gCrop: Internet-of-Leaf-Things (IoLT) for Monitoring of the Growth of Crops in Smart Agriculture

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***Abstract*—Proper growth of a plant is an important parameter for plant status, crop yield and its quality. Traditional methods of analysing the ideal growth and development of crop often are estimation and the farmers intuition. This paper presents a smart solution, gCrop to monitor the growth and development of leafy crops and to update the status in real-time utilizing the IoT, image processing and machine learning technologies. Leaves are readily available and disposable component which could significantly help in analysing the health, environment and maturity of the crops. The gCrop system consists of a smart camera system which would identify the leaf as an object, calculate its dimensions and statistically analyse the measurements correlating with the species age and maturity and predict the same as the ideal conditions. A computer vision algorithm runs on the backbone of the Internet of Leaf Things (IoLT) based gCrop system to calculate the growth patterns of the leaves in real-time. The model shows a great potential with an accuracy of around 98% to predict the growth of the leaves. Thus, it is promisingly expected that this system will effectively contribute in strengthening the current farming practices by ensuring the quality of the crops and improving the production yield.**

***Index Terms*—Smart Agriculture, Machine Learning, IoT, Computer Vision, Plant Growth.**

I. Introduction

With the foreseen increase in global population predicting to exceed nine billion by 2040, food production is a major challenge. Further effects of climate change, reduced water supplies in many regions, and the environmental impacts of intensive plant and livestock production are aggravating the situation. The Food and Agricultural Organization of the UN (FAO) also states that producing more food with less natural resources is a challenge of the future. The usages of smart sensors and information and communication technology (ICT) in agricultural field are converging into smart farming, which includes the smart and precision farming.

In productive agriculture system the growth monitoring of crop is a significant factor. It is often only the farmers understanding, through trial and error and intuition that goes into the process. However, in precision agriculture to maximize the efficiency, a more stable and reliable system is required for measuring the growth of plants. The accurate measuring of growth status of plants will help to optimize the required fertilizer level, time of usages of fertilizer and further control the water and other environmental conditions. Leaves are a readily available and disposable component which could significantly help in analysing the growth, health, and maturity of the leafy crop to improve the yield [1]. Pre-existing traditional techniques include measuring the Leaf Plastochron Index (LPI) of the leaves and correlating the age and growth of the plant based on its length [2]. The LPI is a logarithmic function with the length and index of the leaf from the bottom as its parameters, and has been tested and proven fairly accurate in determining age in Lycopersicon Esculentum, a species of Tomato [2]. However, the present technique still relied on manual precise measurement of leaves dimension, and extensive labour, which is a problematic given that the size of work is enormous. Growth monitoring can be idealised the same way, where the system can detect the growth patterns of crop based on its ideal factors and conditions such as fertilizer control, effects of water and temperature, etc. With algorithms efficient enough to replace the human eye and machines capable enough to compute information in milliseconds, it is a solution to a plethora of problems.

The present work proposed a smart model, gCrop which provides a solution to this problem by analysing leaves with a smart IoLT (Internet of Leaf Things) system. The grow-log system consists of a smart camera system which would identify the leaf as an object, calculate its dimensions and statistically analyse the measurements correlating with the species age and maturity and predict the same as the ideal condition. A computer vision algorithm running on the backbone of IoLT based gCrop system calculates the growth patterns of the leaves in real-time. The model shows a great potential in maintaining the quality of the crop and helps in improvement of yield.

II. Related Work

Smart and precision agriculture, and shortage of people engaged in agriculture sector demand agricultural automation with extended feasibility of applying and controlling the fertilizer, water and other environmental factors both in poly-house farming and open-field farming. In this context, IoT and AI are becoming the potential technologies as a part of automation. The term IoT refers connect, integrate and analytic. IoT offers integration of several physical objects, equipped with sensors, electronics with cloud space via standard communication protocols without human intervention. Similar ideologies have already been put into practice in the agriculture areas, such as monitoring plant stress [3] and several disease detection models [4]. Similarly, some IoT based systems exist to monitor crop in greenhouses [5] and predictive analysis [6].

In recent years, stereo vision has drawn much attention for nondestructive and an effective way to determine external plant features [7], [8]. A computer vision algorithm will classify the leaf, calculate its dimensions and use a machine learning algorithm for the predictive analysis of its growth in terms of age. The advantage of this method is its cost efficiency and the increase of accuracy the more it is used or trained. Similar models have been implemented, as touched upon earlier for disease detection in plants [9]. Most of these available techniques depends on sufficient images of plants and they are high power consuming, which is challenging in a resource constrained environment like on-filed farmers. As per the author's knowledge, there exists limited literature and ideation considering low power consuming model to effectively monitor growth of plants. Therefore, we require a cost effective, low power consuming and accurate (with a steady increase with time) system for automated monitoring and predicting the growth of plants.

III. The Proposed Novel Methodology

A. System Overview

The proposed model setup would consist of a smart camera combined with an ultrasonic sensor as shown in Fig. 1. The camera would use simple object detection algorithms to detect the canopy and segment out an image of a singular leaf for further processing. The ultrasonic sensor, upon identification will measure the distance between the camera module and the object (leaf) for dimension measurement calibration. The image is sent to a cloud server where it is further processed under computer vision algorithms to measure the dimensions in a pixel per metric format. This is later calibrated with the distance measured, and if the angles are varying they are

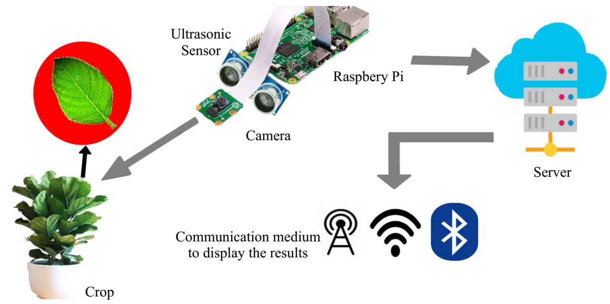


Fig. 1. Overall concept of the proposed IoLT system

accounted for. Thus returning the length, width and area of the sample leaf. This is later fed into the machine learning model of the species, which contains its prediction model based on a training set of observed growth patterns with said dimensions. Age of the leaf is returned in days, under ideal conditions. This information can be used to diagnose problems and monitor the crop with little to no human supervision.

B. Dimensional Analysis

The capture leaf image once sent to the server, a dimensional analysis algorithm as described in Algorithm 1 further processes it. We have used OpenCV, platform for processing the images. Figure 2 shows the block diagram of estimating leaf contour using image analysis. The image is saved in RGB (Red, Green, Blue) format as a 3 element array of matrices with each matrix containing a 'shade'index ranging from 0 to 255. This image is later grayscaled, which makes processing easier as there is now only one matrix to work with. Further, the image is blurred to remove the noise that make the process random. Finally the image is 'thresholded', to further simplify the image. Each pixel is classified into two binary classifications, making it a matrix of two elements which is efficient to process. The whiter parts of the grayscaled image are turned to complete white and vice versa for the black parts. A threshold index is specified, which can be altered to improve accuracy in cases where picture quality might not be the best.

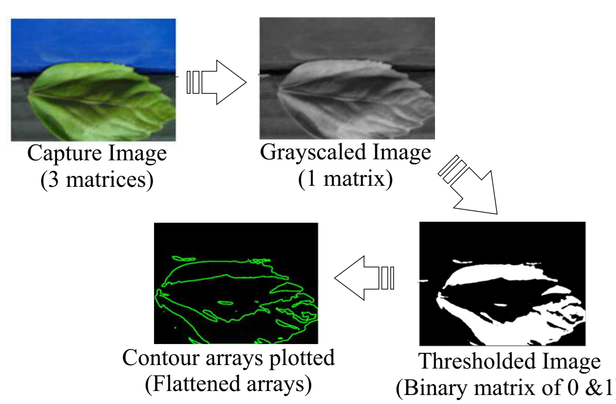


Fig. 2. The conceptual block diagram of estimating leaf contour using image analysis

Algorithm 1 Dimensional analysis

Require: a : contour[0], b : contour[1], m, n : image dimension
  for $x = 0, \quad y = 0$ **do**
    if $(x, y \in a, b)$ **then**
      $x_{min} \leftarrow x$
      $y_{min} \leftarrow y$
      break
    end if
    $x++, \quad y++$
  end for
  for $x = m, \quad y = n$ **do**
    if $(x, y \in a, b)$ **then**
      $x_{max} \leftarrow x$
      $y_{max} \leftarrow y$
      break
    end if
    $x--, \quad y--$
  end for
  print $x_{max} - x_{min}, \quad y_{max} - y_{min}$

Now, using the Algorithm 1 in OpenCV, contours are drawn and stored in arrays. Each array contains a list of points on the image where the edges are detected, creating a neat outline of the leaf. The coordinates of the left and right ends are stored. Using the two end points, we measure the length in pixels, which is directly correlated with the age.

C. Age Prediction

A linear statistical dataset has been prepared using the data obtained from the graphs [10] with the help of graph value mapping software. Since the leaves grow in accordance to their index from ground up, 9 separate datasets have been prepared. The leaves at the tip of the plant grow slower and the ones at the bottom grow the fastest. The index is specified by the models user. A third order polynomial regression curve is fitted in the recorded data. Further, since the predictions will be all done within the spectrum it isnt a problem if the curve overfits the data. The same succession index is also an input in the LPI (Leaf Plastochron Index). Figure 3 shows sample of dataset preparation from available data of tomato leaf growth. The PI and LPI were calculated according to the formula described by Erickson and Michelini (1957) [11]:

$$PI = n + (logL_n, -log10)/(logL_n, -logL_{n+1}) \tag{1}$$

$$LPI_a = PI - a \tag{2}$$

where n is the serial number of that leaf (counting from the first true leaf above the cotyledons) that first exceeds 10 mm in length, $logL$, is the log length (in mm) of leaf n, $logL_{n+1}$ is the log length (in mm) of leaf n + 1, $log10$ is the log reference length (i.e. 10 mm), and a is the serial number for any given leaf on the shoot apex. Algorithm 2 has been implemented to predict the growth of leaf and subsequently, the growth of crop.

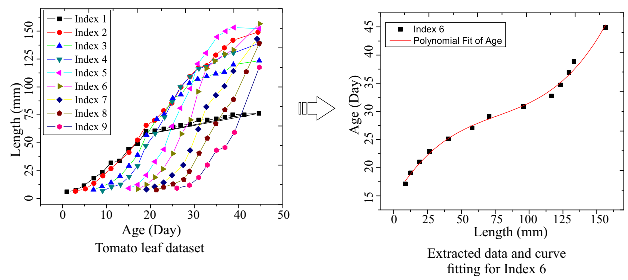


Fig. 3. Dataset preparation from available data of tomato leaf growth [10]

Algorithm 2 Growth analysis of leaf

Require: $ap : append, deg : degree3curve,$
  $da \leftarrow dataset$
  for i **do**
    $x \leftarrow ap(da[i][0])$
    $y \leftarrow ap(da[i][1])$
  end for
  $Input(num) \leftarrow Successionofleaf$
  $num \leftarrow num - 1$
  $fit_{curve} \leftarrow PolynomialRegression(x, y)$
  $poly_{fit} \leftarrow deg(fit_{curve})$
  $Age \leftarrow predict(poly_{fit})$

IV. Results and Discussion

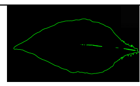
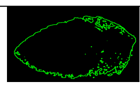
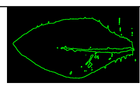
In the present study, the entire extracted data from [10] has been splitted 80:20 ratio for training and testing of the system. Leaves are indexed as 1-9 based on leaf placement on plant from bottom to up as described in Fig. 3. Table I summarizes the accuracy of the gCrop for all these leaf indices. The results shows that higher indexed leaf suffers from lower accuracy of 90%. It infers that the leaves closer to the ground are ideal as the growth rate is strongly mathematically correlated and as succession index increases, there is lesser growth measurement accuracy. In a premature leaf, the growth is mathematically related with the length and they follow an exponential curve which turns into a basipetal one towards maturity. After this stage, the leaf loses its chlorophyll content and develops yellow spots, which can again be measured using a similar algorithm to loosely predict time of fall. The extracted data was cross verified by observation and the values were fairly accurate. The accuracy of the program can be improved by not scaling the image to 20% of its size as done in the algorithm, however the purpose that served was reducing computational power.

The model was further applied to predict the dimension of randomly available leaves of different crops without manual measurement. Table II shows that the predicted dimension exhibits a very good accuracy in measuring the length of the leaves. In this case the actual length was measured by manual scale-tape, which suffers from human error, accuracy. The gCrop system was subsequently applied on the available dataset of tomato leaves to predict the growth of it [12]. Figure

TABLE I
ACCURACY OF GCROP SYSTEM FOR PREDICTING THE GROWTH

Index (leaves: bottom to up)	Accuracy (%)
1	97.95%
2	97.79
3	94.08
4	95.05
5	93.88
6	96.41
7	91.70
8	91.04
9	90.89

TABLE II
DIMENSION PREDICTION OF DIFFERENT LEAF WITH ACCURACY

Captured Image	Processed Image	Actual length (cm)	Calculated length (cm)	Accuracy (%)
		15.25	15.22	99.80
		8.6	8.443	98.17
		6.55	6.507	99.34

4 depicts the comparison of the predicted growth based on our proposed techniques along with the actual data available in [12]. The initial study shows a good agreement with actual growth. However, due to unavailability of sufficient datasets the results lacks to capture the growth phase of longer times. It is also to be noted that in actual scenario the system will be handheld and during capturing the image a group of similar leaves may make the process complex. In that case a image segmentation process [13] will be applied to identify the targeted leaf and subsequently the dimensional and growth analysis will be performed on that targeted leaf image. Further, since the proposed system depends on only edge prediction based on machine learning trained model, the overall power requirement is less.

V. CONCLUSION

The paper presented the an IoT based leaf growth measurement system, gCrop utilizing computer vision and machine learning technique. The system utilizes low-powered training model, which can be utilized in resource constrained environment. The system at first identify the dimension of leaves and then predicts the age of the leaves. The results indicates that the proposed system can measure the dimension with accuracy between 98-99% based on different stages of leaves. Further, the initial results of age prediction also shows a good agreement with actual growth of plants. However, due to unavailability of sufficient datasets the results lacks to capture the growth phase of longer times. The future work includes to create a datasets of different crops and further

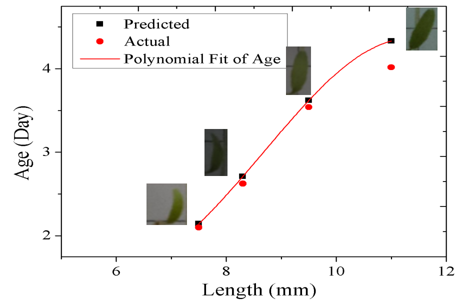


Fig. 4. Predicting the growth of tomato leaves. Black dots, dark red line and red dots represent the predicted age, regression prediction line and actual validation data [12]

validate the model. Overall the system will help to develop smart agriculture system to identify plants health condition, proper growth, time of maturity and subsequently, adjust the necessary amendments of watering, soil fertility, etc.

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