Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

Extending an Application of CNN to Automate Leaf Area Measurement of Groundnut

Rinku Manvani[1], Nabhan Yousef[2], Gaurav Sanghvi[1], Mahendrapalsingh Rajput[1*]
[1]Department of Microbiology, Faculty of Science, Marwadi University, Rajkot - 360003, India
[2]Department of Electronics and Communication, Marwadi University, Rajkot - 360003, India

[1*]Corresponding author: mahendrapalsingh.rajput@marwadieducation.edu.in

Cite this paper as: Rinku Manvani, Nabhan Yousef, Gaurav Sanghvi, Mahendrapalsingh Rajput (2024). Extending an Application of CNN to Automate Leaf Area Measurement of Groundnut . *Frontiers in Health Informatics*, *13 (8) 1910-1926*

Abstract

Groundnut, a vital crop known for its oil and protein content, ranks India as the second-largest producer globally. Enhancing the physical and gravimetric properties of groundnut is crucial for improving overall yield. One key biophysical metric for assessing crop growth is the Leaf Area Index (LAI), which relies on accurate leaf area measurement. Traditionally, the millimeter graph paper method-which is sometimes prone to errors-is used to measure the leaf area. This work investigates the use of machine learning techniques to automate the measurement of groundnut leaf area in order to aid in the estimation of the LAI. To improve the precision of estimating leaf area, a large dataset of groundnut leaf photos was collected from numerous field tests and pre-processed. In addition, a specialized hardware configuration was created to reduce human entry errors by automatically measuring the leaf area and sending data to a cloud server. To reduce the effect of lighting changes, the hardware system has homogeneous illumination This hardware configuration in conjunction with machine learning has proven to be successful in automating the measurement of leaf area and simplifying data administration. The suggested technique offers a dependable way to track crop growth and boost agricultural output because it can be adjusted to various crop varieties.

Keywords

Groundnut, Leaf Area, Leaf Area Index, Convolute Neural Network

Introduction

This In several scientific fields, including plant phenotyping, growth monitoring, environmental impact assessments, agricultural research, and botanical taxonomy, the precise and trustworthy measurement of leaf size is essential. For scientists and experts in the fields of biology, ecology, and agriculture, leaf size is a crucial determinant of plant health, growth rates, and responses to environmental change.

The measuring of leaf size has historically been done by hand using tracing techniques, calipers, or rulers, all of which take a lot of time and effort. Because of their ease of use and accessibility, these methods have been in widespread use for decades; yet, they are frequently limited in their ability to handle huge datasets and are subject to human error and variability. Manual measurements could not be accurate enough for high-resolution research or pick-up on minute changes in leaf morphology. Furthermore, their inability to scale when working with large plant populations restricts their application in contemporary ecological and agricultural studies where high-throughput data collecting is required.

Recent accessional digital technology and innovative image processing developed an opportunity for leaf measurement, which is a more reliable, precise, and scalable assessment. Image processing methods allow for the extraction of leaf size and shape parameters from digital images, with less reliance on manual intervention at scale and increased consistency. These methods use pixel count based on algorithms that show leaf images, edge detection, area calculation, and measurement to a more accurate level. Digital approaches have been exploited for greater raw dataset processing capabilities by enhancing design efficiencies of systems to achieve global leaf analysis through soil-less volumes and global agricultural field monitoring both at large scales.

As smart devices include sophisticated sensors, computational power, and storage, recent advancements have facilitated even more accurate image capture for automatic size measurement's devices combine acquisition, processing, and data analysis into a seamless package for continuous monitoring with real-time information provided to scientists or practitioners. Smart devices employ automation to reduce labor measurement costs, prevent human risks, and deliver consistent reliable data for collection. Advancement in such technologies has laid the foundation for precision agriculture where continuous monitoring of health and growth of plants is vital to scale crop production and manage resources sustainably.

This work presents a detailed review of the methods for measuring leaf area and covers from classical techniques to some recent image processing methodologies. In addition, it presents a new smart device solution that automates the measurement process and represents a fast and practical alternative for researchers and agricultural practitioners. As it traces the evolution from traditional manual methods to automated techniques, it illustrates profound enhancements in measurement precision, speed, and scalability as well as its prospective use cases ranging from plant research to ecological investigations and agricultural applications.

Literature Review

Groundnut, or peanut is an oil crop that has gained popularity because of its edible oil that makes a significant contribution to global food security and agriculture economies. Polished into flour, groundnut becomes easily integrated into the meals in various cuisines, and its edible seeds constitute over 40-50% of oil content, and 25 to 30% of protein content making it very nutritionally important in most developing nations [1]. Consequently, even though India now ranks second behind China in its production, its cultivation is adapted to many agro-climatic zones [2]. Given the economic and nutritional significance of this crop, much research has been directed toward improving its productivity by addressing some of the key issues such as biotic stresses (pests, diseases) and abiotic stresses (drought, poor soil fertility). It has also been shown that altering agronomic practices, such as employing crop rotations, irrigation practices, and fertilizer application has been shown to affect yield and health of the crop [3].

To quantify the growth and production of crops, the LAI is measured. This is the ratio of the total surface area of all green leaves (one side only) to the total corresponding area of the ground surface. For proper evaluation of plant LAI, it is important because of its impact on plant capacity for photosynthesis, light interception, transpiration, and general plant health which are necessary for yield evaluation [4]. They have been adopted widely by agricultural researchers for determining leaf area, for example, millimeter graph paper and planimeter [5]. The millimeter graph paper technique involves tracing onto graph paper the outline of the leaf and estimating its area by counting the unit graph squares it covers while planimeters are cut around the outline of the leaf to measure its area [6]. Even though these methods are cost-efficient, simple, and effective, they are also very labor-intensive, and time-consuming and are open to very high risk of errors of a manual nature as well as those attributed to human emotion and bias [7]. However, variations in environmental factors such as leaf water content and lighting will also influence the results obtained from these methods, the accuracy of which cannot be guaranteed in circumstances where there is a need for more expansive, dynamic, field studies [8].

As researchers realized the drawbacks of measuring leaf area by hand, they sought out other image-based approaches that were automated, more accurate, faster, and more scalable [9]. Advanced algorithms for trait assessments, such as the estimation of leaf area as a component of the plant phenotype, have emerged as a result of the quick development of machine learning in image analysis. Machine learning methods like Decision Trees and Support Vector Machines can identify and categorize plant traits using trained models, greatly increasing accuracy compared to traditional methods [10]. In the last few years, Image processing has benefitted from deep learning using a convolutional neural network (CNN) that learns to detect salient features based only on pixel-level input. Despite the difficulties encountered in biological domains, U-Net is commonly employed in agriculture for segmentation in medical images, and Mask of Region-Based Convolutional Neural Network R-CNN is used to separate particular leaf sections with relative simplicity [11].

Researchers looked for alternative image-based methods that were automated, more accurate, faster, and more scalable after realizing the limitations of manually measuring leaf area. Advanced algorithms for trait assessments, such as the estimation of leaf area as a component of the plant phenotype, have emerged as a result of the quick development of machine learning in image analysis. Machine learning methods like Decision Trees and Support Vector Machines can identify and categorize plant traits using trained models, greatly increasing accuracy compared to traditional methods. In the last few years, image processing has benefitted from deep learning using CNN which learns to detect salient features based only on pixel-level input. Agricultural uses of U-Net are conventionally used for segmentation in medical images and Mask R-CNN can also be used to isolate specific leaf regions with relative ease despite the challenges presented in biological fields [12].

The use of edge detection and image segmentation techniques, as part of the computer vision, has further improved the precision in measuring leaf area. Canny edge detection aids in establishing leaf boundaries, while other segmentation techniques that eliminate the background include K-means cluster analysis and Otsu's thresholding. Recent studies have also employed the Normalized Difference Vegetation Index (NDVI) as a spectral indicator of plant health by emphasizing differences between healthy and severely stressed vegetation, thus augmenting leaves area assessment [13]. Those machine learning models can take leaf area measurements in real-time and in a non-invasive manner, highlighting their usefulness in precision agriculture.

Specialized hardware configurations have been created to further improve the accuracy of leaf area measurements. To make shadows and reflections, which can cause problems in image processing, these systems frequently use controlled lighting conditions with LED lights and diffusers [14]. These configurations lessen the variability brought on by varying natural light by standardizing the illumination conditions, creating a reliable setting for taking crisp leaf photos. Cloud-based data management was applied to enhance the data analysis after collecting it.[15] Researchers can prevent human data input errors and obtain real-time access to huge datasets by streaming measurement data straight to cloud servers. This allows for trend analysis and prompt decision-making [16].

Large datasets need cloud computing to be applied especially when the output of that data will be used for further processing and analysis [17]. With all of these advanced techniques applied still, there are some problems at the end of image segmentation [18]. Data augmentation techniques to improve the performance of machine learning models [19]. The best solution for such types of problems was the integration between machine vision techniques and IoT [20]. The automation of leaf measurement and make it combined with machine vision, and sophisticated hardware systems could greatly increase groundnut yield and total crop production, making them useful instruments in contemporary precision agriculture [21].

Materials and Methods

To measure leaf areas easily, an automated and integrated inspection device was designed to enhance this process. This arrangement lessens mistakes from shadows or changes in the ambient light. To enhance contrast, photos of leaves are taken against a white background. To normalize the dataset, pre-processing techniques such as RGB-to-grayscale conversion, Gaussian filtering for noise reduction, and scaling are used. Otsu's thresholding technique is used for segmentation, and Canny edge detection is used to precisely identify leaf borders. Leaf area is then estimated using a machine learning model, such as a CNN, to increase the data robustness many data augmentation operation was applied like rotation and inversing the photos, and finally to streamline data management, the system transmits the measurement results to a cloud-based server, eliminating manual data entry errors and enabling real-time monitoring. The combination of machine vision models and cloud computing analyzes the storage data very easily and simply. By retraining the model on various leaf datasets, the methodology also demonstrates the system's versatility and suggests that it may be applied to other crop kinds. This all-encompassing strategy, which blends hardware integration and machine learning, provides a scalable and effective way to measure leaf area and monitor crops in a variety of agricultural scenarios.

Hardware

The careful design of a specific hardware setup is the first step in developing an automated system that measures the leaf area of groundnut plants in an efficient and precise manner. The inspection device integrates a real-depth camera for high-precision defect detection, a linear actuator motor for automated camera positioning, an Arduino microcontroller for system control, and a smart touchscreen interface for real-time visualization and user interaction. as shown in Figure 1.

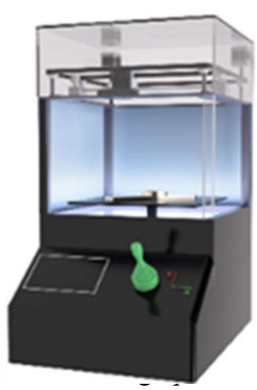


Figure 1. Setup Design

This configuration is essential for guara age acquisition, which has a major influence on the precision and dependability of the next pl g and machine learning.

A. Camera selection and specification

The system's camera is a high-resolution digital camera that was chosen for its exceptional clarity in capturing the minute features of groundnut leaves. As seen in Figure 2, the camera's Intel RealSense 20 MP resolution is essential for accurately capturing even the smallest changes in leaf size and texture. The selection of the camera type was impacted by elements like excellent image accuracy and ease of use, which provide steady, crisp images that serve as the foundation for precise measurement and segmentation. The camera is chosen based on its Vision Processor D4 Board V5, which guarantees that the full leaf is caught in focus, in addition to its resolution. For close-ups of leaves, the focal length of the camera's lens is adjusted to minimize distortion and guarantee that the actual size of the leaf is faithfully caught in the pictures. The camera is mounted on an adjustable stand to keep it in a steady, constant position when taking pictures to further improve the quality of the images.

Figure 2. Intel Real Sense Camera

B. Controlling lighting environment

To avoid irregularities that can add highlights, shadows, or reflections and make the segmentation process more difficult, a consistent and regulated lighting environment is necessary. Advanced LED lights were used to prevent the shadows

and to enhance the quality of images, to ensure uniform illumination across the entire leaf surface, these lights are placed thoughtfully throughout the setup, covering the center and every other corner. the LEDs were positioned accurately and precisely to prevent any light that may come from outside resources.

For proper segmentation and classification, the LEDs are adjusted to a color temperature of 2000K, which guarantees that the leaf colors are depicted faithfully and without any strange shifts. To prevent changes brought on by natural light and outside environmental influences, the entire lighting system is also encased within a tube, guaranteeing constant lighting conditions for every photograph.

C. Background and Image Contrast

A premium white surface is employed to enhance the contrast between the groundnut leaves and the background, as shown in Figure 3. For precise image processing tasks like segmentation, this arrangement improves the visibility of the leaf's margins. For the leaf region to be easily distinguished from the backdrop, high contrast is essential, particularly when segmenting using techniques like Otsu's thresholding. Because of its neutral and non-reflective qualities, the background material was chosen to help avoid reflections and color distortions that may otherwise compromise the analysis. To account for differences in leaf placement during image capture, the backdrop size is modified to fully catch the entire leaf within the frame while leaving some extra room around the margins. With this setup, the system can efficiently handle leaves of varying sizes without sacrificing the quality of the segmentation.

Figure 3. The contrast between the leaves a

Image Capture Process and Control

The system has an advanced GUI to control the camera position to enhance the quality of image capturing. These settings are established before each shot, guaranteeing consistent image quality despite variations in the surrounding illumination. Furthermore, the camera is linked to a PC running camera control software, which allows for remote activation and control of the picture capture, improving data collecting efficiency and repeatability.

D. Environmental Control

Many external factors that can may affect the size or shape of the leaves depending on the image to prevent all of these the device is supported by an advanced controlled environment to show and control it like humidity and temperature.

E. Calibration and Maintenance

Regular calibration is essential to guaranteeing the hardware setup's accuracy and dependability. white background was applied and it was cleaned to prevent any dust or any external factors that may affect the intensity of the pixels also made the segmentation process very easy and accurate.

F. Integration with Software

The software utilized for picture pre-processing, segmentation, and machine learning analysis is completely integrated with the camera and illumination system. The hardware's real-time feedback enables lighting and camera settings to be changed, guaranteeing that every image satisfies the quality standards needed for additional processing. The automated measurement method is made more efficient by the system's ability to handle massive volumes of image data by feeding the taken pictures straight to a processing unit for instant analysis.

Experimental Work

Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

A. *Image Acquisition and Pre-processing*

For accurate leaf area estimation, the quality of the photos taken is essential. A rigorous procedure of image collecting and pre-processing is performed to preserve consistency and data accuracy. To ensure that the machine learning model receives optimal input for analysis, this phase standardizes the dataset, lowers noise, and improves the pertinent information.

Image Acquisition Process

Using the described camera setup to ensure that, each leaf is located at a fixed distance and angle relative to the camera to apply the same conditions across all images. The camera's focus is adjusted to ensure the entire leaf surface is in sharp focus, to prevent any blur that could reduce the segmentation accuracy.

Image Pre-processing Techniques

Following the acquisition, the photos go through several pre-processing stages designed to standardize the images and remove any extraneous data or noise that might obstruct further processing. The pre-processing pipeline includes the following key steps:

a. Resizing - To prevent the shape of the leaf from being distorted, the resizing is carried out while maintaining the aspect ratio. As seen in Figure 4. The final dimensions of 512x512 pixels were selected to balance computing efficiency and image quality, offering sufficient detail for analysis while maximizing processing time.

Figure 4. Resizing the input image

b. Noise Reduction using Gaussian Filtering - Gaussian filtering is used to reduce high-frequency noise while preserving crucial characteristics of the leaf structure to enhance image quality and minimize noise. As a low-pass filter, the Gaussian filter smoothed the image and eliminates pixel-level noise, which may be caused by flaws in the sensor, the surrounding environment, or minute changes made during image capture. The filter's kernel size is carefully chosen to eliminate noise without compromising the leaf's essential characteristics, like veins, edges, and contours. Kernel sizes typically range from 3x3 to 5x5 pixels, depending on the image resolution and noise level. In real-world situations, where external influences might create different kinds of noise, such as grainy textures or inconsistent backgrounds, this procedure is very important.

c. RGB-to-Grayscale Conversion - The RGB (color) format of the photos is changed to grayscale once the noise has been reduced. By focusing on intensity values—which are more important for estimating leaf area than color information—this step simplifies the process.

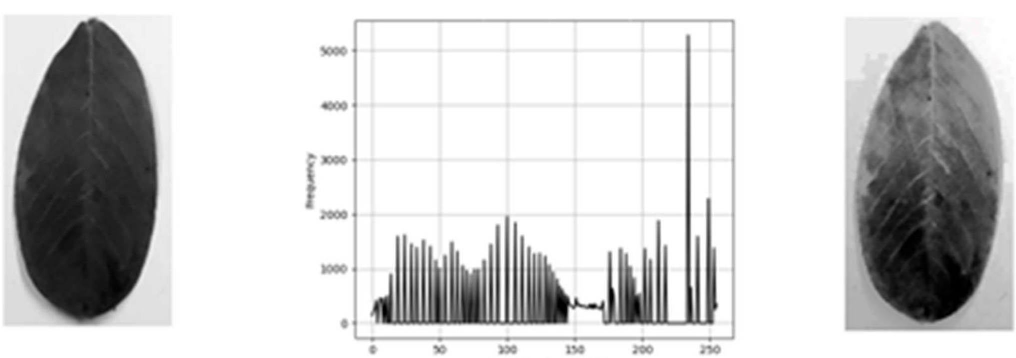
Figure 5. RGB to Gray Scale Conversion

As shown in Figure 5, a weighted sum of the RGB channels is applied to accomplish the conversion to grayscale, typically using the formula:

Gray=0.2989×R+0.5870×G+0.1140×B (1)

Because green usually indicates the most noticeable parts of the leaf, it is given more weight in this translation, which takes into consideration the human eye's variable sensitivity to different colors. The resulting grayscale image preserves the leaf's essential structural features while reducing computational complexity, which is particularly beneficial when working with large datasets.

d. Histogram Equalization - When there is low contrast between the leaf and the background, histogram equalization is used to enhance the image contrast. Redistributing pixel intensity values throughout the whole range makes the leaf's edges more noticeable and simpler to identify during segmentation. It ensures that the grayscale image has a more even intensity distribution, which improves its suitability for thresholding and edge detection, as shown in Figure 6.



(a) (b) (c)

Figure 6: (a)Input Image (b)Histogram of Equalized Image (c)Equalized Image

e. Edge Detection (Canny Edge Detection) - Edge detection is an essential step for accurately defining the boundaries of the leaf. After pre-processing, the Canny edge detection algorithm is used to identify the clear transitions between the leaf and its background, as shown in Figure 7. The Canny algorithm operates in multiple stages, including:

Noise reduction:

A Gaussian filter has been employed on the image for smoothening it and reducing noise before edge detection. Gradient computation: The intensity gradients are calculated to identify areas where the color or intensity changes significantly. Non-maximum suppression: Thin out the edges by keeping (only) local maxima in the images passed through 2nd stage.

Edge tracking by hysteresis:

By taking into account both strong and weak edge pixels, the algorithm determines the final edges. Because it can identify crisp, clear edges while reducing noise and false positives, canny edge detection is the method of choice. The outcomes of this stage help with precise area measuring and segmentation by defining the leaf's boundaries for additional analysis.

f. *Thresholding using Otsu's Method* - As seen in Figure 8, a two-step procedure is used to separate the leaf from its background: first, edge detection is used, and then Otsu's thresholding method is used to turn grayscale values into a binary image.

Figure 8. Otsu implementation (a)Gray image, (b) Otsu Thresholding

Otsu's technique successfully distinguishes the leaf (foreground) from the background by maximizing the between-class variance. This thresholding method constantly adapts to the image's histogram, making it very helpful for photos with different lighting situations. The binary image produced through Otsu’s thresholding allows for effective leaf segmentation, ensuring that only relevant pixels are used in the subsequent analysis.

B. Segmentation and Edge Detection

In image analysis, segmentation, and edge detection are essential for precisely separating the leaf region from the backdrop. Otsu's thresholding, an adaptive technique that automatically establishes the ideal threshold by minimizing intra-class variation, is the first step in the process. As seen in Figure 9, it successfully transforms the grayscale image into a binary image in which the leaf is distinct from the backdrop. To improve boundary accuracy, Canny edge detection employs a multi-step process that includes

Figure9. Image segmentation (a)G.

Gaussian filtering to reduce noise, gradient computation to ascertain edge intensity, non-maximum suppression to thin the edges, and double thresholding with hysteresis to distinguish real edges from noise. The leaf contours are precisely detected thanks to this mix of methods, and contour detection algorithms are subsequently used to extract them. To provide precise and trustworthy measurements for additional analysis, the leaf area is computed by adding up the pixels inside the identified contour and using a pixel-to-area calibration factor.

C. CNN for Leaf Area Estimation

The technique measures leaves from photos using CNN architecture, a complex deep-learning model. Because these networks automatically recognize and process important information, they are very effective for visual analysis. This allows for precise leaf detection and size estimation.

Overview of CNN Architecture

The neural network's architecture combines multiple components: convolution operations, pooling stages, and dense connection layers:The processing segments operate by sliding specialized filters over the image, conducting mathematical computations to identify visual features such as edges, surface patterns, and textures and it is calculated by:

$$\text{Convolution} = (I * K)(x, y) = \sum_{i=0}^{m} \sum_{j=0}^{n} I(x + i, y + j) \cdot K(i, j)..... \quad (2)$$

Where I represent the input image, and K is the kernel.

Activation Function (ReLU): Each convolutional operation is followed by a non-linear activation function, like the Rectified Linear Unit (ReLU), which adds non-linearity and enables the network to identify complex patterns. The ReLU function's definition is

$$\text{ReLU}(x) = \max(0, x) .... \quad (3)$$

Pooling Layers: These layers downsample to minimize the spatial dimensions of the feature maps while preserving the most significant characteristics. often used, max pooling chooses the maximum value inside each pooling window, ensuring the model is not impacted by minor visual distortions or shifts the function of the pooling layer is:

Fully Connected Layers: Fully connected layers serve as a classifier by passing the convolutional layers' flattened feature maps through them. The network can combine the retrieved characteristics and generate predictions about the leaf since every neuron in these layers is connected to every other neuron in the layer above.

Data Preparation and Training Process: To teach a CNN to recognize the distinctive characteristics of groundnut leaves, a significant amount of labeled data is needed. Labeled photos of groundnut leaves with precise area measurements tagged on each image make up the training dataset. To improve the model's generalization ability and performance, several data augmentation techniques are applied.

Rotation and Scaling: The images are rotated at various angles and scaled to simulate different perspectives and sizes, increasing the model's robustness against variations in leaf orientation and size.

Flipping and Cropping: To create a diverse set of training samples and reduce overfitting, random horizontal and vertical flips along with random cropping are applied. The CNN is trained to minimize the discrepancy between the predicted leaf area and the actual area using a loss function, commonly Mean Squared Error (MSE) function calculated using:

$MSE = (1/n) \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$..... (5)

Where $(y_i - \hat{y}_i)^2$ is the squared error for data point i. Squaring ensures that all errors are positive and larger errors are penalized more.

Model Optimization and Validation

Techniques like batch normalization, dropout, and early termination are used to maximize the CNN.

Batch Normalization

By normalizing each layer's output, this method lowers the internal covariance shift and speeds up training.

Dropout

Dropout regularization prevents overfitting by randomly deactivating a subpopulation of neurons during the training Process This approach keeps the model from being unduly reliant on specific traits, which improves its ability to generalize.

Early Stopping

To prevent the overfitting problem, this method is implemented to show the loss in the validation. The accuracy of the trained CNN model in estimating leaf area is next assessed using a different dataset. Calculating Area

The methodology's last phase, leaf area computation, uses the CNN output with the segmented leaf image to precisely calculate the leaf area. To estimate the Leaf Area Index (LAI), a critical indicator of crop productivity and health, this step is essential.

Pixel Count Method

Following segmentation, a binary picture of the leaf is produced, in which the background pixels are dark (value = 0) and the leaf pixels are white (value = 1). To determine the total number of pixels that belong to the leaf area, the pixel count method adds up all of the white pixels in this binary image.

Leaf Pixel Count = $\sum_{x=1}^{m} \sum_{\gamma=1}^{n} I(x, y)$.... (6)

Where I (x, y) At coordinates (x, y), I (x, y) is the pixel intensity, and m, n are the image's dimensions.

Estimation using CNN Predictions

The CNN model provides an alternate way of estimating leaf area in addition to the pixel count method. The CNN learns intricate properties including shape, size, and edge details from annotated leaf photos to forecast the leaf area. Using the same calibration factor, the anticipated area is likewise expressed in terms of pixel count, which is subsequently translated to the physical area.

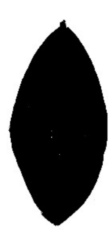
Combining Methods for Enhanced Accuracy

The system can use an ensemble strategy by averaging the outcomes of the CNN prediction with the pixel count method to guarantee great accuracy and dependability:
prediction:

F= (Pixel Count Area + CNN Predicted Area) / 2...... (7)

As indicated in Table 1, this combination minimizes potential mistakes from each technique by utilizing the learned features of the CNN and the accurate boundary detection of the pixel count method.

Table 1: Result of applying pixel count and pixel-to-area calibration and the combining method

Output model	Pixel count method (mm^2)	Pixel-to-Area Calibration (mm^2)	Combining Methods
	35.56	35.50	35.53
	70.22	70.19	70.20

	41.50	41.50	41.50

Cloud Integration and Data Management

With real-time access, centralized storage, and comprehensive analysis of leaf area measurements, cloud integration, and data management are essential components of the suggested system.

Real-Time Data Streaming

The output of the CNN model will be collected and saved using the IoT system and at the same time, it will be timely updated by transferring data from the local device to the cloud via Wi-Fi.

Validation and Performance Evaluation

The predicted leaf areas are compared to manual measurements made using conventional techniques like a leaf area meter or graphical analysis to verify the correctness of the suggested automated approach.

Manual Measurement Process:

Selected leaves from groundnut plants are physically measured using a leaf area meter, which provides precise measurements of leaf area.

In some cases, manual methods such as tracing the leaf on graph paper and counting the squares may also be used for comparison
The automated system's predictions are assessed using these humanly acquired values as the ground truth or reference data.

Dataset for Validation:

A wide range of leaf photos are gathered, encompassing various plant growth phases, leaf sizes, and environmental circumstances.

The validation dataset is separate from the training dataset used to train the CNN model, ensuring an unbiased evaluation of the system's performance.

Performance Metrics:

Several statistical measures that measure the precision and dependability of the forecasts are used to assess the automated leaf area measurement system's performance.

Mean Absolute Error (MAE):

MAE The mean absolute difference (MAE) between the actual and projected values of leaf area is computed. It gives a clear indication of the prediction error.

$$MAE = (1/n) \sum_{i=1}^{n} |\text{Predicted Area}_i - \text{Actual Area}_i| ..... \quad (8)$$

A lower MAE value indicates higher accuracy of the leaf area predictions.
Root Mean Square Error (RMSE):

RMSE is used to assess the standard deviation of the prediction errors. It is more sensitive to larger errors and provides a comprehensive evaluation of the model's performance.

$$RMSE = \sqrt{[(1/n) \sum_{i=1}^{n} (\text{Predicted Area}_i - \text{Actual Area}_i)^2]} ..... \quad (9)$$

A lower RMSE value indicates that the predicted areas are close to the actual areas.
Coefficient of Determination (R^2):

The degree to which the model's predictions match the actual measurements is shown by the R2 score. It shows the percentage of the dependent variable's (leaf area) volatility that can be predicted based on the independent variables (image characteristics).

$$R^2 = 1 - [\sum_{i=1}^{n} (\text{Actual Area}_i - \text{Predicted Area}_i)^2] / [\sum_{i=1}^{n} (\text{Actual Area}_i - \overline{\text{Actual Area}})^2] ...(10)$$

An R^2 value closer to 1 indicates a strong correlation between the predicted and actual values, suggesting that the model accurately captures the variations in leaf area

Discussion

The implementation of machine learning techniques coupled with specialized hardware configuration for groundnut leaf area measurement represents a significant advancement in agricultural monitoring systems. Our findings demonstrate several key implications for both research and practical applications.

First, the automation of leaf area measurement through our proposed system addresses the fundamental limitations of traditional millimeter graph paper methods. While manual measurements have served as a standard approach, they are inherently susceptible to human error and time-consuming. Our system's ability to provide consistent, automated measurements with homogeneous illumination minimizes these sources of error, contributing to more reliable LAI calculations.

The incorporation of cloud data storage presents additional advantages for agricultural research. Real-time data transmission and storage not only streamlines the data collection process but also enables longitudinal studies of crop growth patterns. This feature is particularly valuable for large-scale field trials where manual data management would be impractical.

The system's design with homogeneous illumination proves crucial in maintaining measurement accuracy across varying environmental conditions. This addresses a significant challenge in field-based measurements where changing light conditions can affect image quality and subsequent calculations. Previous studies have highlighted lighting variability as a major source of error in image-based measurements while our system has been specifically developed for groundnut leaves, its adaptability to other crop varieties represents a promising direction for future applications. This versatility could be particularly valuable in developing comprehensive crop monitoring systems for diverse agricultural settings.

Conclusions

This study presents an automated method to measure the size of the Leaf Area Index (LAI), a key indicator of crop growth, specifically for groundnut plants. By utilizing advanced image processing techniques, the system captures high-quality images using a high-resolution camera with controlled lighting to reduce the effects of shadows and lighting variations. The approach uses Otsu's thresholding and the Canny algorithm for effective segmentation and edge detection, while a pixel-to-area calibration factor helps estimate leaf area accurately.

Cloud-based data management is integrated, enabling real-time monitoring and centralized analysis for informed agricultural decision-making. The system's accuracy is validated through comparisons with manual measurements and traditional methods, with statistical metrics confirming its precision. The methodology offers a scalable solution for precision agriculture, supporting applications in yield prediction, crop health assessment, and resource management, ultimately enhancing agricultural productivity and sustainability. Future work may expand the system's capabilities with additional environmental data and multi-spectral imagery.

Declarations

A. Acknowledgement

Authors would like to acknowledge the support of Marwadi University for supporting experimental work through Minor

Research Project.

B. Conflicts of interest/Competing interests

The authors have no relevant financial or non-financial interests to disclose.

C. Funding

The authors declare that no funds, grants, or other support were received during the preparation of this manuscript.

D. Authors' Contribution

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

E. Availability of data and material

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to containing information that could compromise the privacy of research participants.

F. Ethics approval

Not Applicable

G. Code availability

The code that support the findings of this study are available on request from the corresponding author.

H. Consent to participate

Not Applicable

I. Consent for publication

Not Applicable

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