaf features for plant classification [27]	Feature extracted based on shape, texture, color, and venation. But height, width, and biomass are not considered	In this work CNN is used for feature extraction, and deep net is used to species identification; therefore venation feature is effective to give species identification detail very accurately
5	A review of neural networks in plant disease detection using hyper spectral data [28]	It will give the information about the hyper spectral data, but features are required to match with the data. Therefore explanation of features is missing	In this work the architecture of all the neural network models is discussed with the purpose of disease identification. Learning vector quantization (LVQ) NN with PCA and RBF network with PCA are discussed for rice disease detection
6	Factors influencing the use of deep learning for plant disease recognition [29]	Factors which are influencing the performance are discussed here, but some more features are required to affect the method like biomass calculation and height of the plant	In this work method which is applied as transfers learning network which can reduce the numbers of the pre-trained network layers according to the effective result. Deep neural network will provide the effective result with all the considerations

(continued)

Table 10.1 (continued)

S. No.	Paper title	Gap analysis	Methodology used/Description
7	Method of plant leaf recognition based on improved deep convolutional neural network [30]	Complex background like biomass recognition is not identified	In this work image is preprocessed, and taking its effective size only so that the segmented image will give good result by using deep learning's layered approach
8	Tomato crop disease classification using pre-trained deep learning algorithm [31]	Features which are analyzed are size and weight; still some features like biomass will be effective for further analysis	In this work deep learning architecture will provide the stepwise analysis of tomato plant for disease detection. Transfer learning method is used for disease classification
9	High-throughput phenotyping with deep learning gives insight into the genetic architecture of flowering time in wheat [32]	Flowering time analysis is depend upon the regular automation of the plant, and it will be difficult for biomass, but it will be effective that at the same time bulk of analysis can be done by using biomass analysis	In this work CNN network is trained to analyze the image without wasting time to labeling the images
10	Three-channel convolutional neural networks for vegetable leaf disease recognition [33]	For disease detection, color, texture, and shape of the plant are used; at the same time, growth analysis is also one of the factors to analyze	In this work, each channel of TCCNN is fed by one of three color components of RGB diseased leaf image, the convolutional feature in each CNN is learned and transmitted to the next convolutional layer and pooling layer in turn, and then the features are analyzed through a fully connected network layer to get a deep-level disease recognition feature vector

First section is dedicated to introduction part and the second section, related work with the most recent work has done on image processing is described. In the third section, experimental setup has been discussed for automation of the crop field production. In the fourth section, results and discussion is described with a case study of highly efficient image processing techniques, and in the fifth section, conclusion and future work is discussed briefly.

10.2 Related Work

Plant phenotyping is a broad area which includes work on the plant varieties for improvement of the agriculture-based research field. Plant growth is correlated with the gene selection process for further improvement. Pasion et al. [1] proposed that computer-based technologies are showing the better result on processing plant physical properties like seed density analysis, panicle counts, spikelet's count, plant height measurement, grain quality assessment, gene binding assessment, tiller growth analysis, etc. Counce et al. [2] introduced grain quality assessment as major task to enhance the productivity of the rice crop. There are different techniques which are used to capture the different stages of the rice crop, and after achieving a particular growth, the seed fertilization is calculated in terms of seed density. For plant growth analysis it is necessary to recognize the stages, from stage 1 to stage 9, to know when the complete process of rice growth is done, but the main stage will come after stage 6; in this stage the rice grain is in mature condition. At stage 7 it has been observed that precaution is required because at this stage, plants are easily affected by the amount of water given, which will result in the damage of the grain and fungal infection and crucial disease infection. Identification of these problems has become a major issue to rectify the plant disease by using its properties e.g. white blast, brown spots etc. Singh et al. [3] discussed about various rice grain properties that will enhance the method of image based techniques to increase the productivity by regular assessment of crop field. Grain contains different properties, e.g., color, shapes, and quality; image analysis helps in predicting the good-quality grain production method. Atkinson et al. [4] proposed grain quality also depends upon the strong impact of internal root phenotyping of rice crop. Root phenotyping is the method to analyze the root of the crop according to climate changes as well as nutrition and water level assessment for better production. Previously it is implemented by the researchers that at stage 7, it is important to access the root functionality because in this stage, water level absorption can affect the grain quality; root phenotyping is one of the studious tasks. Zou and Yang [5] proposed that rice crop is very useful worldwide; therefore all the parts of the crop, from root to top, are point of the research. Rice grain is composed of rice husk, endosperm, bran, and germ. Rice husk contains high silicon, which is useful for power generation, but can be a source of environmental pollution, dust, smoke, and greenhouse effects. Panicle is another feature which is discussed by Zhou et al. [6] that image analysis techniques are very effective for tedious work like panicle architecture analysis of sorghum plant. Konovalov et al. [7] recommended image analysis techniques, which are effective in terms of less time automation with low cost. By using deep learning and machine learning concepts, it is easy to classify the problem and identify the precautions before the plant gets affected by diseases; automatic scaling of image will give the growth stage analysis of crop images. Cai et al. [8] introduced an approach to analyze the growth of the plant by using height calculation, which is the major task for growth analysis, and by using stereo image data, height is calculated very efficiently. Singh et al. [9] introduced deep learning concepts such as convolutional neural network which is used for the semantic segmentation for the images to preprocess the data with the effective result. Most popular image segmentation methods are like semantic segmentation, thresholding, region segmentation, edge based and clustering based segmentation and Ubbens et al. [10] discussed about image segmentation approach will provide the lack of complexity to analyze the area of interest so that by applying feature extraction method images will give the fast result analysis. Barbedo [11] proposed the image segmentation as the preliminary stage of image analysis which is very useful for noise minimization, and it will generate the low error rate also. Segmentation will give the focus upon the region of interest (ROI) which means only the selected and clear vision of the image. Jeon et al. [12] said the clarity of image is also one of the great issues recognized by the author to improve the image processing analysis. Jimenez-Berni et al. [13] processed information about plant biomass property, and it is easy for the ground surface because image clarity is not a big issue for the surface analysis. Most recent method for feature extraction is deep learning method and Kamilaris and Prenafeta-Boldú[14] also introduced about the deep learning concept for the complex feature extraction by using images. Malambo et al. [15] introduced an approach of density-based clustering; it is like biomass calculation of the images so it will show directly the yield production of the sorghum crop. Liakos et al. [16] introduced the complex feature calculation by machine learning techniques, which is also very useful for fieldwork analysis. Son et al. [17] introduced machine learning techniques such as support vector machine and random forest analysis for very effective analysis of yield production. Another useful technique for feature extraction is machine learning technique and Riegler-Nurscher et al. [18] introduced machine learning techniques which are useful for the pixel wise calculation, and for this technique image clarity is necessary. Bai et al. [19] introduced the multi-classifier cascaded methods, which are also used to analyze the image by using the SVM, gradient histogram, and CNN methods. In conclusion it has been observed by the study that plant growth analysis is based on its physical property analysis, and Tikapunya et al. [20] proposed grain physical characteristic measurement, and Santos et al. [21] proposed an approach to calculate rice grain dimension and chalkiness of the rice crop. Most of the papers are dedicated for height calculation and tiller count of the plant, which is very effective [22]. Sritarapipat et al. [23] proposed an approach for simple and effective baseline measurement for height calculation. Now, it is proven that many of the research works have done very effectively by their method of image analysis. Recently deep learning is very new and effective in terms of cost and time, and there are lists of papers which are based on classification and prediction-based model using deep learning. In Table 10.1, it is shown that some of the model is exclusively dedicated to limited numbers of parameters like color, texture, and size, but it will be effective if used in the growth analysis of the plant also. Some of the methods are direct approach toward the growth analysis of plants and also effective for the disease detection in terms of morphological property analysis. Table 10.1 shows gap analysis that focuses upon mainly three things according to future work crop analysis which are as follows:

1. Biomass analysis of rice crop by using deep learning algorithms
2. Plant growth analysis (plant height, panicle counts, tiller count) of rice crop correlation with grain density calculation by using deep learning algorithms
3. Comparison between feature extraction techniques and deep learning algorithms for huge amount of real dataset in relation to gene association of rice crop

In Table 10.1 some of the research papers have been discussed which is basically showing the disease-based method for classification and prediction instead of discussing about the features related to plant growth analysis. Therefore features are specific according to the analysis of the problem, and it is required to study the features which will give analysis of the plant growth as well as disease detection.

10.3 Experimental Setup

10.3.1 Dataset Gathering

(a) Dataset is taken from Indira Gandhi Krishi Vishwavidyalaya, Raipur.
(b) Drone-based images are captured with the height of 5 ft or 10 ft, but the clarity of the single plant is not accessible through the camera. Therefore it is the next task to make a clear vision of the drone-based images for field analysis.
(c) It is rice crop dataset with 30 images.
(d) Rice crop is planted in around 1 acre of 4046.86 square meter field area.
(e) Observation is started after 1 month of plantation, and images are taken within a week for the calculation of the plant height.
(f) Previous images are taken with the help of a drone-based system at the particular height of 5 ft or 10 ft from the ground in all the directions.
(g) Rice crop growth is hazy and complex and with uneven height creates the different image resolution sites.
(h) Drone-based images are not very useful to calculate the image height because the top view creates the problem.
(i) Therefore a single plant is taken for observation.
(j) For preliminary study, it is difficult to calculate the plant height for the whole field; the authors have chosen a particular area for capturing the images.
(k) Growth depends on the internal as well as external effects. Internal growth depends on the nutrients and water level basically and external on factors like climate and environmental changes.
(l) Plant growth is observed very slowly during the winter season, so panicles will generate after the month of March onward.
(m) Regulated observation by manual effort is time-consuming; therefore systematic image-regulated observation is required for the panicle counts.
(n) Panicle is the smallest unit of the rice crop, and at stage 7 it starts to get mature; therefore it is very important to take care of the rice crop after a particular growth in height.

(o) Every single plant has 4–5 tillers minimum, and each tiller has a number of spikelet which are the grain holder; therefore regulated observation is required by the researchers.

10.3.2 Preprocessing Module

Image processing has some predominant steps which are productive toward the image quality enhancement. Before using any technique, it is required to process the raw data by using preprocessing techniques:

(a) Preprocessing module uses the color thresholding to enhance the color quality of the image as shown in Fig. 10.3 for grayscale image.
(b) For image preprocessing, grayscale image has been taken for the further process instead of color images. Before going for height calculation, the image has some noises which are removed by the median filter with 0.5 errors, and then proceed to edge detection technique by using different techniques.
(c) Image is taken for background removal, so that pixel value can be calculated in an efficient way.
(d) Pixel value of the topmost point of the image will give the information about the height of the plant.
(e) In previous papers it has been discussed that plant height calculation is proportion to plant growth analysis [22] and height is calculated as the conversion of pixel value into inches.
(f) Preprocessing the images using the concept of deep learning includes change of size; direction of the image will be very easy to implement.
(g) Labeling of the image data by using train network for image classification is another approach to calculate its morphological properties.

10.3.3 Height Calculation Module

In this module preprocessed image is cropped for further calculation. Image is converted in grayscale, and then pixel value of the area is calculated. When method is applied for the cropped image, the selected area is masked, and then it is separately analyzed. Single plant height calculation is easy, and preprocessing will also take very less time. In conclusion, cropped area will give fast result as compared to the full image. Figure shows the calculated value of the pixel for the particular image.

10.3.4 Region of Interest Calculation

Region of interest will give the information about the particular plant top area so color image is converted into grayscale intensity image, and background is removed to capture the desired area. The desired area shows the actual region of interest (ROI). It will help to calculate the plant area as limited area will give efficient result to calculate the pixel value. For the field area, it will be difficult to calculate the separate region of interest (ROI) because of complex and hazy structure of the image. Drone-based image or the 3D image property calculation is required for the particular area of interest. Plant phenotyping is the application which is correlated with the gene association also; therefore classification of the image should be accurate to justify the physical property of the plant growth.

10.4 Results and Discussion

In this work it is described that the rice crop dataset has been taken from the Indira Gandhi Krishi Vishwavidyalaya, Raipur, and all the modules are described here. Result for single plant analysis is also showed. Rice crop images are taken with the particular timestamp so that growth can be easy to measure. For the single plant, drone images are not fully suitable for the experiment. Therefore front view images are taken for the experimental analysis of the rice crop images.

Figure 10.1 shows the image quality is improved by applying the method of median filter to remove the noise from the image. By applying this method into the gray intensity image, the color quality is improved. Image preprocessing is the part where the quality of the image is improved, and there are numerous stages for this method. Some other methods like erosion and dilation are used to improve the blur image. Figure 10.2 shows the edge detection method of the image by applying the different methods to select the best part of the image for the further analysis. Different methods are applied such as Roberts edge detection method, Sobel edge detection method, Prewitt edge detection method, Canny edge detection method, and LoG edge detection method. Above all the techniques, it has been

Fig. 10.1 Image filtering by using median filter

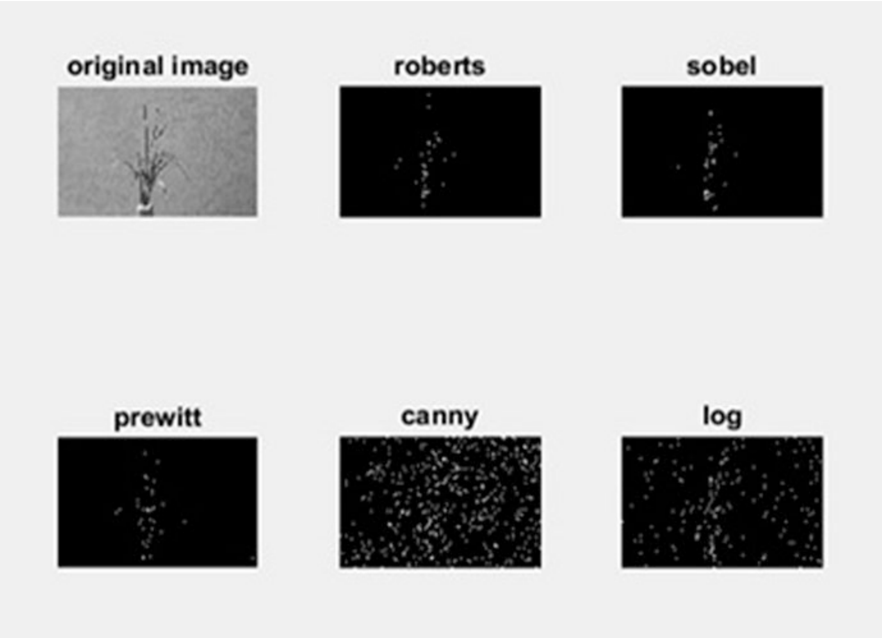


Fig. 10.2 Edge detection by using different techniques

concluded that Roberts, Sobel, and Prewitt methods are effective for edge detection as compared to other methods. It also shows the area which is highly demandable for the calculation of the pixels. Image contains pixel values in matrix formate which shows the range of the colors in the matrix form; so that it is observed that area which is detected having the different pixel values therefore it is important to take the right pixel value for the image. Sometimes real-time images are affected by environmental changes, and then the image quality will differ according to external factors like resolution of the camera, climate effect, different plant positions and directions, light reflection, and so on.

Real-time data testing is very useful for the new dataset because all the concerns are already tested by the researcher and in Fig. 10.3, it is tested means thresholding is the method of color balancing of the image. Image shows the effective approach to detect the region of the desired area. In plant image it is complex to recognize the leaf count and other panicle counts very easily. Edge detection technique will provide the density-based area to classify the image property. Feature extraction for a hazy field is not an easy task unless it has a better quality. Therefore image segmentation and background removal methods are useful if the image is cropped from the original.

In Fig. 10.4, the background is removed by the selection of the particular area. Then the grayscale image is cropped from the original image, and the selected area is now ready to give the details about the preprocessed image. In Fig. 10.5 it is

Fig. 10.3 Color thresholding for grayscale image

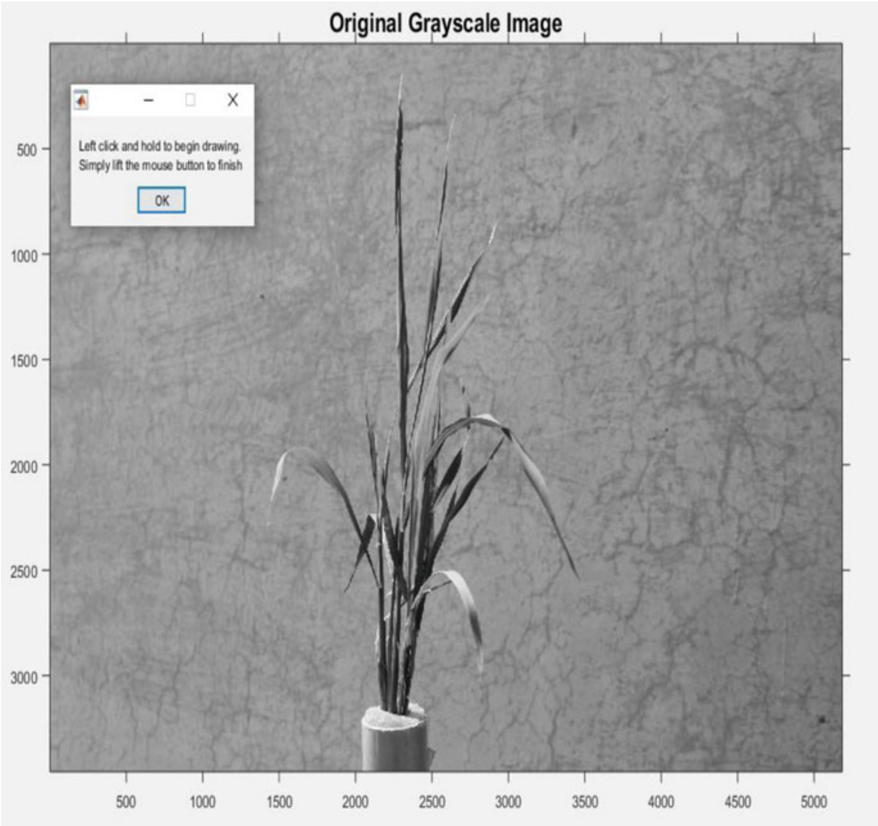


Fig. 10.4 Image masking technique

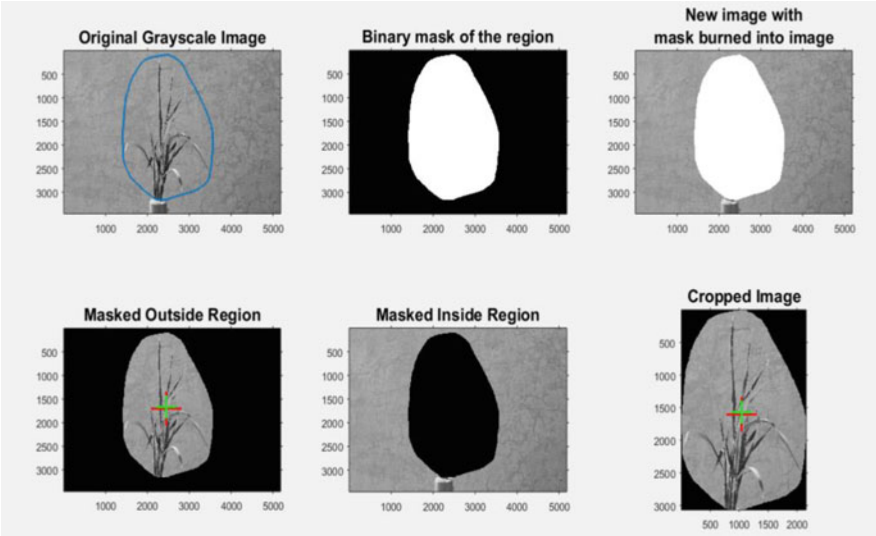
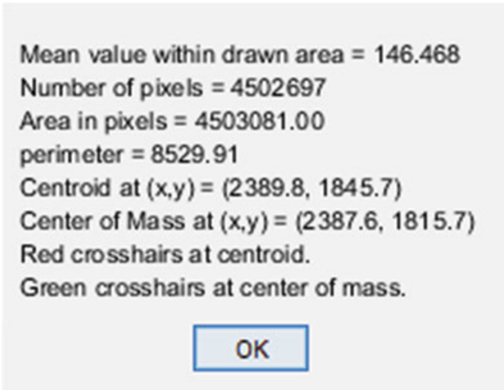


Fig. 10.5 Height calculation with pixel values and ROI of the image

Fig. 10.6 Pixel value calculated values



shown that the image is masked, and the masked image is showing the segmented area of the original image. In Fig. 10.6 calculated values are expressed, and those values are as follows: the mean value of the selected area, number of pixels of the image, area in pixels calculation, total perimeter, centroid at point of (x, y), center of mass at point of (x, y), red cross marking at the point of centroid, and green cross marking at the point of center of mass. Therefore all the pixel value calculation is done; now the selected area removed by the method of centroid is separated from the original image. Original image shows the gray level image with the different pixel values, and according to that, the selected area is calculated. Figure 10.6 shows another method of image pixel calculation, so that manually it can be converted into centimeters or inches. Plant height calculation is showing the regular assessment

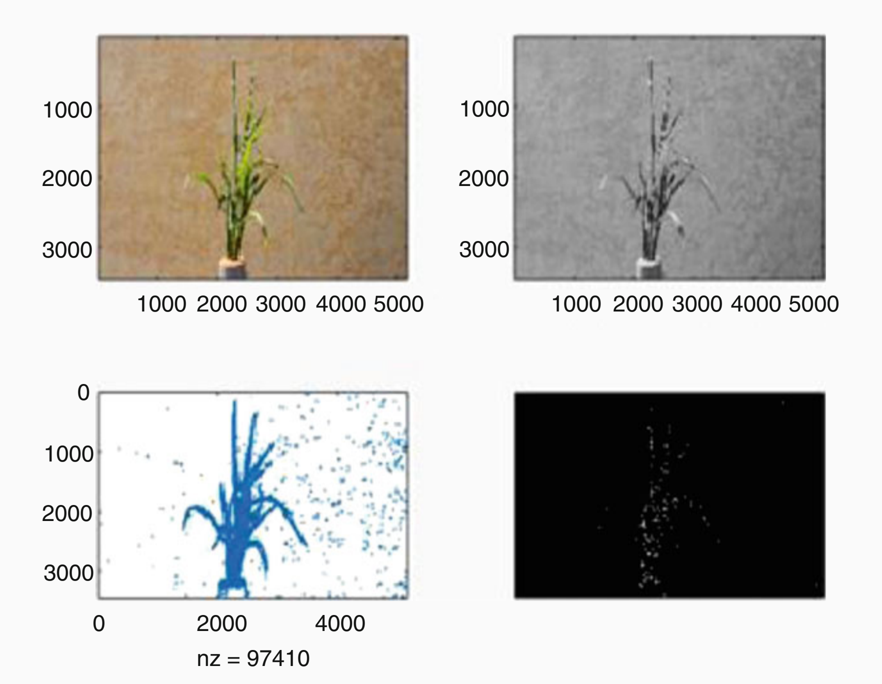


Fig. 10.7 Edge detection (Skeletonization) approach to calculate the pixel value for height calculation

of the plant growth, so that maturity level can be checked by the researcher to improve the plant growth. Necessary precautions are taken to capture the images like (early morning means around 8–9 o'clock) it is recommended to take the images at daytime, and after that, select 10 images for the testing and the 20 remaining images for training set.

In second method for image analysis is applied in Fig. 10.7 and that is to take the highest pixel value for the captured image, and same for the bottom level pixel value for the same image.

10.5 Conclusion and Future Work

This chapter mainly explores the important factors considered for yield prediction such as grain quality assessment and gene association analysis. It is dependent on various environmental factors like climate, weather analysis and internal plant growth analysis, i.e., root phenotyping, physical characteristic analysis, etc. Therefore the fastest approaches are required to capture the changes according to time and with regular automation. Such systems are which are free from manual calculation to design so that images can only capture the changes on the plants. Therefore programming techniques with imaging tools are going to be used by the researchers to make the automation effective with respect to time and cost. According to the survey, deep learning has been found a highly demandable approach for image feature extraction with less noise and also for huge dataset. It outperforms as compared to other techniques so it is highly useful for many of the areas like water level assessment, resource of nutrition scaling and for automatic scaling of the growth of the plant as well as grain quality assessment of the rice crop. But it is a great challenge for the researchers to implement the method on huge dataset with the fewer amounts of intermediate layers.

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