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Statistical Growth Analysis of Rice Plants in Chhattisgarh Region Using Automated Pixel-Based Mapping Technique

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ABSTRACT

The statistical growth analysis of field crop has become a great challenge in agriculture. Analyzing the growth of crop through automation provides extensive significance to the farmers for getting information about the problem arising in plants due to irregular growth monitoring. The idea behind this work is the importance of mapping with pixel-based clustering technique for growth analysis in terms of height calculation of rice crop (rice variety is MTU-1010). Height measurement plays a vital role in regular assessment for a healthy crop, and the approach proposed in this work achieves 97.58% accuracy of 14 sampled datasets taken from Indira Gandhi Agriculture University of Raipur, Chhattisgarh; a real-time dataset has been prepared. Proposed work is used for analyzing vertical as well as horizontal scaling technique. Vertical mapping provides the height of a single plant whereas horizontal mapping using k-means clustering provides an average height of the whole field. This work uses machine learning, and image processing techniques are used for this work.

KEYWORDS

Image Processing, K-Means Clustering, Leaf Growth Analysis, Machine Learning, Scale-Based Images, Top and Bottom Pixel Calculation

INTRODUCTION

The agriculture field has become an eminent research area for real data analysis combined with machine learning and computer vision techniques. Recently, the machine learning concept is expanded everywhere, including interdisciplinary applications. Some of the useful methods used by the researchers such as Support Vector Machine, Transfer Learning, Clustering, and Visualization Techniques. Specifically, computer vision co-relation with agriculture computes very high performance for statistical production growth of various crops. Rice plant is an important food grain for regular commentary, and it can be observed through height evaluation of plant data.

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The main contribution of the proposed work is: It exhibits plant phenotyping applications such as height measurement of a single and field plants by using pixel-based clustering technique. It is also useful for disease detection at an early stage of plant data by regular observation. The proposed scheme is a hardware-free technique that avoids the complexity of the calibration setup, and it gives an easy method to calculate the height with less time and error. The heterogeneous dataset is supposed to have more noise because of environmental effects, and this work resolves those problems by using a color conversion technique. It is more useful for the massive farming or field farming analysis by calculating average height, which is not yet implemented in recent works. The proposed approach provokes digitized evaluation of real datasets with less possibility of human error rate. The primary significance of this work is the utility of machine learning combined with the image processing technique. This proposed combination gives 97.58% accuracy from the previous growth evaluation results, e.g. percentage error of 17.25% for height calculation discussed by Constantino et al. (2015). Height calculation is implemented by many methods, such as skeletonization technique. The hardware detected red and green band technique proposed by Constantino et al. (2018) with ground truth data, contour-based masking technique and feature fusion-based approach (Patel & Sharaff, 2020). Furthermore, a short discussion is listed here according to plant phenotyping (Patel & Sharaff, 2019) for growth analysis of rice crop:

Influential Factors Related to Rice Plant

Rice crop life cycle is within 120 days from the plantation to the grain filling. There are many stages which have very influential factors for the growth production, such as germination seed quality analysis, Leaf emergence, Tiller observation, vegetation growth and panicle growth analysis, **Plant height observation,** Panicle dry weight analysis (Best approach for market growth prediction), Dark respiration, Grain fissuring analysis, and Biomass calculation (Cai et al., 2018), etc. There are many more rice production analysis methods, but most of the work is related to disease detection using image processing techniques. This method provides an automatic scale based observation called a pixel mapping technique exclusively for height calculation.

Study of Statistical Growth Analysis of Plant

Significance of the term statistical growth analysis of grain filling procedure comes under production rate analysis (Beadle, 1985).

$$Harvested\ Index = \frac{\text{Economical Yield Production}}{\text{BiologicalYieldProduction}} X100 \tag{1}$$

Equation (1) shows the overall production rate according to leaf growth analysis. The formulation for 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). Highest leaf or average height is directly proportion to plant growth. Some of the prescribed combinations of growth factors are as follows: plant weight (kg) and leaf area (m2) calculation, biomass calculation, panicle count, tiller count, per tiller spikelet count and evaluation of crop density function etc. classical growth analysis method shows the result of Relative growth rate (C), Unit leaf rate (E), Leaf area ratio (F), Leaf area index (L), Crop growth rate (C), Leaf area duration (D) and therefore according to leaf growth analysis, the yield prediction value is the product of Leaf area duration (D) and Mean Unit leaf rate (E). The classical analysis study shows the complexity of growth calculation whereas, the proposed work directly gives the result of leaf area analysis with the combination of plant height calculation.

Short Description of Direct Automation Technique

Direct automation requires the standard morphological features of the plants in terms of color, dimension, width, height, shape, and most crucial element is the plant's texture. Through these features, researchers can easily recognize the external changes. The pixel value is the essential part of the image dataset, and mapping the pixel value to the actual value gives accurate results for the crops' height calculation. Automatic height calculation needs automatic pixel detection with the respective values; therefore, scaled images are authentic and ground truth value to perform the direct automation pixel detection.

Distributed Workflow of the Proposed Work

Sections are divided according to their respective task; first module discusses the introduction. Second module is topic-wise literature review, and the third module is a methodology with its significance. The proposed model with result analysis has been discussed in the fourth module. Last part concluded the importance of this work and the future scope of the proposed method.

LITERATURE REVIEW

Plant phenotyping is a very vast area of research in terms of yield production. There are many phenotype applications out of which the researchers highly recommend plant growth monitoring and disease detection. Anilkumar & Sridharan (2019) has taken initiative for supply chain management over the recent computer vision techniques. There are many advanced techniques and tools available for field monitoring using complex systems in today's world. Genotyping is one of the examples of complex traits analysis approach towards production management. A list of other applications are mentioned as:

Statistical Growth Analysis Correlation with Environmental Changes

Basic requirements for crop growth analysis include climate changes, temperature, water assessment, stress analysis, and diseased plant detection (Kamilaris et al., 2017; Naugle et al., 2019). In this work, the author emphasizes most of the uncertainties and respective parameters for healthy growth, such as volume (V1), velocity (V2), variety (V3), veracity (V4), and valorization (V5). One of the most critical parameters is visualization (V6), which comes under the statistical growth analysis for the plant data. Pantazi et al. (2017) proposed an idea about visualization in terms of classes and features. Three most fundamental studies are, healthy plant analysis, nitrogen stressed investigation, and diseased plant analysis using a supervised learning approach. This approach requires a labeled dataset to classify the respective class according to its features. Korres et al. (2017) also took a visualization feature for rice production and abiotic/biotic stress calculation (García-Cristobal et al., 2015). An approach for climate change analysis affects the external feature changes of rice crops (Araus & Kefauver, 2018; Guo et al., 2021) through which it is easy to analyze the problem earlier. In conclusion, plant phenotyping is very efficient for maximum feature utilization of a real-time dataset.

Exclusive Effect of Temperature on Statistical Growth Calculation and Physiological Process of the Rice Crop

Dubey et al. (2011) described the effect of temperature on different parts of the plant as called physiological process; Initially, Germination of seed takes temperature between (15^0C to 47^0C), seeding growth (22^0C to 35^0C), tillering stage (25^0C), panicle appearance (30^0C to 35^0C) and so on. These stages require a high-temperature rate to grow appropriately. After tillering and panicle appearance, high temperature is not suitable for panicle dry weight, dark respiration, grain filling, grain quality, and grain fissuring. Observation is limited for the stage of leaf emergence. In Asaari et al. (2018), temperature, pressure, stress detection, ground soil, and moisture are essential factors for agriculture.

Method to analyze all the above values with low cost is possible through its physiological growth analysis (Sharaff & Roy, 2018). The plant's height is mostly dependent upon the environmental changes; therefore, some of the techniques are already automated for the yield prediction such as LiDAR sensor, machine learning (Laing et al., 2018), deep learning tools for statistical growth analysis of crops, and so on. According to Jimenez-Berni et al. (2018), height is one of the crop's essential physiological properties.

Importance of Growth Analysis for Early Disease Detection

Atole & Park (2018) has described healthy and unhealthy plant classification after the leaf emergence, and the Alexnet method gave 26.2% error rate. It is concluded that leaf appearance analysis is essential to fetch the diseased plant with its stage of occurrence. Leaf emergence is the initial stage for a plant growth cycle, whereas future growth can only be predicted by SWOT monitoring of field plants for sustainable agriculture (Mishra et al., 2021). For better leaf emergence, Height calculation is the only way to extract the leaves' features. Zhang, S. et al. (2020) has taken IOT based technique for diseased plant monitoring using k-means clustering. Li et al. (2018) found another way with three observed features represented as 3-D vector features: color, texture, and vein feature. Recently, machine learning techniques provide efficient results in terms of dimensionality reduction (Roy et al., 2021).

Importance of Growth Analysis for Regular Monitoring in terms of Deficiency Detection

Guma et al. (2018) has been discussed farmers' constraints for better food production. Such as ensemble learning for regular monitoring of food insecurity proposed by Lukyamuzi et al. (2020). (Soni & Singh, 2018) proposed the water-saving method for an irrigated field using the OFR reservoir and implemented with a setup on the area using a lined on-farm pool and pan evaporation meter.

Consequently, wastage of water during photosynthesis activity (time of leaf appearance) requires less water for crop growth. Like after panicle appearance and grain filling (improves grain chalkiness) requires less water. Rainfall water is uncertain according to environmental changes; therefore, water level analysis is also an area of concern for the production rate.

Statistical Growth Analysis to Avoid Hardware Complexity Using Recent Trends of Machine Learning Techniques

Field analysis requires proper setup between the instruments and ground crops. Some of the necessary arrangements are needed to be covered for the ground truth values such as; focal length of the camera, camera apertures, pixel size of the sensor, normalized disparity and average disparity of the ground level. But this method gives a ground depth estimation error called a mistake in disparity values. Direct height calculation is still challenging by the hardware setup. Another method is the use of sensors for controlling the surroundings like a rain gauge, tipping bucket sensor for sensing the water consistency, anemometer sensor for wind pressure and speed calculation, pyrometer sensor for solar radiation, flux density calculation, soil moisture sensor for the evaluation of the amount of moisture in the ground soil, temperature and humidity sensor for the weather forecasting etc. Consequently, this kind of setup is very costly, complicated, and for farmers, it is not so easy to understand. Therefore, hardware and sensor-based configuration are only useful for a vast field, but it requires knowledge about the devices' instrument and operations.

All the above concern indicates implementation of different techniques for the various problems. System complexity and time reduction is still a great challenge for the humanity (Kizito & Semwanga, 2020). Therefore, Tay et al. (2018) proposed statistical growth analysis of rice crop using Smartphone, is a successful example for small data analysis. Kamilaris & Prenafeta-Boldú (2018) discussed deep learning-based methods, such as CaffeNet, AlexNet, transfer learning, and different hybrid classifiers. Authors concluded that feature extraction is a keyword for the processing stage. Ubbens et al. (2018) accepted prominent features for plant leaf detection and another application of leaf counting methods using deep learning techniques. (Kuska & Mahlein, 2018; Bai et al., 2018) Plant dataset requires feature extraction techniques for better classification. One of the famously proposed applications of plant datasets is; multi-temporal type of data analysis. Deep learning is efficient for this type of multi-variant dataset, and applications come under the yield prediction (Cao et al., 2021), spike detection, genetic gain analysis, etc. Grain analysis includes counts of spikes per tiller and so on. Machine learning has various approaches for the massive dataset such as market-rate prediction (Sharaff & Choudhary, 2018) from the real-time dataset.

Statistical Growth Analysis as a Subsection of Plant Phenotyping Applications

Araus et al. (2018) has given a short explanation about genetic gain analysis, which is a crucial point for breeders to get good seeds. Breeders explore research for phenotyping analysis which comes under its external feature evaluation of the crops such as size, shape, color, variety of crop detection etc. whereas, genotyping is the chemical calculation for the combination of the crops. Phenotyping parameters include mean value, variance and standard deviation (square root of the variance/conflict). Choudhury et al. (2019) discussed recent advancement in image-based plant phenotyping in detail. Some of the related area for image-based phenotyping are: structural phenotype (2D, 3D), temporal phenotype and physiological phenotype. After this detailed discussion, it has been found that phenotyping is the most effective method for a variety of crops. Popat et al. (2018) initiated this statistical growth analysis approach for linear growth compared with the excellent seed quality analysis for a multisource dataset (Karamat et al., 2019).

Growth Analysis of Rice Plant Leading Other Phenotype Applications for Multiple Datasets using ML Techniques

Mohan & Gupta (2019) contributed one of the critical applications on plant dataset: the leaf chlorophyll estimation technique, directly shown by statistical growth measurement of a plant leaf. Concenço et al. (2019) also introduced a seed treatment (Cheng et al., 2019) method as an application for the evaluation of production rate. The proposed irrigation method enhanced the outcomes, same as applying nitrogen estimation status discussed by Sethy et al. (2019). One useful strategy is introduced by Konovalov et al. (2018) on the scaling technique that is very useful compared to others technique because of its regular detection-based analysis and data can be changeable according to the dynamic growth rate. In conclusion, inspiration came to make an automated model for farmers and normalize the real-time data evaluation. Machine learning has been explored for the listed dataset such as; Hyperspectral image analysis, Multi-temporal, Synthetic, Multispectral, Spatially-resolved spectral image implementation, Bitmap image gathering, Stereo scoping image, Optical image, Tomography vs. x-ray, Magnetic resonance vs. CT image, Ultrasound resonance imaging, Analog vs. Digital image analysis and so on. At last Gafi & Javadian (2018) have concluded that the modernization of production facilities is supposed to be the best strategy for the coming years.

METHODOLOGY

The methodology of proposed work is presented in Figure 1, which contains five sub-sections:
Step 1: image preprocessing module.
Step 2: object detection by using the ROI method.
Step 3: calculation of the coordinate values by using the mapping technique.
Step 4: conversion module from pixel to inch conversion or parameter evaluation using the per-pixel ratio method.
Step 5: The last subsection is result analysis between actual and calculated values. There is a list of processing steps for height calculation involved some segmentation atoms and extraction of features, followed as; Flowchart design of the proposed work:

Figure 1. Methodology of Proposed Work

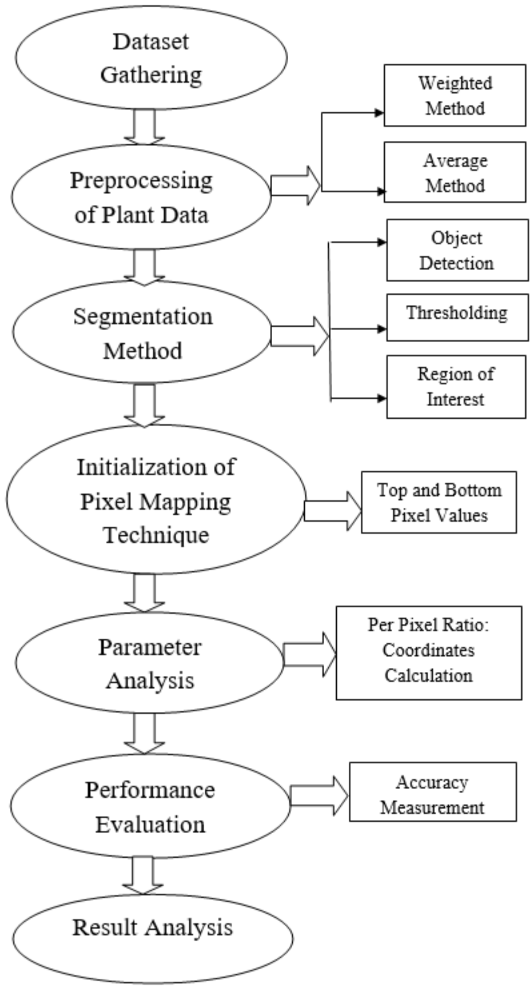


Image Preprocessing

Pre-processing aims to remove the physical phenomena. Two methods are introduced to change RGB scale images into grayscale images, which are as follows: Weighted method and Average method; these two methods show the intensity value of the given image. Scalar value-based image dataset is grayscale images.

Weighted Method

In this method, different wavelength value of colors and percentage contribution is made in the images in short called as a color conversion method. All the shades have their various contributions, which are all about 33.33% of the pictures.

$$Grayscale\ \ image = \left(\left(0.3 * \mathrm{Re}\,d\right) + \left(0.59 * Green\right) + \left(0.11 * Blue\right)\right)$$

Average Method

The average method is the simplest and commonly used in the preprocessing task. All the color wavelengths are designated to get the average of the absolute wavelength values of three colors.

Gray scale image = (Red +Green +Blue)/3

Segmentation of the Processed Dataset

Segmentation of an image extracts the features of the images. Dhanachandra & Chanu (2020) discussed the segmentation method of fuzzy c-mean combination with particle swarm optimization technique. This proposed hybridization method improved the accuracy of synthetic and real datasets. Segmentation is an essential part of noise reduction. It considers each pixel as a point of observation, and segmentation has a list of works which are as follows:

Image Resizing

It defines image resizing. The original image size is 3456x5184 in the proposed work dimension, but the image size is reduced to 512x512 in dimension for further analysis.

Color Balancing Technique

This technique distinguishes the object from its background. Assuming an appropriate threshold value 't' changes the image's color, it makes recognition and simplification easier and reduces the data complexity.

Region of Interest (ROI)

Region of Interest shows the focused object for the experiment. Multiple areas are supposed to ROI according to the mapping of the features gathered from the preprocessing steps. They use some specific functions such as circle or polygon, which are highly recommended to crop the area. Another way is "ROI creation classes", such as the image.ROI.Circle or Image.ROI.Polygon. The Region of Interest classes supports different properties, functions, and incidents that can be used to normalize the behavior of the ROI based levels. The use of an ROI is a masking technique.

Coordinates Calculation of Processed Dataset

In this section, coordinate values are calculated using data lines (mark as upper coordinates and lower coordinates). Figure 2 shows X and Y coordinate values for the sampled plant data. A pixel value of plant data is used to calculate the object coordinate values.

Coordinates Conversion Technique

Pixel to inch conversion requires assimilating with some values. Manually, the pixel value is fixed for per pixel inch value. According to ROI, an object can detect the pixel values from top to bottom and then calculate the distance between the pixels; after that, conversion of inch format for height measurement is implemented using mapping technique.

In Figure 2, the distance between pixels is calculated and converted into an inch format. The experimented image outcome is shown: e.g., distance in 903.66 pixels is equal to 9.4 inches. Figure 3 and Figure 4 show the experimental plant dataset. In this work, RGB images (Originally captured images) are taken for the result analysis.

Figure 2. Region of Interest (Top and Bottom Pixel Value)

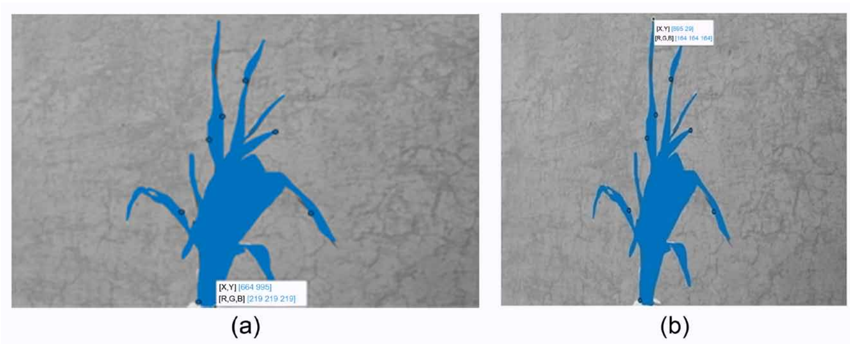


Figure 3. Experimental Plant Dataset Using Pixel Mapping Technique

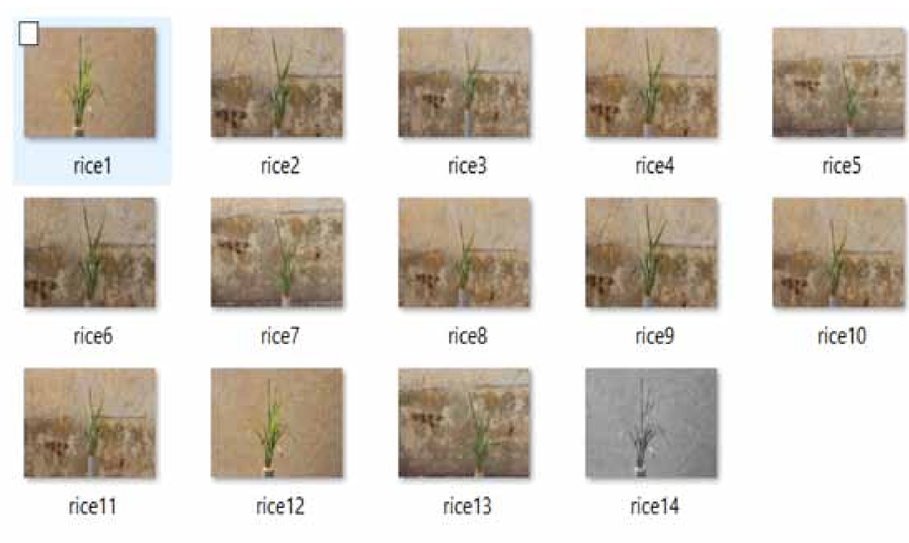


Figure 4. RGB Color Image

EXPERIMENTAL ANALYSIS

Dataset has more than 50 plant data images with different heights. In this work, growth percentage is estimated using the mapping technique. Concern area of making benchmark dataset is, captured images should have less noise. The proposed work described the noise reduction technique in preprocessing steps. It is a scale conversion of plant dataset for quality improvement, and the next task is exhibiting this purpose.

Dataset Gathering

In the proposed work data has been taken from the University of Indira Gandhi Krishi Vishwavidyalaya, Raipur, a reputed educational organization amongst the other colleges and working towards a better future of Chhattisgarh farmers. It was established on 20th January 1987 as a branch of Jawaharlal Nehru Krishi Vishwavidyalaya, Jabalpur.

Result Analysis Using Weighted Method

Figure 5 defines the leaf analysis of the rice crop, and the list of outcomes is shown in the result section. In grey image analysis, the estimated value contains more error than original value: Original value for 8.91 inches = 22.63 cm, whereas the calculated value is, 22.21cm.

Figure 5. Scale Based Object Detection in Grayscale Image (with Scale Mapping)

Experimental Growth Analysis Using Vertical Scale-based Pixel Mapping Technique

In this section, plant data is directly taken from the field using a DSLR camera with high resolution. The scaling technique provides the normalized value for the given list of the experimented images shown in Figure 6.

Figure 6 shows the evaluation of pixel to inch conversion using a scale-based mapping technique; the evaluated result is shown as- 678.55 pixels 7.06 inches =17.93cm. It is imparted with less error rate between actual and observed leaf height. In every image, top and bottom pixels are calculated in the centimeter scale. In Figure 6, the color-based mapping technique is experimented, and observed height is closer to the actual size. In comparison with figure 5 (grayscale image), it seems to be more error rate.

Experimental Growth Analysis Using Horizontal Scale-based Pixel Mapping Technique

This section describes that field data analysis is difficult by ordinary eyes. Some automation technique is required to regulate the images for the real-time application of statistical growth analysis. The field crop's average height calculation is analyzed in the proposed work instead of a single plant height measurement.

The Proposed Algorithm

Proposed Algorithm describes the real time data analysis by using machine learning technique. 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 will be calculated for the whole field.

Figure 7 expressed the outcome of the proposed algorithm. The scale is placed in the given image, through which the leaf extracts the same pixel distance (vertically and horizontally). It will provide a range of pixel values and the extracted result represents the top and bottom of the pixel values. Proposed algorithm offers the automated average height measurement of the given field using horizontal scale analysis for the field crop.

RESULT AND DISCUSSION

In this proposed work, vertical and horizontal pixel values are computed to apply the pixel mapping technique. It is challenging to normalize the object's value according to the desired value in a real-time dataset. The proposed work contains novelty by taking the original field dataset for the experiments with normalized value.

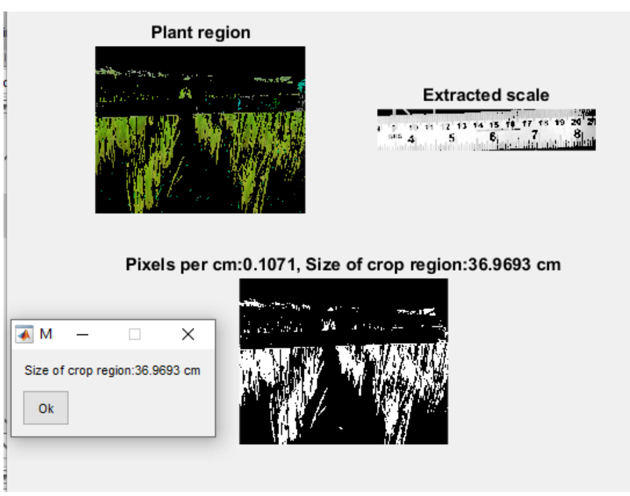
Figure 6. Scale Based Object Detection in Color Image

(a) (b)

Algorithm 1. Rice crop growth analysis using horizontal scaling technique

Step 1: Making Dataset Ready:
a. Take input Plant dataset from the open field.
Step 2: Clustering Technique: Apply K-means to Divide the Image into 2 Clusters:
a. Find the leaf cluster, which has the greatest number of green pixels;
if $Count\_G = 0$, **then**
Do this
For r as each row in current cluster,
For c as each column in current cluster;
b. Find R, G and B of this pixel;
if $G > R$ & $G > B$, **then**
Do this
Count_G++;
c. Repeat the loop for each of the clusters, to get Count_G1 and Count_G2;
if $Count\_G1 > Count\_G2$, **then**
Do this
Cluster 1 image is the leaf portion,
Else
Cluster 2 is the leaf portion;
d. For the non-leaf cluster, find the pixels which match the measuring scale's grey level.The grey level of the measuring scale is generally between 100 to 150;
For r as each row in non-leaf cluster,
For c as each column in non-lead cluster,
e. Find R, G and B of this pixel
f. Convert the pixel to grey
If Grey level is between 100 to 150 then,
Put this pixel at the output;
Step 3: Identification of ROI and Segmentation:
a. From all these pixels, find the area of the image which has the highest number of pixels,
b. Segment this area, and mark it as the measuring scale;
Step 4: Initialization of Pixel Mapping Technique:
a. Find the width of the scale, and the number of pixels on the scale,
b. Divide them to find the ratio of pixels per cm,
Step 5: Growth Analysis:
a. Find the number of pixels of plant growth, and divide the number of pixels with the factor, to get the growth in terms of cms;
Step 6: Result Evaluation:
a. Evaluating growth analysis using direct automation technique.

Figure 7. Horizontal Scale-Based Plant Data Analysis Over the Field Crop



Result Analysis and Comparison Table

Proposed pixel calculation gives an accurate height of the plant for color images; therefore, this work shows the simple measure of per-pixel height calculation. Given images have top and bottom pixel values, which are indicating their coordinate values. Pixel distance calculation can perform through coordinate values only. Fourteen images are taken as a sample image for coordinate analysis shown in Table 1. Height is calculated using the vertical/horizontal scaling technique, and a comparison is performed in terms of the difference between actual and observed size. Error rate calculation defines the maximum difference rate between exact and experimental measurement. As an outcome, after implementing the proposed technique in terms of accuracy, evaluation has performed using computer vision technique.

Accuracy and Error Rate Calculation

Distance Calculation

$$P1 = \left[X1, Y1\right], here\ \ X1 = P1\left[0\right] and Y1 = P1\left[1\right]$$
$$P2 = \left[X2, Y2\right], here\ \ X2 = P2\left[0\right] and Y2 = P2\left[1\right]$$
$$Pixel\ \ Dis\tan ce = Sqrt\left(\left(P1\left[0\right] - P2\left[0\right]\right) * *2\right) + \left(P1\left[1\right] - P2\left[1 * *2\right]\right) \quad (2)$$

In this section, coordinate values are calculated in terms of P1 and P2 for the given plant dataset. Whereas pixel distances of co-ordinate values are calculated from equation (2) by the pixel value representation.

Pixel to Inch Conversion:

$$H = Pixel\ \ Dis\tan ce$$

Table 1. Accuracy Measurement with Error Rate Calculation

Input Image	Calculated Pixel Values(H)	Calculated Height(in cm)	Calculated Height in Inches (H_inch)	Actual Height (in cm)	Actual Height (in inches)	Co-ordinate Values				Error E (%)	Accuracy of the Proposed Work (%)
						X1	Y1	X2	Y2		
riceg1	976.062	25.824	10.167	27	10.629	701	19	690	995	4.34	95.66
riceg2	942.435	24.935	9.817	25	9.842	734	45	786	986	0.254	99.746
riceg3	694.103	18.364	7.230	20	7.874	825	98	837	792	8.178	91.822
riceg4	911	24.102	9.489	24.5	9.645	738	32	738	943	1.61	98.39
riceg5	696.646	18.430	7.256	20	7.874	828	275	924	965	7.848	92.152
riceg6	988.273	26.146	10.294	27	10.629	713	1	780	987	3.151	96.849
riceg7	859.843	22.748	8.956	23	9.055	762	99	885	950	1.093	98.907
riceg8	741.151	19.608	7.720	20	7.874	753	155	768	896	1.955	98.045
riceg9	953.000	25.214	9.927	25.5	10.039	738	1	737	954	1.115	98.885
riceg10	816.352	21.597	8.503	22	8.661	707	146	731	962	1.824	98.176
riceg11	754.721	19.966	7.861	20	7.874	795	115	828	869	0.165	99.835
riceg12	952.411	25.196	9.920	25.5	10.039	708	29	680	981	1.185	98.815
riceg13	754.721	19.966	7.861	20	7.874	795	115	828	869	0.165	99.835
riceg14	952.411	27.736	10.920	28	11.023	708	29	680	981	0.934	99.066

$$H\_inch = H / 96 \tag{3}$$

Where, H variable shows the calculated pixel value of the detected plant object, and H_inch variable shows an inch conversion variable from pixel value to inch value to measure the plant growth. There are given formula (3) is an inch conversion method for the single plant object.

Error Calculation

$$\begin{aligned} &Caculated\ Height\ in\ inches = H\_inch \\ &Maximum\ Height\ in\ inches = M \\ &Error\_Percentage\left(E\right) = \frac{\left(\mathrm{M}\right) - \left(\mathrm{H\_inch}\right)}{\left(\mathrm{M}\right)} 100 \end{aligned} \tag{4}$$

In this section, calculated and original height has significance for error percentage calculation. Equation (4) shows the error rate percentage of applied technique for different image formats based on the actual and observed value of the respective plant dataset.

Accuracy Calculation

$$Accuracy\left(\%\right) = 100 - Error\_Percentage\left(E\right) \tag{5}$$

Equation (5) represents an accuracy percentage which is calculated by the error percentage rate.

Average Accuracy Calculation

$$\begin{aligned} &Average\ Accuracy = \frac{\sum \mathrm{Accuracy}\left(\%\right)}{\mathrm{Total\ Number\ of\ Sample\ Images}} \\ &Average\ Accuracy = 97.58\% \end{aligned} \tag{6}$$

Equation (6) is the final equation for the accuracy calculation of the given data set. Highest accuracy is achieved by proposed technique as 97.58%, resulting from all the color-based rice crop dataset.

Graphical Representation of Experimental Results

Result section (Table 1) represents growth rate analysis by projecting error percentage on 14 sampled datasets. Figure 8 is the height measurement of the rice crop, which shows the height measurement by ruler scale. It is graphed with day-wise rice crop growth analysis (The rice crop's life cycle is approximately 120 days to get mature stage). Figure 9 is the overall distance measurement of pixel values with different scales.

Accurate measurement of gathered data is a very challenging task without using complicated hardware setup; therefore, according to the proposed technique, figure 10 represents high accuracy and less difference between the actual and observed height of sampled dataset. A less error difference graph represents a more accurate result. The major significance of image data is; it proves direct observation of real-time dataset analysis with high efficiency.

Next section concludes the graphical representation of coordinate values. Direct Data observation is a difficult task for each plant of the whole field, and the growth rate is also unpredictable. The proposed horizontal scaling technique overcame this problem by average height calculation of the

Figure 8. Life Cycle of Rice Leaf Growth Analysis

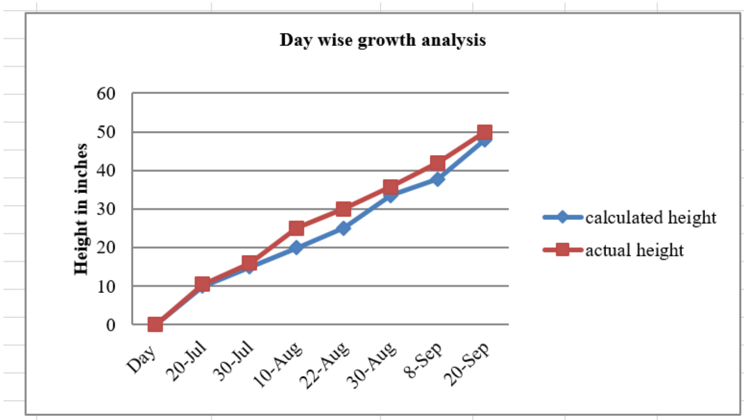


Figure 9. Height Measurement of Crop Dataset in Different Scale

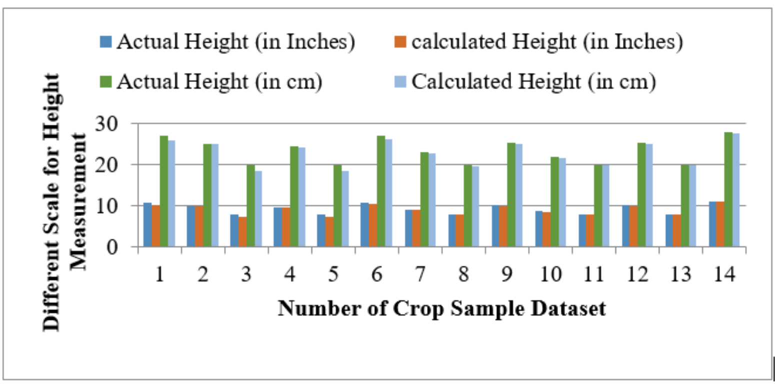
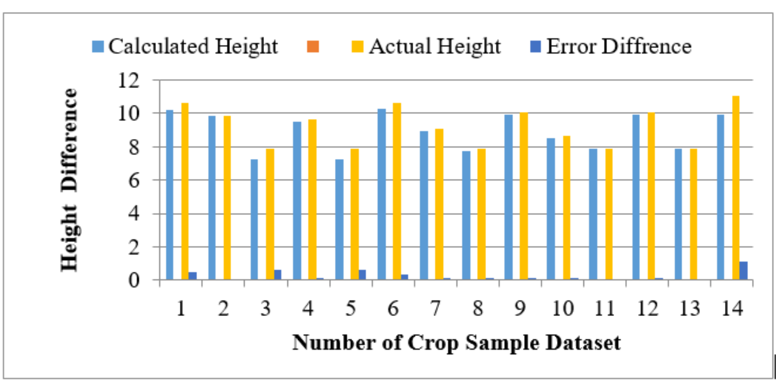


Figure 10. Height Difference Measurement of Crop Dataset (in Inches)



given field crop. Proposed vertical scaling technique improves the pixel distance calculation method's accuracy from the plant dataset, despite significant differences observed in the sampled dataset. Figure 11 gives pixel coordinate values for rice crop leaf observation.

Figure 12 represents the error percentage rate between actual and observed height. Pixel-based mapping technique provides a more accurate result which is expressed in Figure 13. Accuracy of the given observation is found 97.58% after the observation of a calculated height. Figure 14 concludes the comparison graph and accuracy measurement of the proposed methodology.

CONCLUSION AND FUTURE SCOPE

Due to the rice crop's heterogeneous property analyzing the growth rate measurement of the real-time dataset has become a crucial task. The combination of image processing and machine learning techniques play a vital role in proving accurate data analysis. In this work result shows vertical image data analysis done well for a single plant of a rice crop. In contrast, another application is

Figure 11. Pixel Coordinate Values

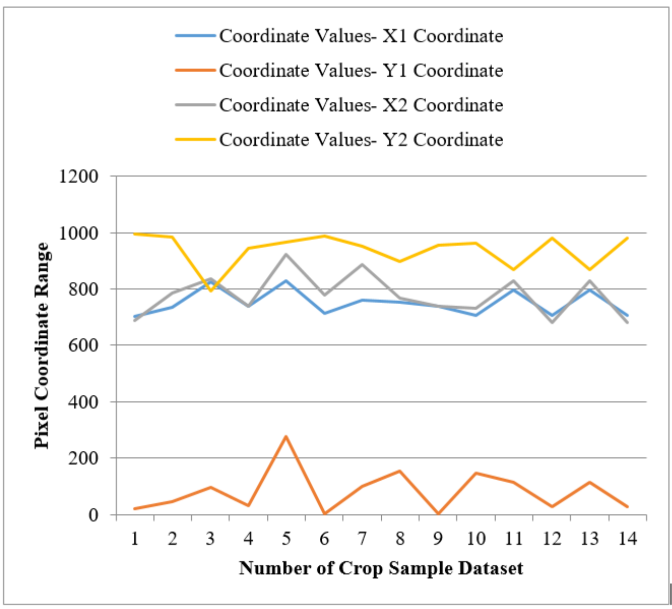


Figure 12. Error Percentage Calculation (in Inches)

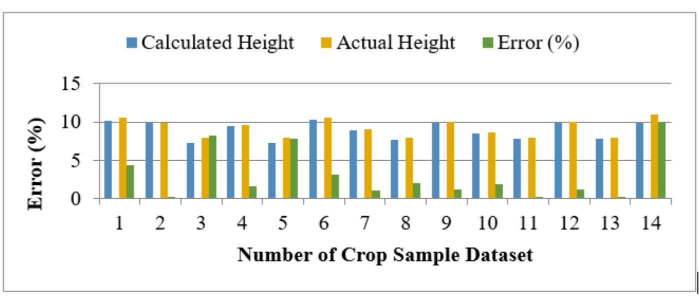


Figure 13. Accuracy Percentage Calculation (97.58%)

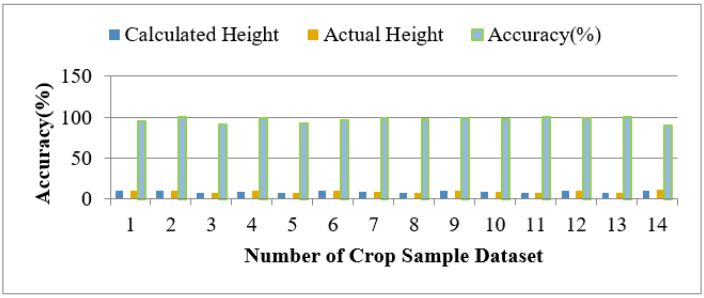
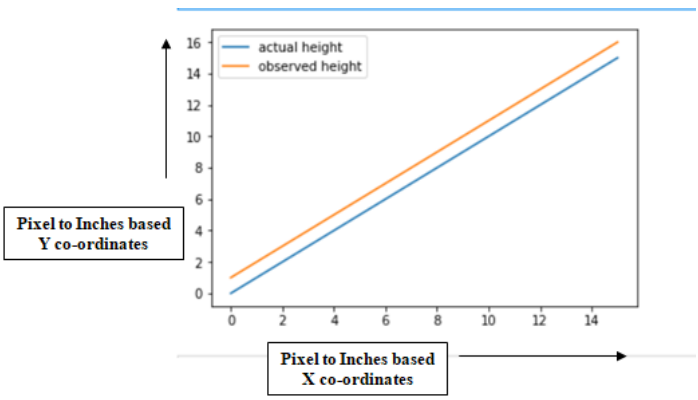


Figure 14. Comparision Between Actual Height and Observed Height



implemented, called horizontal detection of pixel-based image analysis. Horizontal scaling provides more accuracy than vertical scaling for the whole field because the dataset has color and height variations. The scaling technique for height calculation has some limitations, such as reference point is necessary for the growth analysis. Although, the proposed method is providing an average height of every plant. Whereas in vertical scaling, accurate values are only for a single plant data. Hence, the proposed work can be used as plant phenotyping automation application for rice crop statistical growth analysis more precisely and accurately. The utility of the neural networks as a future work for this application of plant phenotyping.

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