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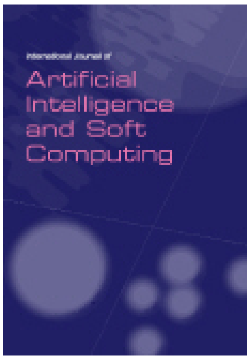

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Monika Mangla, Vaishali Mehta, Sachi Nandan Mohanty, Nonita Sharma, Anusha Preetham

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Statistical growth prediction analysis of rice crop with pixel-based mapping technique

Monika Mangla*

Department of Information Technology,
Dwarkadas J. Sanghvi College of Engineering,
Mumbai, India
Email: manglamona@gmail.com
*Corresponding author

Vaishali Mehta

Department of Computer Science and Engineering,
Geeta University,
Panipat, India
Email: vaishalimehtawadhwa@gmail.com

Sachi Nandan Mohanty

School of Computer Science and Engineering (SCOPE),
VIT-AP University,
Amaravati, Andhra Pradesh, India
Email: sachinandan09@gmail.com

Nonita Sharma

Department of Information Technology,
Indira Gandhi Delhi Technical University for Women,
Delhi, India
Email: nonitasharma@igdtuw.ac.in

Anusha Preetham

Department of Artificial Intelligence and Machine Learning,
BNM Institute of Technology,
Bengaluru, India
Email: raoanusha1606@gmail.com

Abstract: Agriculture has attracted eminent researchers during the past few decades owing to revolutionary advancements in the field of data analysis using machine learning and computer vision techniques. The continuous monitoring of plant growth is an important aspect in the field of agriculture and has associated challenges also. The current work aims to define the significance of the pixel-based clustering techniques for analysing plant growth in terms of height calculation. In this study, pixel-based mapping has implemented its two applications viz. vertical and horizontal scaling for height calculation.

Here, vertical mapping implements an image processing technique to monitor the height of a single plant whereas the horizontal mapping technique determines the average volume of the whole field using k-means. During the result analysis, it is observed that the proposed model provides an accuracy of 97.58% outperforming the state-of-the-art models.

Keywords: image processing; pixel based mapping; leaf growth analysis; scaling; machine learning; k-means clustering.

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Biographical notes: Monika Mangla received her PhD from the Thapar Institute of Engineering & Technology, Patiala, Punjab. Currently, she is working as an Associate Professor in the Department of Information Technology at Dwarkadas J. Sanghvi College of Engineering, Mumbai. Her interest areas include IoT, cloud computing, algorithms and optimisation, location modelling and machine learning.

Vaishali Mehta is working as a Professor in the Department of Computer Science and Engineering at Geeeta University, Panipat. Her major areas of interest include approximation algorithms, machine learning, and fuzzy logic.

Sachi Nandan Mohanty received his Postdoc from the IIT Kanpur in 2019 and PhD from IIT Kharagpur, India in 2015, with MHRD scholarship from Government of India. He has edited 24 books in association with Springer and Wiley. His research areas include data mining, big data analysis, cognitive science, fuzzy decision making, brain-computer interface, cognition and computational intelligence. He has received three Best Paper Awards during his PhD. He has awarded Best Thesis Award First Prize by Computer Society of India in 2015. He has published 60 research papers in international journals of international repute and has been elected as Fellow of Institute of Engineers and senior member of IEEE Computer Society Hyderabad Chapter.

Nonita Sharma is working as an Associate Professor in the Department of Information Technology at Indira Gandhi Delhi Technical University for Women, Delhi. Her major area of interest includes data mining, bioinformatics, time series forecasting and wireless sensor networks.

Anusha Preetham has completed her PhD under VTU in 2021. She worked as an Assistant Professor in the Department of Computer Science Engineering, SDMIT, Ujire, DK, India, for three years. She worked as an Assistant Professor in the Department of Information Science Engineering, DSATM, Bangalore, India for six years. She is currently appointed as an Associate Professor in the AIML Department, BNM Institute of technology, Bangalore, India. She has over a 9+ years of teaching experience. Her areas of interest are in machine learning and deep learning. She is a life member of ISTE and many other professional forums.

1 Introduction

Computerised tools and techniques have evolved significantly influencing each aspect of human life viz. healthcare, transportation, and industrialisation, etc. Agriculture is not an exception and has witnessed a considerable transformation as a result of advancements in computer vision. It has also attracted various researchers. Among various research challenges, crop yield is one of the most prevalent areas of research among researchers as it involves a number of complicated steps. Resultantly, a variety of models have been designed and validated in order to automate the process of yield prediction based upon different factors viz. seed quality, fertiliser, weather conditions and soil type, etc. As crop yield is influenced by unpredictable environmental factors, crop yield prediction can be helpful to plan storage and marketing strategies. Additionally, it is also an important aspect for global food production.

Different measures of plant growth include root mass index, vegetation index, leaf area index, plant colour and plant height. Among various indexes, plant height is the most important criteria of plant growth measurement and its productivity. On an average, plants grow to a specific height under normal circumstances. However, in adverse situations like distress of a disease or weather conditions, its growth may be adversely affected that impacts the yield. Lot of research has been done in the domain of plant height measurement that employs various technologies. Among various technologies, machine learning is the latest and most competent technique in connection to plant growth prediction as it predicts the crop yield based upon various features. In this paper, authors propose an image processing approach that analyses the height of rice crop based on images. The prime contribution of the proposed model is that it uses pixel-based clustering technique to analyse plant phenotype traits such as height measurement, their correlation, and their variations with respect to environmental conditions. Additionally, the proposed method is also helpful in disease detection during early stage based on sluggish growth of the plant (Gana et al., 1985; Kamilaris et al., 2017). The most important task in this process is the field work analysis as it is quite challenging to analyse growth of each plant through visualisation. Unlike traditional image processing techniques, the proposed approach employs image processing and machine learning based automatic growth prediction that takes less time and effort. The current model uses a statistical method for prediction of rice crops growth levels based on colour conversion technique.

For height calculation, there are several existing techniques available in literature. Current approach uses scale for pixel mapping that provides the ground truth data implementation. A salient feature of the proposed model is that it treats the output as input for training the next dataset. It is based upon cropland mapping of high resolution images using pixel-based analysis. It also provides a digitised knowledge discovery, pattern identification and evaluation of real dataset with enhanced accuracy. The prime significance of current work is utility of machine learning technique and image processing for the height calculation.

The current manuscript has been organised into various sections. Section 2 discusses the various factors related to rice plant. The section also discusses the statistical growth analysis for the same. Related work has been discussed in Section 3. Proposed methodology and its significance have been elaborated in Section 4. Results are discussed in Section 5 and finally the conclusion and future work is presented in Section 6.

2 Factors related to rice plant

Rice crop life cycle generally takes 3 to 6 months starting from plantation to grain filling. The growth of rice plants mainly depends upon the seed variety and climatic conditions. During the growth process rice plants undergo three different phases viz. vegetative, reproductive, and ripening. The rice plant growth analysis process undergoes various stages. Among various stages, numbers of methods have been proposed by various researchers for rice growth analysis. These methods are generally based on image processing technique and provide an automatic scale-based technique called as pixel mapping for height calculation.

2.1 Study of statistical growth analysis of plant

The term statistical growth analysis signifies the production rate analysis of grain filling procedure which can be computed by using the formula given in (Atole and Park, 2018):

$$\text{Harvested Index} = \frac{\text{EconoNicaS FieSd Production}}{\text{BioSogicaS FieSd Production}} \times 100 \tag{1}$$

Here, equation (1) computes the overall production rate which is based on leaf growth analysis. Plant growth is directly proportional to the leaf height. Some other components of growth analysis are as follows: plant weight (kg) and leaf area (m^2) calculation, biomass calculation, panicle count, tiller count, per tiller spikelet count and evaluation of crop density function, etc. Classical growth analysis method provides us the relative growth rate (C), unit leaf rate (E), leaf area ratio (F), leaf area index (L), crop growth rate (C), leaf area duration (D). According to leaf growth analysis, the yield prediction is the product of leaf area duration (D) and mean unit leaf rate(). The study of growth analysis shows that the statistical factors may differ if a different method for growth calculation is used. In this work we present a pixel mapping based method for leaf area analysis that calculates the plant height calculation by using pixel-based leaf height detection technique. As shown in above formulation, the statistical growth analysis depends upon the harvested index which is the ratio of economic yield production (dry mass) and biological yield production (total ground dry mass).

2.2 Leaf growth analysis

Field analysis requires proper setup of hardware and equipment for capturing crop images from different positions. Some of the important arrangements which are necessary to be covered for ground truth values are; focal length of the camera, camera apertures, pixel size of the sensor, normalised disparity and average disparity of the ground level. But this method has a high error rate because a slight variation in the equipment settings causes ground depth estimation error which is also called as error in disparity values. Direct height calculation is still challenging by the hardware setup. Another method for the field analysis is the use of sensors for controlling the surroundings like rain gauge, tipping bucket sensor for sensing the water consistency, anemometer sensor for wind pressure and speed calculation, pyranometer sensor for solar radiation, flux density calculation, soil moisture sensor for the evaluation of amount of moisture in the ground soil, temperature and humidity sensor required for the weather forecasting and at last good quality of camera for dataset gathering. As a consequence, this kind of setup is very costly, complex and for farmers, it is not so easy to understand. Therefore, hardware and sensor-based setup are only useful for a large field, but it requires knowledge about the instrument and its functioning.

2.3 Direct automation of rice crop

The above mentioned hardware is used for the purpose of forecasting or data gathering but for direct automation, statistical analysis of essential features of the plant is required. Plant features include colour, dimension, width, height, shape and most importantly the texture of the plant leaf. Through these features, plant growth can be easily recognised with respect to external influencing factors. In the proposed work, pixel value mapping has been experimented for the analysis of plant growth in less amount of time. The pixel value is an essential part of the image dataset and mapping pixel values to actual values gives accurate results for height calculation of the crops. Automatic height calculation requires automatic pixel detection with specific values; therefore, scaled images are appropriate for the direct automation pixel detection.

3 Literature review

To understand and predict the plant growth, its performance and yield, it is vital to understand the relations between genotype, phenotype and environmental factors. Most of the suggested work in plant phenotyping is focused upon the usage of image processing and machine learning techniques which are discussed below.

3.1 Statistical growth analysis correlation with environmental changes

Kamilaris et al. (2017) discussed the basic requirements for crop growth analysis such as climate change, temperature, water assessment, stress analysis, and diseased plant detection. In this work authors emphasise the uncertainties and associated parameters for healthy plant growth. These are: volume (V1), velocity (V2), variety (V3), veracity (V4) and valorisation (V5) (Kamilaris et al., 2017). Later, it was felt that authors missed considering the most important parameter that is visualisation (V6), an essential factor for statistical growth analysis of plant in Kamilaris et al. (2017). This was addressed by authors in Pantazi et al. (2017) who proposed a visualisation based approach that considers features and classes. In Pantazi et al. (2017), authors used a supervised learning approach for distribution of classes viz. healthy plant, nitrogen stressed plants and diseased plants. The approach required a labelled dataset to classify the respective data according to its features. Korres et al. (2017) also considered visualisation features in terms of rice production analysis and abiotic and biotic stress calculation (García-Cristobal et al., 2015). Araus and Kefauver (2018) introduced an approach for climate change analysis by analysing the changes in external features.

3.2 Significance of growth analysis for early disease detection

Atole and Park (2018) discussed the classification of healthy and unhealthy plants after the leaf emergence. Authors also presented the Alexnet method which gives an error rate of 26.2%. Further, Li et al. (2018) also presented other method with three observed features which were represented as a 3-D vector: colour, texture and vein. Here also, leaf appearance is an important factor to obtain these features. Hence, plant growth analysis evaluates nutrient deficiencies in a more precise way than other methods of examination such as quick tissue scan, soil testing, or checking other deficiency symptoms.

3.3 Statistical growth analysis to avoid hardware complexity in terms of complexity and time by using recent trends of machine learning techniques

Above discussion indicates that different techniques are required for different kind of problems related to plant growth. However, system complexity and time for its execution is still a topic of research. Kamilaris and Prenafeta-Boldú (2018) proposed a statistical growth analysis of rice crop. For statistical analysis smartphone is one of the successful examples for small data analysis as discussed by Bai et al. (2018). Also deep learning based methods are used such as CaffeNet, AlexNet, transfer learning, and different types of hybrid classifiers that produce different outcomes. Here, authors discussed that feature extraction is the key for the processing stage. Ubbens et al. (2018) performed the analysis of prominent features, which is based on plant leaf detection. Another analysis is based on the leaf counting method which is implemented by using deep learning technique. Similarly, Barbedo et al. (2018) described that plant dataset requires a classification method and segmented data for accurate output in feature extraction. Kuska and Mahlein (2018) and Bai et al. (2018) proposed multi-temporal data analysis of plant dataset. Deep learning technique is efficient for multivariate dataset and is therefore applied for disease detection, spike detection, genetic gain analysis, etc. Grain analysis includes counts of spikes per tiller. Various other machine learning techniques are also used for classification and feature extraction of huge dataset such as market rate prediction (Sharaff and Choudhary, 2018) of the real-time dataset.

3.4 Statistical growth analysis assists plant phenotyping application

Growth analysis also plays an important role for plant phenotype identification. Araus et al. (2018) discussed genetic gain analysis which is a crucial factor for breeders to get good quality of seeds. Research is also done on plant genotyping analysis as well as phenotyping analysis which are also performed using external feature evaluation of the crops such as: size, shape, colour, variety of the crop. Genotyping is the chemical calculation for the variety of the crops. Phenotyping parameters for the variety of crops are: mean value of the crops, variance and standard deviation. Choudhury et al. (2019) discussed the recent advancements in image-based plant phenotyping. Some of the areas related to image-based phenotyping are: structural phenotype (2D, 3D), temporal phenotype and physiological phenotype. It concludes that phenotyping is the greatest source for increased production rate. Initially, Popat et al. (2018) focused on the statistical growth analysis for linear growth analysis of rice production. Further, the comparison of good seed quality analysis was implemented by Karamat et al. (2019) for the evaluation of multisource dataset. Among various image based plant data analysis techniques, most popular are hyper spectral image, multi-temporal image analysis, synthetic images, real data analysis, multispectral image analysis, spatially-resolved spectral image implementation, bitmap image gathering, stereo scoping image analysis, optical image analysis, tomography image vs. x-ray image analysis, magnetic resonance image vs. CT image analysis, ultrasound resonance imaging analysis, and analogue image vs. digital image analysis, etc.

3.5 Statistical growth analysis of rice plant initiating other applications such as chlorophyll estimation and seed quality detection

Plant growth analysis has also found its applications in chlorophyll estimation and seed quality detection, etc. Mohan and Gupta (2019) focused upon the leaf chlorophyll estimation technique, which is a direct measure of statistical growth of plant leaf (Khadidos et al., 2021). Concenço et al. (2019) also introduced a seed treatment method as an application for the evaluation of production rate. The outcome of the proposed method enhanced the irrigation levels (Cheng et al., 2019). In the similar aspect, Sethy et al. (2019) in their work described application of nitrogen estimation status. It is now observed that a lot of applications and a huge variety of techniques are available for statistical growth analysis. But the area of concern is how to make an automated model for farmers and how to normalise the dataset for the real-time data evaluation. One of the methods introduced by Konovalov et al. (2018) is based upon scaling technique. This is more useful than others techniques because of its regular detection-based analysis and also data is changeable as per the growth rate (Garanayak et al., 2021).

Thus, it is evident from the literature survey that the most significant tool for the rice plant growth analysis has been statistical analysis. As statistical analysis primarily focuses on retrieval of significant features based on enormous data and thus accuracy takes the backseat. Now with advancement in machine learning, this concern over accuracy can be addressed as machine learning has demonstrated unprecedented performance in the domain of prediction and classification.

Owing to effectiveness of machine learning, it has been widely used in various domains. Further, although there is good quantity of research for growth/disease prediction of general crop; practicing machine learning approaches for rice crop growth prediction is still lacking to the best of knowledge of authors. This seldom usage of machine learning in rice growth prediction may be due to unavailability of sufficient data. Another factor that limits the usage of machine learning methods is bewilderment regarding methods in the concerned community (Chen et al., 2020).

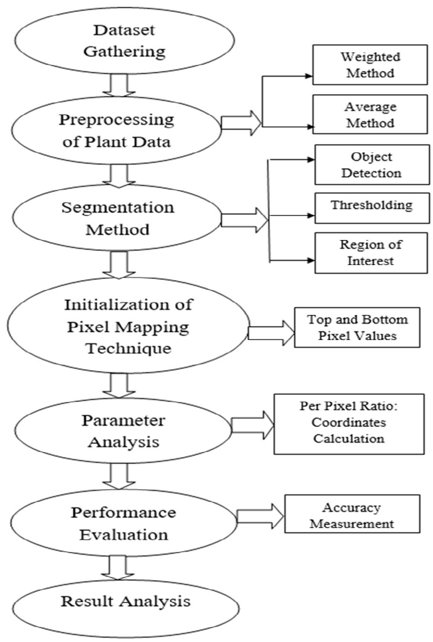
4 Proposed methodology

In this paper, authors propose a pixel mapping-based growth analysis approach. The motive behind usage of this approach is its effectiveness and efficiency for obscuring pictures. The pixel mapping approach through machine learning has demonstrated its competence and hence is widely used by various researchers. The proposed approach does not require to reconstruct the obscured image as the same is stored in the training dataset which can serve as an aid to identify the blurred segment of the image. Hence, it implies that the machine learning can serve as an efficient choice for the pixel mapping and image segmentation (Garanayak et al., 2021; Kunar et al., 2018; Chowdhary et al., 2022).

The proposed method is divided into various steps as illustrated Figure 1. Here, step 1 describes the image pre-processing module while step 2 describes object detection using

ROI method. Thereafter, step 3 calculates the coordinates using mapping technique and step 4 acts as a conversion module from pixel to inch conversion. The final step performs the result analysis among actual and calculated values of the proposed model.

Figure 1 Experimental flowchart of proposed technique



Here, authors present a list of processing steps for height calculation which are involved in measuring the height of tallest rice leaf for growth analysis. These provide us segmentation atoms and extraction of features used in statistical growth detection. These are as follows.

4.1 Band selection and filtering method

This method eliminates the redundant rubber variables so as to avoid unwanted noise and produce the desired output image (Sritarapipat et al., 2014). For example, a Gaussian filter is helpful for the images used in this work as it gives a quality image for further processing.

4.2 Thresholding method of plant data

This method is applied to differentiate the essential objects and unwanted boundaries of the region of interest on plant data (Sritarapipat et al., 2014). Histogram is one such method that provides the colour balancing information of the image for pixel value calculation.

4.3 Measurement of peak height

Here, more than 50 images are used as plant data of different heights and their growth percentage is estimated. There are several ways to find out the approximate height of the crop by the setup of a DSLR camera. The camera should be appropriately positioned to capture the images of the crops for the avoidance of noises. Noise reduction technique consists of the scale conversion of plant dataset for the purpose of quality improvement.

After pre-processing phase, the data is segmented based on similarity of features using k-means clustering, an unsupervised machine learning approach. The proposed approach considers RGB value of pixels as a metric for similarity and performs a two-means clustering. Here, one cluster contains the images with highest number of green pixels (demonstrating fine quality leaves) and other consists of images with lesser number of green pixels (poor quality leaves). Although 7 there are numerous clustering algorithms in existence but no single algorithm demonstrated supremacy across all scenarios. Here, authors propose a two-stage framework that integrates machine learning and image segmentation for prediction of rice crop growth.

4.4 Experimental setup

In order to implement the proposed model, authors have taken the dataset from the University of Indira Gandhi Krishi Vishwavidyalaya, Raipur which is working towards a better future for Chhattisgarh farmers (Shrivastava and Pradhan, 2021). The dataset consists of 619 images which have been captured in the morning and evening. The images are captured using a high resolution digital camera. The collected data is pre-processed so as to remove the physical overhead. The pre-processed data is classified into training and testing data in the ratio of 70% and 30% respectively. It also improves the efficiency of regression and classifiers. For the same, authors employ two methods viz. weighted method and average method as follows:

4.5 Weighted method

In this method of colour conversion, percentage calculation is done for different wavelength values of colours of the images as below:

$$\text{Grayscale image} = (0.3 * \text{Red}) + (0.59 * \text{Green}) + (0.11 * \text{Blue}) \tag{2}$$

4.6 Average method

The average method is the simplest and most commonly used in the pre-processing task. In this method, all colour wavelengths are designated to get the average of the contribution from each colour as follows:

$$\text{Grayscale image} = (\text{Red} + \text{Green} + \text{Blue}) / 3 \tag{3}$$

4.7 Image segmentation

The image is segmented to extract different objects in it. It is based on the colour information, shapes, texture and edges. Method of segmentation considers each pixel as a point of observation. Basically, image segmentation process constitutes following steps:

1 image resizing

2 thresholding

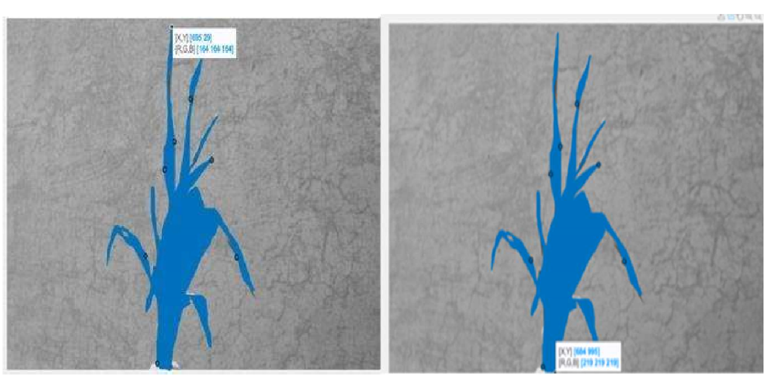
3 region of interest

4 coordinates calculation

5 pixels to inches conversion.

Image resizing refers to image scaling and is implemented through geometric transformations for upscaling or downscaling. In the current work, authors resized the original image of size 3,456 *X* 5,184 to 512 *X* 512 image. Further, in order to identify the required objects in an image, thresholding is employed. For the same, the intensity of pixels is compared with a threshold value and they get divided accordingly. Thereafter, region of interest indicates the focused objects from the perspective of experiment using some specific functions to crop the area of the image such as circle or polygon. Identification of region of interest is followed by calculation of coordinates that involves calculation of position coordinates and object orientation in the image. During this process, boundary lines are used to calculate the coordinates that differentiate the upper coordinates and lower coordinates. The *X* and *Y* coordinates of the plant data is illustrated in Figure 2 which are used to calculate the object coordinate values. Further these pixel values are used to convert it into inches that require assimilation of the values. Pixel value is set manually per inch that helps to detect the pixel values from top to bottom which helps to determine height of the crop. For instance, the height of the experimented image is 903.66 pixels which are equal to 9.4 inches.

Figure 2 Region of interest (top and bottom pixel value) (see online version for colours)



Further, Figure 3 shows the experimental plant dataset. In the current work, RGB images (originally captured images) are taken for the result analysis as shown in Figure 4.

Figure 3 Experimental plant dataset by using pixel mapping technique (see online version for colours)

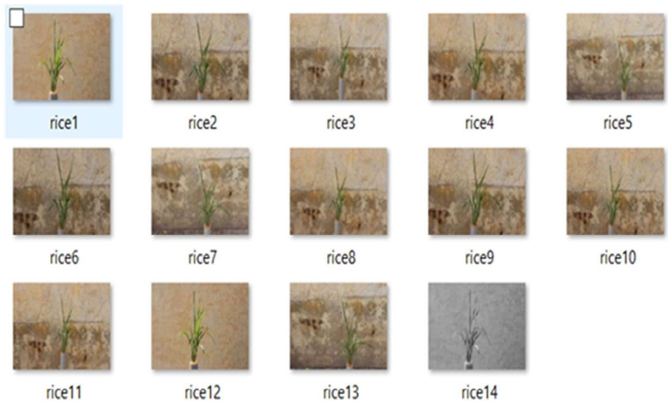
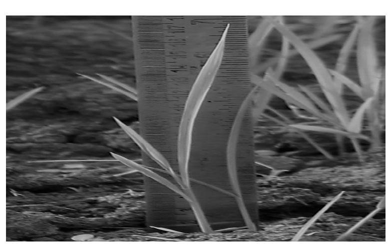


Figure 4 RGB colour image (without mapping) (see online version for colours)

5 Results and discussion

The proposed approach uses vertical and horizontal pixel values for pixel mapping technique. For a real-time dataset, it is challenging to normalise the value of the object according to desired value. In proposed work authors have considered the original images for the experiment. Figure 5 illustrates leaf analysis and the outcomes are listed in Table 1. It represents grey scale image analysis with high error rate (standard value for 8.91 inches 22.63 cm but calculated value is 22.21 cm).

Figure 5 Scale-based object detection in greyscale image (with scale mapping)



5.1 Plant data analysis by vertical scale-based pixel mapping

In this section, plant data is directly taken from the field by using a DSLR camera with high resolution. Scaling technique gives the normalised value for the set of images used for experimentation.

Figure 6 shows the evaluation of pixel to inch conversion by using scale based mapping technique; the evaluated result is shown as –678.55 *pixel* (7.06 *inches*, 17.93 cm). It results in a reduced error rate. In Figure 6, colour-based mapping technique is implemented. Gradual analysis shows that the observed height is closer to the actual height which is much better than in Figure 5 (grey scale image).

Figure 6 Scale based object detection in colour image (see online version for colours)

5.2 Plant data analysis by horizontal scale-based pixel mapping

It has already been discussed that field data analysis is very difficult by naked eyes. Therefore, some automation technique is required to regulate the images for the real-time application of statistical growth analysis. Here, average height calculation of the field crop is done rather than height measurement of single plant, referred as horizontal scale-based mapping.

Algorithm

```
Step 1: Making dataset ready
Take input plant dataset from the open field
Step 2: clustering: Apply k-means to divide the image into two clusters
Find a leaf cluster which has the greatest number of green pixels
if count.g = 0 then
    for each row in cluster do
        for each column in cluster do
            find R, G and B of this pixel
        end
    end
end
if G > R and G > B then
    for each leaf cluster do
        count.g++
    end
end
```

```
if count.g1 > count.g2 then
    add leaf image to cluster 1
else
    add leaf image to cluster 2
end
for each non-leaf cluster do
    find the clusters which match the measuring scale's grey levels
end
for each row in non-leaf cluster do
    for each column in non-leaf cluster do find R, G, B of this pixel
    end
end
convert the pixel into grey
if grey level is between 100 to 150 then output this pixel
end
```

Step 3: Identification of ROI and segmentation

1. From all these pixels, find the area of the image which has highest number of pixels
2. Segment this area and mark it as the measuring scale

Step 4: Initialisation of pixel mapping technique

1. Find the width of the scale, and the number of pixels on the scale
2. Divide them to find the ratio of pixel per cm

Step 5: Growth analysis

Find the number of plant growth to evaluate its growth in terms of cms

Step 6: Result evaluation

Evaluate growth analysis using direct automation technique

Proposed algorithm describes the real-time data analysis by using machine learning techniques. Clustering technique is applied for the separation of green pixels from the background pixels. Segmented area of green pixels is marked with ruler scale in a horizontal manner. Ruler scale is placed in such a way so that average height can be calculated for the entire field.

As shown in Figure 7, scale is placed in the given image such that the same pixel distance is evaluated (vertical and horizontal). Hence proposed algorithm provides the automated average height measurement of the given field by using horizontal scale analysis for the field crop.

Vertical image calculation gives an accurate height of the plant for colour images. Here, pixel distance calculation is performed through coordinate values only. For the same, 14 images are captured for coordinate calculation as illustrated in Table 1 indicating the accuracy of the sampled dataset. Height is calculated through vertical scaling technique and the same is compared with actual height so as to evaluate the error. The outcome of the proposed technique is shown in terms of accuracy.

Figure 7 Horizontal scale based plant data analysis over the field (see online version for colours)

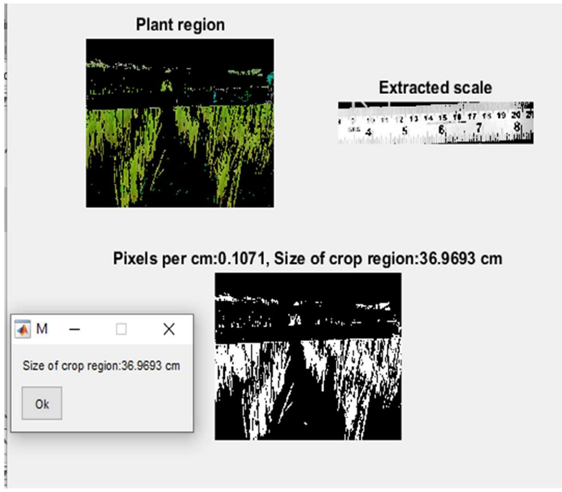


Table 1 Result analysis with error rate calculation

Input image	*Calculated pixel values*	*Calculated height*	*Actual height*	*Coordinate values*				*Error*	*Accuracy (%)*
	(H)	*(in cm)*	*(in cm)*	*X1*	*Y1*	*X2*	*Y2*	*E (%)*	
riceg1	976.0	25.8	27	701	19	690	995	4.34	95.6
riceg2	942.4	24.9	25	734	45	786	986	0.2	99.7
riceg3	694.1	18.3	20	825	98	837	792	8.1	91.8
riceg4	911.0	24.1	24.5	738	32	738	943	1.6	98.3
riceg5	696.6	18.4	20	828	275	924	965	7.8	92.1
riceg6	988.2	26.1	27	713	1	780	987	3.1	96.8
riceg7	859.8	22.7	23	762	99	885	950	1.0	98.9
riceg8	741.1	19.6	20	753	155	768	896	1.9	98.0
riceg9	953.0	25.2	25.5	738	1	737	954	1.1	98.8
riceg10	816.3	21.5	22	707	146	731	962	1.8	98.1
riceg11	754.7	19.9	20	795	115	828	869	0.1	99.8
riceg12	952.4	25.1	25.5	708	29	680	981	1.1	98.8
riceg13	754.7	19.9	20	795	115	828	869	0.1	99.8
riceg14	952.4	27.7	28	708	29	680	981	0.9	99.0

Table 1 uses sampled data analysis using pixel mapping technique. In the following equations (4) and (5), $P1$ and $P2$ represent X and Y coordinate values for the given plant dataset. Whereas pixel distance from coordinate values is calculated using equation (6).

$$P1 = [X1, Y1], \quad here\ X1 = P1[0] \text{ and } Y1 = [P1]1 \tag{4}$$

$$P2 = [X2, Y2], \quad here\ X2 = P2[0] \text{ and } Y2 = [P2]1 \tag{5}$$

$$Pixel\ Distance = f\left(P1[0] - P2[0]^2 + P1[1] - P2[1]^2\right) \tag{6}$$

In equation (7), variable H represents calculated pixel value of the identified plant object and H_{inch} represents pixel to inch conversion value for the measurement of plant growth.

$$\begin{aligned} &H = Pixel\ Distance \\ &H_{inch} = H / 96 \end{aligned} \tag{7}$$

Here, variable E considers the inches value of plant data used equation (8) as well as in equation (9). Standard plant height is predefined according to original value. Equation (10) shows percentage error of proposed technique for different image formats which is based on actual value and observed value of respective plant dataset.

$$Calculated\ height\ in\ inches = H_{inch} \tag{8}$$

$$Maximum\ height\ in\ inches = M \tag{9}$$

$$Error\_Percentage(E) = \frac{M - H_{inch}}{M} \tag{10}$$

Equation (11) represents accuracy percentage which is calculated by error percentage rate.

$$Accuracy(\%) = 100 - Error\_Percentage(E) \tag{11}$$

Finally, equation (12) calculates the accuracy of the proposed method applied to various image datasets. 97.58% accuracy is obtained by proposed method, implemented over all the colour based rice crop dataset.

$$Average\ Accuracy = \frac{\sum Accuracy(\%)}{Total\ Number\ of\ samples} = 97.58\% \tag{12}$$

Table 1 represents growth rate analysis by projecting error percentage on 14 sampled dataset. Figure 8 represents the height measurement of rice crop by using ruler scale. Y-axis represents day wise rice crop growth analysis (life cycle of rice crop is approximately 120 days to reach mature stage).

Figure 8 Life cycle of rice leaf growth analysis (see online version for colours)

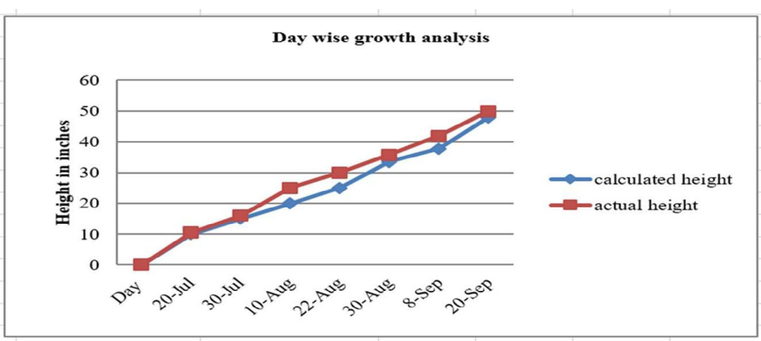


Figure 9 is the overall distance measurement of pixel values with different scales. Proposed technique is useful for both (centimetre range as well as inch format) the scaling pattern.

Figure 9 Height measurement of crop dataset in different scale (see online version for colours)

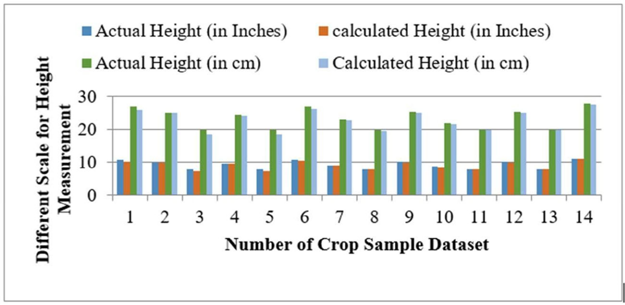


Figure 10 Height difference measurement of crop dataset (in inches) (see online version for colours)

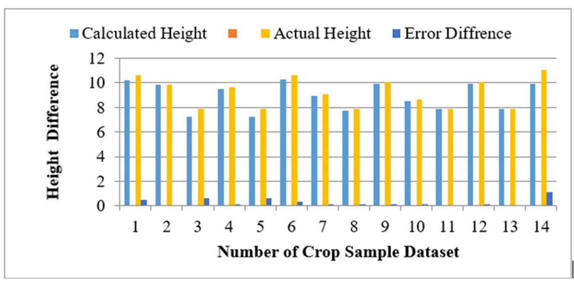
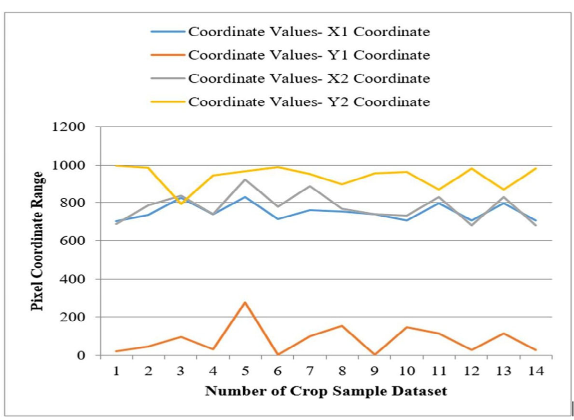


Figure 11 Pixel coordinate values (see online version for colours)



Accurate measurement of gathered data is a very challenging task and requires a complex hardware setup. However, the proposed approach as shown in Figure 10 results in a very low error rate (i.e., difference between actual and observed height of sampled dataset).

Less error leads to more accurate results. Growth analysis of rice crops is taken directly from the field through manual observation. But it's not possible to observe every plant for growth analysis. Image data is very effective for direct observation of real-time dataset for growth analysis.

Above experiments conclude that direct data observation is a difficult task for the whole field and the growth rate of each plant is also unpredictable. Proposed horizontal scaling technique overcomes this problem by average height calculation of given field crop, and vertical scaling technique improves the accuracy of the pixel distance calculation of plant dataset, though major differences have been observed in sampled dataset. Figure 11 gives observed pixel coordinate values for rice crop leaf.

Figure 12 Error percentage calculation (in inches) (see online version for colours)

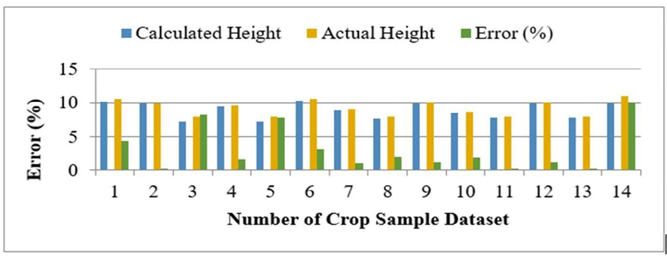


Figure 13 Accuracy percentage calculation (97.58%) (see online version for colours)

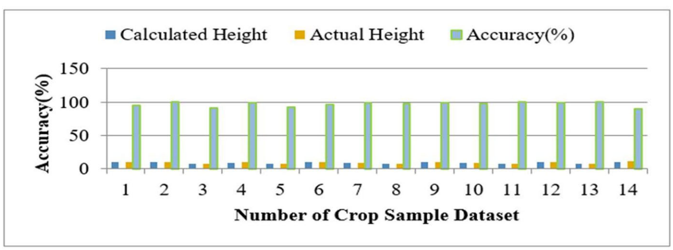


Figure 14 Comparison between actual height and observed height (see online version for colours)

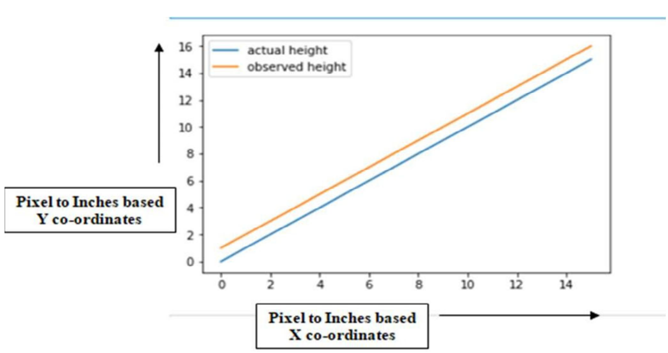


Figure 12 represents error percentage rate between actual height and observed height. Pixel based mapping technique provides more accurate results as shown in Figure 13. Accuracy is found to be 97.58% after the observation of calculated height. Figure 14 is the comparison graph and accuracy measurement of the proposed methodology.

6 Conclusions and future scope

On the basis of experiments and observations authors conclude that external features of a rice crop are significant to analyse its growth rate. Thus, image processing and machine learning techniques play a vital role for accurate data analysis. In addition, use of neural networks might prove an important area of future research in this field. Utilisation of neural networks will provide more accurate results for real-time data analysis. In present work, vertical image analysis is done, whereas a similar approach can be used for horizontal detection of pixel values-based image analysis. The efficiency and effectiveness of the proposed approach is advocated by the experimental results as it achieves an accuracy of 97.58%.

Future work is certainly required to perform horizontal scaling which will give more accuracy as compared to vertical scaling for the whole field. However, horizontal scaling technique for height calculation has the limitation of scale dependency for ground truth value. It provides an average height of every plant according to captured plant image and in vertical scaling single plant analysis gives the accurate value. The current research can also be extended to incorporate atmospheric conditions that affect plant growth by exploring advanced classification and clustering algorithms.

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