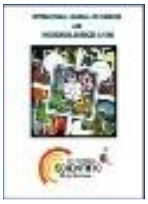
International Journal of Chemical and Biochemical Sciences

(ISSN 2226-9614)



Thermal Imaging Based Plant Growth Estimation and Yield prediction Using Deep Learning -A Systematic literature review

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Abstract

This study provides an overview of image processing strategies for extracting major plant development metrics from thermal and spatial data that have been suggested in the literature. Crop canopy cover, above ground biomass, leaf area index (including green area index), and growth stage are the descriptive crop growth indicators studied. The article provides an overview of basic image processing methods such as colour spaces, colour indexes, and picture segmentation. Crop growth measures are specified in detail. The study highlights shortcomings in image processing systems for cereal crop monitoring, such as sensitivity to lighting conditions, camera orientation, and self-obstruction. Future research directions to increase performance are indicated.

Keywords: Leaf area index, canopy cover, above ground biomass, Image Processing

Full-length review article *Corresponding Author*, e-mail: nbankhele.7777@gmail.com

1. Introduction

Agriculture is one of the most significant aspects on which mankind depend. The United Nations has included a goal in its 17 sustainable objectives to promote sustainable agriculture in order to produce enough food for everyone, with the goal of eradicating hunger [1]. One of the aims is to enhance crop production and plant breeding efficiency so that more than nine billion people's food needs can be met by 2050 [2]. Height is a significant trait for assessing how much a plant has grown, as it also determines how much product the plant will be able to deliver. A plant's height may be measured in numerous ways, including the depth of the root system, the surface area of individual leaves, the distance from the lowest root point to the tallest plant point, and the distance from the soil level to the top of the plant. Also, biological features like as protein and cell wall production may be evaluated to determine how much the plant is growing [4]. Because the root system is difficult to measure because it is underground, and protein extraction and cell wall analysis need a lab, the quickest technique to assess a plant's height is to measure its height above ground [3], [4]. Manually measuring anything is generally time consuming, boring, and monotonous. Such duties are often disliked by humans, who prefer to make the most of their ability. To avoid having to do time-consuming and costly labor, the work must be judged outdated or automated. Because measuring the height of plants cannot be considered outdated, it must be automated.

Thermal remote sensing is a subset of remote sensing that focuses on the collection, processing, and interpretation of data obtained largely in the thermal infrared (TIR) part of the electromagnetic (EM) spectrum [5]. Thermal remote sensing differs from optical remote sensing in that it monitors emitted radiations from the target item's surface, while optical remote sensing measures reflected radiations from the target object [6]. Plant leaves' thermal characteristics are influenced by a complex heterogeneous interior structure that includes a specific quantity of water per unit area. As a result of the variety, precision, and high resolution of infrared thermography, it is feasible to conduct study on individual plants using thermal remote sensing [7] However, precise thermal measurements are dependent on environmental factors, which alter the thermal characteristics of the crop being measured. Calibration of pictures based on meteorological conditions is therefore required for comparing image data gathered during various measurement periods and growth seasons [8]. Thermal remote sensing technology may be used to any agricultural substance or process in which heat is created or lost across time and space [9]. Nursery monitoring, irrigation scheduling, soil salinity detection, disease and pathogen detection, yield prediction, maturity appraisal, and bruise detection are all potential applications for thermography in agriculture. Plant characteristics may also be extracted using image-based 2D approaches.

A single camera set above the plant to generate a top view is sometimes paired with one or two additional cameras to produce side views to compute the leaf area or biomass of the plant. However, calculating a plant's biomass using single camera pictures has limited accuracy since these approaches are dependent on the camera's location relative to the plant (because the whole plant is not seen from a single 2D camera). If the camera inspects a view perpendicular to the leaf, precise leaf measurements may be obtained.

The difficulties in crop metric evaluation, along with the promise of the most recent image processing tools, encouraged this study as a catalyst for more research in the field. It is probable that applying these new concepts to crop monitoring applications will result in improvements in both accuracy and robustness.

- Crop canopy cover (CC)
- Above ground biomass (AGB)
- Leaf area index (LAI), including green and plant area indexes
- Chlorophyll content, including leaf chlorophyll content (LCC) and canopy chlorophyll content (CCC)
- Growth stage

In Section 1, the relevance of the measure is highlighted (introduction) and reference techniques are described. Following that, the previously suggested image processing algorithms for metric estimation are discussed in chronological sequence (Section 2). Section 3 concludes with a summary that compares the suggested image processing algorithms. Section 4 discusses the limits of current approaches and recommends future research areas. Section 5 brings the paper to a close. To the best of the authors' knowledge, this is the first published literature review on image-based cereal crop growth monitoring. The report, we believe, is a timely overview of a research area on the verge of considerable upheaval.

2. Survey

Combining computer vision with agriculture may provide producers with a variety of advantages in monitoring the development and health of plants in the field. Several researches have been conducted in recent years to investigate the possibilities of computer vision and deep learning approaches in this setting. Researchers used (manual or semi-manual) monitoring leaf size (and other plant dimensions) as an indication of yield/plant development to optimize plant growth in greenhouses. Zhang et al. [10] employed a convolutional neural network (CNN) to track lettuce development in a greenhouse. Based on photos captured by cameras in the greenhouse, the CNN was taught to recognize and categories distinct phases of lettuce development. The findings demonstrated that the CNN achieved great accuracy in tracking lettuce growth. Bauer et al. [11] investigated the use of computer vision and deep learning approaches to ultra-scale airborne phenotyping and precision agriculture. The researchers employed aerial photos, ground-based sensors, and machine learning techniques to track lettuce growth in their study. The findings demonstrated that this method could reliably predict plant features such as leaf area and dry weight.

Kosmopoulos et al. [12] discuss the current state and future activities of the SOUP project (Soilless culture UPgrade), which aims to automate plant growth monitoring through sensor networks, as well as to introduce robotic technology for labor-intensive tasks like pest management and harvesting. The initiative specifically looks into tomato farming. Kounalakis et al. [13] share their work on the creation of a tomato harvesting robot that uses computer vision methods to recognize and approach tomato peduncles. The detection and approach technique was determined to be 65% accurate, with visual processing accuracy of 92.6% in determining the right cutting spot. Georgantopoulos et al.[14] use machine learning methods to create a collection of multispectral pictures (RGB and NIR) of tomato plants at different phases of infection with two common tomato pests, Tuta Absoluta and Leveillula Taurica.

A. Nugroho et al. [15] developed a depth perception-based plant height monitoring system utilizing a stereo camera. The crop growth monitoring system is made up of a stereo camera that uses depth perception to estimate the distance from the camera to the tallest point in the crop. The system has been implemented with several sorts of leaves and characteristics for (a) Samhon, (b) Lettuce, and (c) Pagoda.

The crop growth monitoring system developed could conduct time series crop height estimate with a maximum error of RMSE 0.875 cm on Pagoda and MAPE of 5.56% on Lettuce. The system outperforms the competition on Samhong, with an RMSE of 0.408cm and a MAPE of 2.27%. Paturkar, A. et al. [16] used a single mobile phone camera and a structure from motion algorithm to predict the development of chili plants (Capsicum annum L.) under outdoor circumstances. There is also a technique for measuring leaf length and breadth while the leaf is curled. At various plant development phases, the rebuilt and segmented 3D models were used to measure plant attributes such as the number of leaves, stem height, leaf length, and leaf breadth.

Y. Xing et al. [17] created a non-destructive image-based measurement method that leverages 2D and 3D data from a Zivid 3D camera to create 3D virtual representations (digital twins) of tomato plants. The identified leaf masks are used to map the detected leaf masks to their 3D point cloud, which is then sent to the plane fitting technique to extract the leaf size to give data for growth monitoring. Huang, Y. et al. [18] provide an overview of the use of remote sensing from various sources, particularly airborne remote sensing from manned aircraft and unmanned aerial vehicles (UAVs), to monitor crop growth in the lower northern Mississippi from the Mississippi Delta to the Black Prairie, one of the most important agricultural areas in the United States. In this paper, three sites typical of the area are demonstrated for remote sensing monitoring of crop growth, and issues and challenges for future opportunities to integrate remote sensing data from different sources to improve crop monitoring in this area and surrounding areas are identified and discussed. Kazemi, F., et al. [19] use the RGB indices to track the progress of the rice crop. The normalized difference vegetation index (NDVI) is the most commonly researched and used crop growth indicator. G Kaur et al. [20] are interested in creating and building an IoT-enabled smart vertical farming system with a regulated environment for plant development. The hydroponic Deep Flow Technique (DFT), different sensors, and an auto pH and Total Dissolved Solids (TDS) balancing system are all used in this system. In terms of plant development metrics such as plant height, maximum leaf length, maximum leaf breadth, and fresh and dried weight of the plant, this article compares an IoT-based controlled environment vertical farming setup to an uncontrolled configuration for Romaine lettuce.

K. Dong et al. [21] use red, green, and blue (RGB) images collected with UAVs to measure the growth characteristics of onion and garlic at several development stages. Canopy coverage and plant height were employed as predictor factors in the development of mathematical models to estimate fresh onion and garlic weights. The employment of a CIE L*a*b* colour space and a mean shift (MS) algorithm improved the extraction of onion and garlic canopy coverage from complicated backgrounds such as plastic mulch, earth, and shadows under varied lighting conditions. To bridge the gap between computer vision methods and the horticulture cultivation sector, R. Shinoda et al. [22] present the Rose Blooming dataset and an effective rose-monitoring system named Rose Tracker. The Rose Blooming dataset is a novel collection of labeled photos of cut flowers in the growing stage. Rose Tracker can recognize little roses while moving the camera, lowers detection omissions, and gets an F1 score of 0.950, exceeding traditional methods. Aside from monitoring growth, computer vision and robots may aid in the detection of nutritional deficits in plants. Kamarianakis et al. [23] devised and built a chlorophyll content meter out of low-cost components. Ahsan et al. [24] employed deep learning algorithms to detect nutrient concentrations in lettuce cultivars cultivated hydroponically. To effectively forecast the nutritional contents of various lettuce cultivars, the researchers employed a mix of computer vision methods and machine learning algorithms.

3. Methods

This system may give producers with reliable data on plant development and health by integrating the capabilities of cameras and sensors, enabling them to optimize growing conditions and increase crop quality and consistency. A device like this can automate the capture of high-resolution photographs of individual plants. These photos may then be analyzed to discover patterns and make data-driven fertilization and pruning choices to improve crop output and quality. This level of automation reduces the need for manual labor, which can lead to lower labor costs and a more efficient operation by achieving the required accuracy and repeatability in plant image acquisition from the exact same spot and angle, at any time of day or night, without the need for human presence.

a) Colour spaces

Traditional digital cameras produce RGB colour pictures since this is the region of the electromagnetic spectrum that the human retina is sensitive to [25]. An image is composed of a grid of coloured dots known as picture components or pixels. Every pixel in the picture has its colour recorded as three integers that indicate the intensity of red, green, and blue light at that position. RGB intensities are often scaled in the (0,1) range. For processing reasons, RGB colour pictures are often mathematically translated into different colour spaces. Grey scale, HSV, and CIELAB colour spaces are common RGB replacements. Grey scale photos include just brightness (luminance) information and no colour. These photos are shown in monochromatic grayscale hues ranging from black to white [26]. The hue, saturation, and value of a picture are represented by the HSV colour space [27]. Hue is typically thought of as the pixel's colour, saturation is a measure of how pure or strong the colour is, and value is the brightness of the colour. Colour is represented by three integer values in the CIELAB colour space: L* for brightness and a* and b* for the green-red and blue-yellow components, respectively [28].

b) Image segmentation

Crop segmentation and identification are critical components of precision agriculture utilizing pictures. This method entails separating areas in a picture, preferably segmenting the plant from other things such as background objects (e.g., dirt), foreground objects (e.g., equipment), and weeds. Image segmentation is commonly accomplished by applying a threshold to a colour index derived across the image's pixels. The Otsu technique [29] is a popular segmentation method. Object recognition, in addition to picture segmentation, is sometimes employed to enforce identification of a crop's physically feasible structure, which leads to crop localization in images.

Scantips Calculate Distance or Size of an Object in an Image, n, d notes that in order to calculate the width of a plant using a camera and a distance sensor, one must resort to elementary arithmetic, notably the application of the equation controlling comparable triangles with equal and opposite angles. As seen above, this equation applies squarely to our situation.

$$\frac{P}{f} = \frac{D}{L} \Leftrightarrow \frac{PL}{f} \qquad (1)$$

Plant’s actual width

$P = Plant's\ width\ on\ sensor\ (mm)$

$f = focal\ length\ of\ the\ camera\ (mm)$

$D = Plant's\ actual\ width\ (mm)$

$L = Plant's\ distance\ from\ the\ camera's\ sensor$

The camera's manufacturer specifies the focal length to be:

$$f = 3mm \pm 5\%. \qquad (2)$$

Open CV allows the pixel-based measurement of the plant's diameter. In addition, the manufacturer claims that each pixel is 3 micrometers squared. The width of the plant in millimeters on the camera's sensor may then be represented as:

$$P = Plant's\ width\ in\ pixels\ * 0.003 (mm) \qquad (3)$$

However, owing to the plant's shape, which causes fluctuations in its height over its breadth, calculating the distance L from the plant to the camera's sensor is difficult. The decision to use both distance sensors was reached after extensive testing with both devices. Per sensor takes three readings: one in the center of the plant, and one per two centimeters to the right and left. The ultimate distance L from the facility is determined by averaging these readings.

c) Crop canopy cover

Crop Canopy Cover (CC) is the proportion of total ground surface covered by the crop's vertical projection. It is, in other words, the percentage of soil surface covered by plant leaves [31]. It is also known as vegetation crop area (VCA). Crop CC is regarded as an essential parameter for forecasting crop yields as well as an indication of land usage, degradation, and desertification [32]. Crop CC is quite simple to compute since it simply needs segmentation and crop coverage determination from the residual backdrop. The statistic is an excellent predictor of early-stage growth.

d) Above ground biomass

The plant stem, leaves, head, spike, seeds, and foliage are all examples of aboveground biomass (AGB). The whole dried mass of organic materials above ground is referred to as above ground dried biomass. AGB is a key feature in crop growth monitoring [33]. Tracking biomass and/or AGB throughout the growth season is an excellent predictor of crop production. [34] Conducted research to assess wheat productivity by evaluating total biomass, straw yield, and harvest index.

e) Leaf area index

In [35], the leaf area index is defined as the total one-sided leaf area per ground surface area. It is a measurement of the photosynthetic area of the canopy. LAI is often used as an indication of crop growth stage and biomass. LAI measures have also been shown to correlate with canopy microclimate and evapotranspiration characteristics.

f) Growth stage

On commercial farms, crop growth is usually measured using a growth stage scale. A crop growth scale provides a monetary value to a distinguishable crop development stage. Normally, scales are presented using annotated diagrams with images displaying the crop stage and its accompanying number.

The Zadoks scale [37] is one of the oldest and most widely used agricultural growth scales for cereal crops. To indicate development stage, the scale employs numbers in the range (00-99). Germination (00-09), seedling growth (10-19), tillering (20-29), stem elongation (30-39), booting (40-49), inflorescence emergence (50-59), anthesis (60-69), milk production (70-79), dough development (80-89), and ripening (90-99) are the ten primary growth phases for cereal crops in Zadoks. The Biologische Bundesanstalt, Bundessortenamt, and Chemical industry (BBCH) created another scale for consistent categorization of phonologically identical development phases of all mono and dicotyledonous plant species [36].

4. Discussion

Despite considerable research effort, the majority of previously suggested image processing-based crop growth monitoring systems is limited. The bullet points below illustrate the primary constraints that we observed and provide possible remedies for each.

1. Due to the time-consuming nature of acquiring picture and ground truth data, most research depend on short training and test datasets. Most approaches have been studied under limited circumstances, such as the absence of drought, insect damage, and disease. More broad data acquisition or, in certain situations, synthetic data augmentation may enhance the range of conditions.
2. Existing approaches have only been applied to a small number of developmental stages. This is attributable, once again, to the effort necessary for data collecting. Unfortunately, artificially enhancing photos to resemble growth is challenging since development changes the form of the plants, not just the colour.
3. Errors in segmentation and feature recognition were common. Advances might be achieved by using cutting-edge feature recognition methods, such as deep neural networks trained on representative picture datasets.
4. Methods are not resilient to changes in ambient lighting circumstances caused by shifting amounts of cloud cover, as well as seasonal and daily fluctuations in the sun's position relative to the crops.
5. Current approaches are not resistant to changes in camera location and orientation. Such difficulties might be solved by improved sensing during picture capture.
6. Self-obstruction of thickly planted crops may occasionally give inaccurate findings. Recent improvements in machine learning may aid in picture Segmentation allowing for more accurate separation of individual plant structures.

The system's effectiveness for long-term plant monitoring was very impressive. Researchers and agronomists may benefit much from the system when it is set up correctly and used under stable lighting conditions. In particular, it can automatically recognize plants, take pictures of them while keeping them in the center of the frame, and measure some basic attributes.

- The system's user-friendliness allows for accurate setup, and the repeatability of the processes performed using the system is great.
- The system can be carried, transported, and set up in a greenhouse by one person, despite its high functionality.
- Users may operate their devices from a distance. In conclusion, there are still a few spots that need work:
- The interface might be sluggish, so you have to pay close attention so you don't hit the incorrect button by mistake. Investigating other UI frameworks might be a step towards fixing this problem.
- It was discovered that distance sensors used to calculate plant diameter and area were not always reliable. Possible solutions include more costly laser distance sensors and a more powerful stepper motor, both of which would increase the speed of the carriage and hence the overall performance of the device. Optimal use of such methods given the difficulty of tracking crop development.

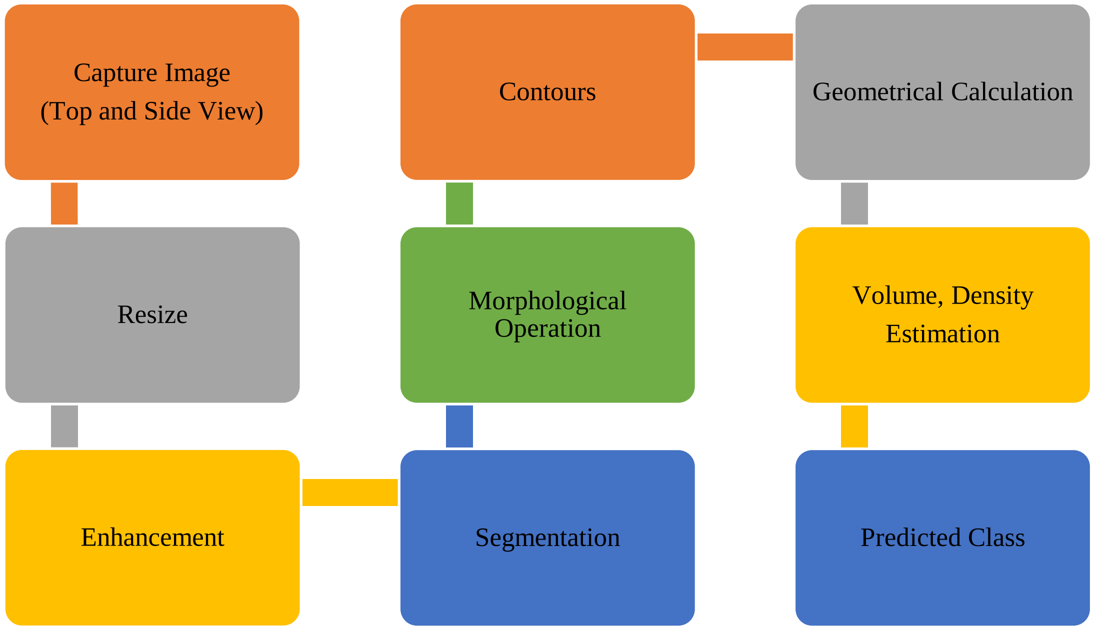

Figure 1. General Architecture

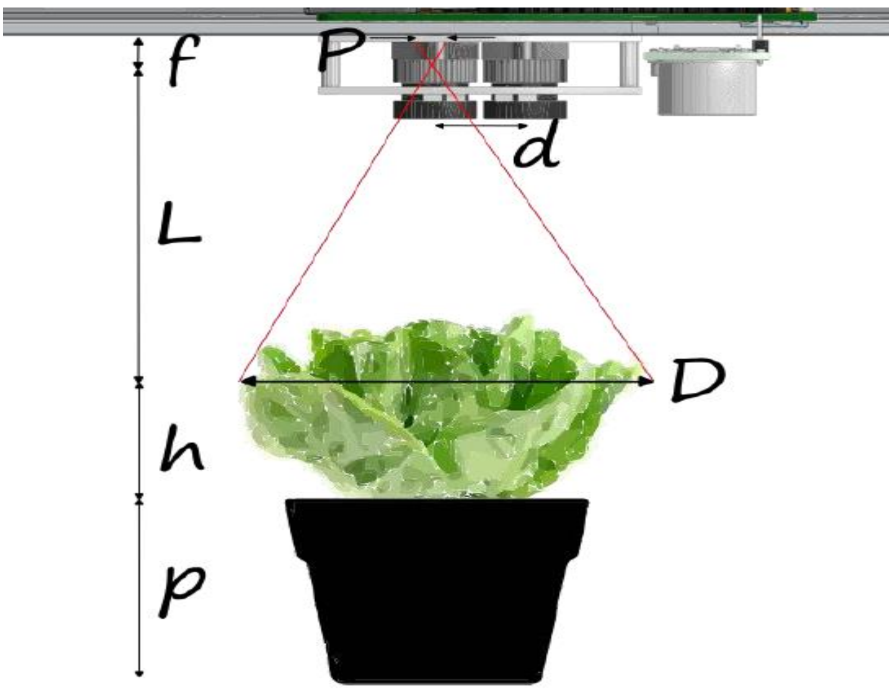

Figure 2. General Camera Setup

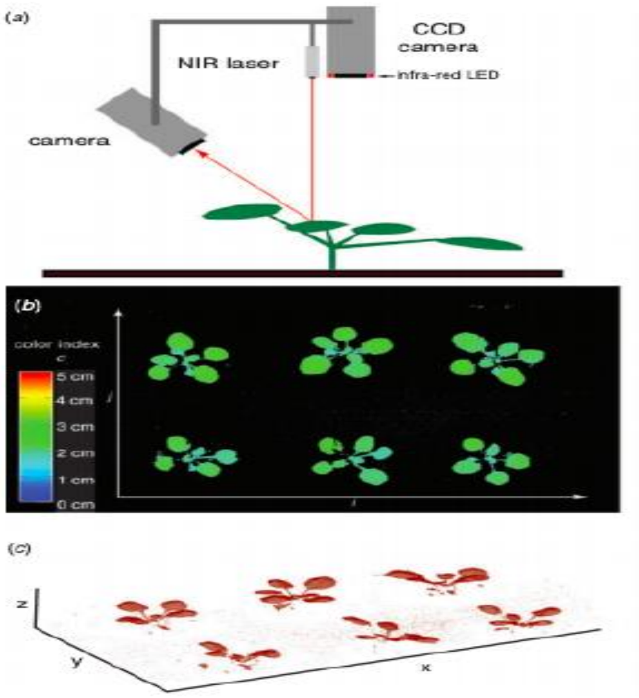

Figure 3. Taken from [30] showing their setup and results from the 3D scans of the plants to give an understanding of how it worked

5. Conclusion

Using proximate pictures of cereal crops, this research provides an overview of existing methods for estimating five major crop growth parameters. High-resolution digital photography captured in the field has the potential to greatly hasten and improve the accuracy of agricultural progress monitoring. These problems may be solved by new directions being taken in image processing. However, numerous unanswered problems remain about the optimal use of such methods given the difficulty of tracking crop development.

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