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Article

DEEP LEARNING AND PHYSIOLOGICAL FEATURE MODELING FOR PLANT GROWTH ESTIMATION BASED ON THERMAL IMAGING

Neeta B. Bankhele[1], Rekha P. Labade[2], Sachin V. Chaudhari[3]

[1] PG Research Center in Electronics & Telecommunication Engineering, Sanjivani College of Engineering & Research, Savitribai Phule Pune University (SPPU), Pune, Maharashtra, India. nbankhele.7777@gmail.com
[2] PG Research Center in Electronics & Telecommunication Engineering, Sanjivani College of Engineering & Research, Savitribai Phule Pune University (SPPU), Pune, Maharashtra, India. rplabade@gmail.com
[3] PG Research Center in Electronics & Telecommunication Engineering, Sanjivani College of Engineering & Research, Savitribai Phule Pune University (SPPU), Pune, Maharashtra, India. chaudharisachinetc@sanjivani.org.in

Abstract: Precision agriculture, climate-resilient farm management, and yield forecasting require proper and timely estimation of crop growth. Traditional growth measurements are typically either labor intensive, destructive or time-ridden. The paper suggests a non-destructive, thermal imaging-based system of quantitative estimation of plant growth using deep learning and modeling of physiological features. The thermal images of the canopies are taken at a high resolution, both under control and field conditions, to derive physiological useful variables, such as the percentage of canopy cover, average canopy temperature, and temperature fluctuations, which indicate plant health, transpiration rates and responses to stress. An overall Growth Index (GI) is obtained by combining these thermal descriptors so as to be able to standardize the crop development stages. Sequential measurements of canopy cover are modelled by logistic growth curve fitting to capture the growth behavior in the time. The growth parameters obtained are biologically interpretable including the maximum growth rate and the inflection point. Simultaneously, a shallow Convolutional Neural Network (CNN) is trained, which applies the Growth Index directly to thermal image density, without the need to employ manual feature engineering and on the basis of that, is able to run quickly and automatically to derive the growth index. Using experimental analysis, there is a good correlation and low estimation error has been shown between the predicted and reference growth measures at the various stages of growth. The suggested solution would be able to combine physiological interpretability and the efficiency of deep learning by providing a rapid, scalable, and dependable solution to real-time monitoring of plant growth. The framework is used to facilitate agronomic decisions based on data, and enhance intelligent crop phenotyping within the precision agriculture systems.

Keywords: Convolutional neural networks (CNNs), deep learning, plant growth prediction, thermal imaging, canopy temperature, plant phenotyping, image processing, and non-destructive monitoring

1. Introduction

Real-time crop growth measurement is a guiding necessity of precision agriculture in the context of enhancing resource capacity, better prediction of yield, and sustainability of farming activities. Manual measurement of plant height, biomass and canopy size are the traditional crop growth estimation techniques, which are labor intensive, time consuming and in most cases not able to capture spatial variation in a large agricultural plot. Remote sensing and imaging technologies have been adopted to phenotype and manage crops due to the growing need to have high throughput and non-destructive technologies to monitor the plants (Zheng et al., 2021; Wu et al., 2023). They can be used to gather data-driven agricultural decisions because these technologies are faster, spatially explicit, and continuous in the way they provide information on plant growth and physiological status.

Complex imaging techniques such as RGB, multispectral, hyperspectral imaging and thermal imaging have extensively been utilized in the field of plant phenotyping and crop monitoring. The methods offer great data on the structure of canopy, chlorophyll, and condition of plants (Li et al., 2014; Zapata-Londoño et al., 2025). Of them, thermal imaging has become one of the potent instruments because of the possibility to record different canopy temperature which is closely linked with physiological processes, including transpiration, stomatal conductance, and plant stress responding (Jones, 2018; Wen et al., 2023). Temperature variations of canopies are usually used as a sign of water stress, diseases, and faster or slower growth, and thermal imaging is especially well-adjusted to real-time monitoring of plant development and health (Jin et al., 2024). To convert thermal images into significant growth variables, quantitative variables like average canopy temperature, temperature variability and canopy coverage need to be plucked out and processed. Conventional methods of vegetation indices and plant growth models have offered the basis of crop observation (Huete et al., 2002; Tsoularis and Wallace, 2002). These methods however tend to be manual, and may not be useful in extracting complex spatial patterns in thermal data.

The developments in artificial intelligence specifically deep learning have improved, to a great extent, image-based plant phenotyping and growth prediction. Convolutional Neural Networks (CNNs) have shown superior abilities in identifying hierarchic or spatial characteristics as well as regression or classification operations on complicated image data (LeCun et al., 2015; Murphy et al., 2024). Models based on deep learning have been effectively used to detect plant stress, monitor plant growth, and phenotype using different modalities of imaging (Gao et al., 2020; Tong et al., 2022). Those models are able to acquire meaningful features automatically extracted in a thermal image, which leads to a correct prediction of plant growth indices and physiological conditions. In spite of the progress, there is a problem of combining the modeling of physiological features with model-free deep learning-based thermal image analysis to estimate the growth. In this regard, the current work suggests a hybrid model that incorporates CNN-based regression to predict Growth Index and time-series modeling to predict the canopy coverage with the help of the logistic growth curves. The proposed approach will provide a powerful, interpretable, and non-destructive system of accurate estimation of crop growth and precision agriculture using spatial features of thermal-time dynamics and temporal features of growth.

2. Related Work

Proper monitoring of plant development and physiological condition has been one of the major goals in farming studies and crop production. Initial methods of plant monitoring were mainly based on the physiological and biochemical measurements of plant health and productivity including chlorophyll fluorescence and spectral reflectance. These pointers offered good information regarding photosynthesis efficiency and crop stress status which allowed better crop production strategies and management choice (Baker and Rosenqvist, 2004). Plant phenotyping has over time with the development of imaging technologies shifted to less invasive and high throughput methods, which can be used to obtain morphological and physiological characteristics without harming crops. The hyperspectral analysis and probabilistic models have been tested in imaging-based phenotyping to decipher the spectral signature of the plants and detects stress or disease patterns with great accuracy (Wahabzada et al., 2016).

Besides hyperspectral imaging, the technologies of LiDAR and three-dimensional imaging have been offered to improve the structural analysis and canopy modeling. LiDAR-based high-throughput phenotyping systems have facilitated the precise determination of the height of plants, canopy structure, and growth dynamics in the field conditions (Sun et al., 2018). In four-dimensional models of plant phenotyping, the addition of multispectral images and LiDAR data has been applied to record spatial and time changes in plant development, which provides the growth of crops in a comprehensive understanding (Rincón et al., 2022). Plant analysis systems based on machine vision have also been designed so that automated three-dimensional phenotyping can be done to enhance the scalability and efficiency of such phenotyping (Chaudhury et al., 2018). There has been a lot of research on plant growth modeling in order to investigate and model growth dynamics of various crop species and environmental conditions. The mathematical growth models that took into account the plant architecture and structural development have also proven to be becoming more and more relevant in explaining the pattern of plant development and the development of yields (Fourcaud et al., 2008). Recent research has focused on the relevance of canopy architecture and phenology to the extent of crop productivity and growth efficiency, and therefore, there is a need to be able to measure the canopy at specific levels in order to estimate growth efficiently (Nateshkumar et al., 2025). Other vegetation indices that have been broadly used in monitoring vegetation vigor and crop health at various levels of growth have been traditional remote sensing-based vegetation indices such as infrared-based indices (Tucker, 1979).

Due to the development of the computer vision and artificial intelligence, high-throughput phenotyping systems have incorporated the use of machine learning and imaging technologies to improve crop monitoring and yield prediction. The contemporary phenotyping system is a combination of computer vision, sensor fusion, and machine learning algorithms in order to analyse big portions of data and retrieve significant growth indicators (Singhvi et al., 2024). Convolutional neural networks and enhanced image processing methods have greatly enhanced the precision of trait acquisition and prediction of growth in crops through automated phenotyping methods. Nonetheless, the combination of thermal imaging and temporal growth models and CNN-based growth index prediction is poorly developed even with the advances in multimodal sensing and deep learning-based phenotyping. The current literature is mostly concentrated on individual sensing modalities or single modeling methods, which implies that a single framework should be created to integrate physiological features detection, deep learning, time-related development models to predict crop growth comprehensively.

2.1 The proposed study's novelty

As a non-destructive means of measuring plant growth, the main innovation of the given study is the integration of deep learning-based regression and physiological indicators, which are collected through thermal imaging. The proposed system employs cheap thermal imaging to simultaneously measure the dynamics of canopy temperature and canopy structure as opposed to the conventional phenotyping approaches that rely on manual measurements or multispectral information.

To be more precise, this piece of work contributes the following:

- Composite growth measure, a measure of growth that involves the combination of canopy coverage and heat response has been developed and quantitative growth can be assessed without the complications of destructive sampling.
- Image-based nonlinear growth pattern modeling by convolutional neural network + physics-based thermal indicators.
- An entirely automated pipeline which can potentially be applied in high-throughput phenotyping, since it performs canopy segmentation, feature extraction, and growth prediction.
- Presentation of a non-invasive method, which is scalable, and uses only thermal information to monitor the physiological condition of plants over time.

3. Materials And Methods

The figure 1 shows the general scheme of the proposed thermal imaging-based plant growth estimation system. Images of thermal canopy are initially obtained and analyzed to obtain physiological characteristics like coverage and temperature measures. Logistic growth modeling is used to capture the dynamics with time whereas the Growth Index is predicted using a lightweight CNN. The combined system allows proper, non-destructive, and real-time evaluation of the growth of plants.

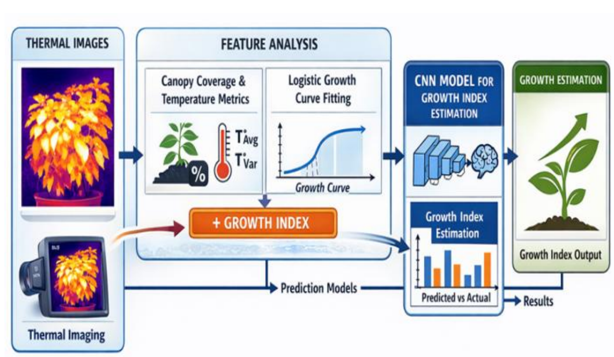

Figure 1. Deep Learning and Physiological Feature Modeling Framework for Thermal-Based Plant Growth Estimation

3.1 Framework for Research

This paper combines physiological measurements obtained after image processing with a convolutional neural network (CNN) regression model to introduce an automated thermal imaging-based system to estimate the quantitative growth of a plant. The aim is to measure thermal and structural characteristics of the plant canopies and find out how they correlate with a composite growth measure. The whole process consists of acquisition of thermal images, preprocessing, canopy segmentation, feature extraction, growth indices development, CNN modeling, dataset compilation and statistical analysis. The figure 2 represents the workflow of the acquisition and preprocessing of thermal images to canopy segmentation, feature extraction, regression analysis, and eventual Growth Index prediction to predict precise plant growth.

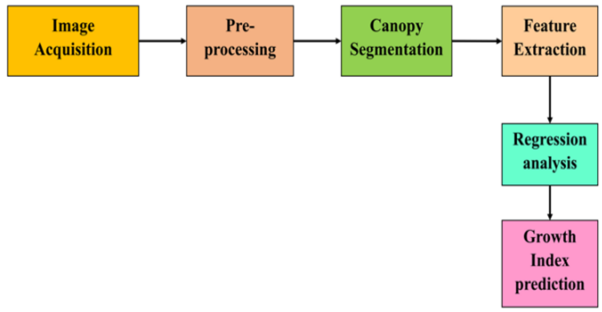

Figure 2. Overview of Process Block Diagram

3.2 Description of the Dataset

The dataset in this study consists of time-series thermal images of plant crops at different stages of growth to monitor the variation in canopy temperature and structural development with time. Each image represents a single observation of a specific moment in the growth cycle, and was collected to minimize geometric and environmental variation by controlling imaging conditions. To ensure uniformity of processing the deep learning, the thermal images were initially stored in grayscale mode and then rescaled to a uniform spatial resolution of 128 x 128 pixels.

3.3 Preprocessing Images

Preprocessing was carried out to all thermal pictures prior to analysis in order to increase the consistency of the data and to be able to extract the features reliably. Each image was resized to a fixed resolution in order to give it a set of input dimensions to the CNN model. Inter-image variability due to the effect of the environment and sensor noise were reduced by normalizing pixel intensity values to a common numerical range. Besides, in neural network training, this normalization stabilizes the gradient propagation. Data cleaning was used to remove invalid samples and ensured accuracy of the subsequent analysis.

Image resizing:

All the thermal images I(x, y) are resized to a constant resolution M N to provide the same CNN input size:

$$I_{r(i,j)} = I\left(\frac{iH}{M}, \frac{jW}{N}\right)$$

Where H and W denote the original image height and width.

Pixel intensity normalization:

Pixel values are normalized to decrease inter image variation as a result of environmental conditions and sensor noise:

$$I_{n(i,j)} = \frac{I_{r(i,j)} - I_{\min}}{I_{\max - I_{\min}}}$$

Where I_min and I_max are the minimum and maximum pixel intensities.

Mean–variance standardization:

Normalization Standardized normalization is used in order to stabilize gradient propagation in CNN training:

$$I_{s(i,j)} = \frac{I_{n(i,j)} - \mu}{\sigma}$$

Where μ and σ denote the average and standard deviation of pixel intensities.

Noise reduction:

Thermal noise is reduced using spatial smoothing:

$$I_{f(i,j)} = \Sigma\,\Sigma\, I_{s(i+m,j+n)} \cdot K(m,n)$$

Where K(m, n) is a smoothing kernel of size (2k + 1) × (2k + 1).

Invalid sample removal:

Images of low quality or corrupt images are rejected by intensity variance:

Discard image if $\sigma\_I > \tau$

Where σ_I is the image intensity variance and τ is a preset value.

3.4 Segmenting the Canopy

The threshold based segmentation method was utilized to distinguish between plant and the background. This method uses the physiological assumption that actively transpiring flora tend to be colder than the soil around it. The binary mask was used as a representation of the plant regions by defining pixels with intensity values below a set threshold as canopy pixels. In each image, the temperature data and canopy structural information were obtained with the help of this mask.

3.5 Extraction of Features

Three important traits that indicated the physiological and structural condition of the plant were extracted out of the segmented canopy region. To firstly estimate the average canopy temperature, the mean intensity of canopy pixels was employed as an indicator of transpiration of plants and water conditions. Second, in order to quantify the regional heterogeneity of canopy temperature, which is often associated with the variability of plant stress, the standard deviation of temperature was calculated. Third, canopy coverage was estimated by means of the ratio between the number of canopy pixels and total image pixels expressed as a percentage. This is an indicator of plant size and aboveground biomass accumulation in place of plant size.

3.6 Development of the Growth Index

An index of growth (GI) was developed to integrate the data on the canopy coverage and the inverse temperature factor to form a single quantitative variable. The index assumes that the lower canopy temperature and size of the canopy area of plants results in increased physiological activity and, consequently, increased growth. This created metric is a continuous variable that can be used in regression modeling and allows supervised learning in the absence of damaging ground-truth data.

3.7 Construction of Datasets

The matching growth index of each processed thermal image was then compared with the image to generate a labeled dataset. The regression target was the calculated index of growth, and the input characteristics of the CNN model were the images. The dataset was divided into a training and a testing subset in an 80:20 manner. To preserve temporal dependency and prevent information leak, the photos were disaggregated based on the chronological order since they were accumulated over time.

4. GROWTH ESTIMATION BASED ON CNN

4.1 Architecture of Networks

An automatic learning of discriminative thermal cues associated with the growth of plants was developed using a convolutional neural network. Two convolutional blocks are followed by a fully connected regression head of the architecture. The first convolutional layer is followed by a 2 × 2 max-pooling layer to perform spatial down sampling and which contains 32 filters with a 3 × 3 kernel and ReLU activation. The second convolutional layer is followed by a second pooling layer that has 64 filters and the same kernel. To extract finer representations, extracted feature maps are flattened and input to a dense layer having 64 neurons and ReLU activation. In the end, a single linear neuron produces the expected growth index value.

4.2 Methods of Training

The CNN model was trained by the Adam optimizer with the learning rate of 0.001. The loss function was taken to be mean squared error (MSE) because it is suitable in the case of continuous regression. A validation subset was also used to monitor convergence of training and over fitting when the network was trained to 50 epochs with a batch size of 4. Back propagation was employed in an attempt to minimize the prediction error by updating the model parameters.

4.3 Assessment of Performance

To test the performance of the model, the values of predicted growth indexes were compared with reference values by standard regression measurements, including: mean squared error (MSE), mean absolute error (MAE), and coefficient of determination (R2). Both numerical measures and a graphical representation of the predicted and actual growth curves were used to evaluate the predictive consistency of the model over time.

4.4 Specifics of Implementation

The suggested framework was developed in Python programming language. Image preprocessing and image segmentation were done using OpenCV, numerical computations and data management was done using NumPy and Pandas. The CNN model was developed using the TensorFlow/Keras, and the results were visualized with Matplotlib. To have successful training, the trials were conducted over an average computer system with the GPU acceleration turned on. The proposed approach has a non-destructive, automated means of estimating plant development, involving both deep learning and thermal image analysis. The system can be used to enable high-throughput phenotyping as well as offer a scalable method of monitoring plant growth under diverse environmental conditions by integrating physiological markers through canopy temperature and CNN-based regression.

4.5 Mathematical Modelling

In canopy temperature measurements, estimation of coverage and to provide the composite growth index, mathematical formulae were developed to provide a quantitative description of plant physiological state.

Normalized thermal intensity at the pixel position (x, y) can be denoted by $I(x, y)$. Mean canopy temperature can be obtained by the following formula in case C represents the set of canopy pixels that were obtained during a segmentation:

$$Tavg = \frac{1}{C} \sum_{(x,y)}^{\in C} (x, y)$$

Variability in Temperature

The spatial variability of canopy temperature is represented with the help of the standard deviation:

$$Tstd = \frac{1}{C} \sum_{(x,y)}^{\in C} (I(x, y) - Tavg)2$$

Plant stress distribution and transpiration heterogeneity are reflected in this measure.

Coverage of canopies

Nc is the number of pixels in the image in total and Nt is the number of canopy pixels. Canopy coverage definition can be defined as:

$$Coverage = \frac{Nc}{Nt} \times 100$$

This is a structural proxy of biomass amassing and plant magnitude.

Index of Growth

A composite growth index (GI) is a combination of physiological and structural traits, and thus is defined as follows:

Where, $Tmax$ is the highest value of normalized temperature,

$$GI = Coverage \times \left(1 - \frac{Tavg}{Tmax}\right)$$

Because of good transpiration and photosynthetic rate, this formulation assumes that plants with a larger canopy cover and low canopy temperature have a higher growth potential.

CNN Regression Model

A nonlinear mapping is learned by the CNN:

$$GI^{=f_\theta(X)}$$

Here

- X indicates the thermal image
- f_θ represents the CNN with parameters θ
- GI^ is the predicted growth index

This Model training minimizes the mean squared error:

$$L(\theta) = \frac{1}{n}\sum_{i=1}^{n}(GIi - GI^i)^2$$

5. RESULTS ANALYSIS

5.1 Changes in canopy thermal properties over time

The time series of the average canopy temperature exhibited obvious short-term changes throughout the period of observations, but the values remained in a moderate range of operation. Although the absence of a unified upward or downward trend means that the climatic conditions are relatively steady over the time of data collection, the presence of peaks in between suggests short-time warming events. The standard deviation of the variability of the canopy temperature depicted short instances of increased thermal heterogeneity in the canopy microclimate, but otherwise remained relatively unchanged with occasional spikes.

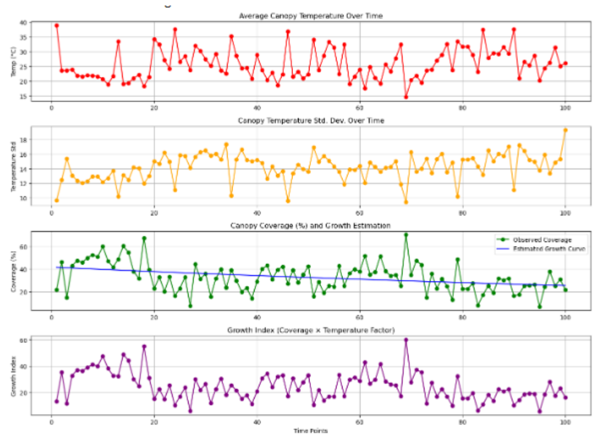

Figure 3. Canopy Statistics estimation

The figure 3 shows the time study of the canopy thermal properties and growth estimation of the plants. The former plot reveals the changes in the average canopy temperature with time which demonstrate the physiological processes of plants to the environmental conditions. The second plot depicts the changes in temperatures, which represent thermal stability and changes in stress. The third plot shows a comparison of observed canopy coverage and the predicted logistic growth curve which illustrates that model-based canopy growth trends can be predicted. The last plot is the calculated Growth Index based on the canopy cover and temperature. The combination of these visualizations points to the correlation between thermal processes and vegetation, which allows one to monitor the development of crops with thermal imaging and analytical modeling methods accurately and without destruction.

The graph 4 shows the performance of Convolutional Neural Network (CNN) model at predicting the Growth Index based on thermal imaging-derived features. The graph is used to compare the values of real growth indices and the predicted values of growth indices in several test samples. The fact that the two curves are very parallel proves that the model is capable of clarifying the variations in growth of plants. Minor variations between the predicted and the actual values are caused by variability in the environment and noise in the sensors, but the general trend is similar. The highs and lows of both curves indicate actual physiological variations in the growth conditions of plants which are practically trained by CNN model. The predictive consistency of the model is very high in most samples which implies that the model is robust and reliable in estimating the growth. This analogy proves that the suggested deep learning model can give precise, real-time and non-destructive monitoring of plant development, thus being an excellent fit to precision agriculture and intelligent crop management systems.

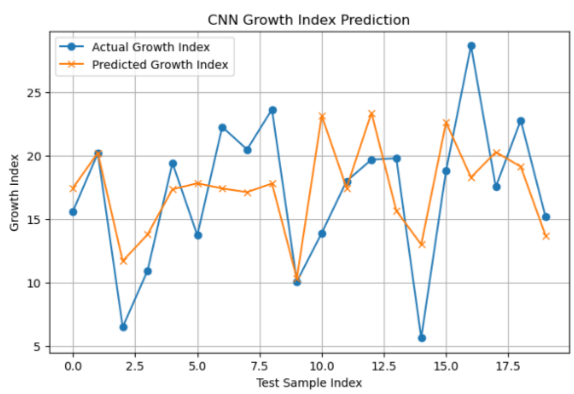

Figure 4. CNN growth index prediction

5.2 Dynamics of canopy covering

The canopy coverage observed had significant temporal variability that could have been due to the environmental factors and also due to natural changes in growth. The growth trend line fitted showed that there was a change in the mode of active vegetative growth into a more stable or mature growth stage with a slight declining tendency towards the later time points.

5.3 Analysis of growth indices

The resulting Growth Index, which was the product of the temperature factor and canopy coverage, was capable of representing the joint physiological responses. The sporadic peaks in the index were periods of positive structural growth and thermal conditions. Everything said and done, according to the trend, optimum growth conditions did not occur in a regular fashion but at intermittent intervals.

5.4 Growth index prediction performance using CNN

The convolutional neural network was able to learn the underlying relationship between the input features as evidenced by the fact that the actual and expected growth index values are similar. The test samples were highly predictive, with the majority of the test samples exhibiting a strong predictive consistency of the values compared to general trends of the values measured. The model was able to hold the overall trend and variability of the growth index even though there were slight deviations at extreme levels, which points to the good ability to extrapolate over unknown samples.

An overview of the results

In general, the findings show that:

- The temperature of the canopy was relatively constant with short-term fluctuations.
- Canopy covering had erratic behaviour and then maintained a slow stabilization trend.
- The integrated growth index was a good representation of the combined environmental and structural responses.
- The ability to reproduce growth dynamics through the CNN model supported the suitability of the model in automated plant growth monitoring.

6. Discussion

The experimental results indicate the quality of integration of the proposed multimodal model that uses thermal and canopy structural data to describe the dynamics of plant growth. The convolutional neural network is successful in learning the nonlinear relationship between the variability of temperature, canopy coverage, and growth behavior, which is reflected in the fact that the growth index projected is similar to the observed trend. Although the variations are slight at the extremes, the variations are to be anticipated due to the difference in biological diversity and environmental changes which influence plant physiology. The validity of the thermal data is proved by the time analysis of canopy temperature, which shows the real fluctuations within the normal physiological range. The trends of canopy cover also confirm the image-based feature extraction method as they are aligned with the expected growth trend. The uniformity of the growth index that is obtained and computed as a ratio of temperature and coverage factors demonstrates that the mathematical formulation is a good representation of the conditions in plant development.

Compared to the traditional unimodal approaches that have been reported in the literature, the addition of temperature cues provides extra physiological insight enabling more sensitivity to the stress-related changes. This shows that the proposal feature fusion method is advantageous since it relies on complementary sources of information to enhance prediction strength. Even after the encouraging performance, it is necessary to note some limits. The relatively moderate size of the data can reduce the possibility of making generalizations to different kinds of crops or different environmental conditions. Moreover, external factors that may enhance the accuracy of prediction such as humidity, soil moisture or the intensity of light have not been considered specifically in the current model. In future study, the dataset will be extended, additional environmental features will be added and lightweight architectures of real-time field deployment will be explored. On the whole, the results indicate the applicability of the proposed approach within automated crop monitoring systems and precision agriculture because they show that it provides a reliable and biologically relevant prediction of plant growth.

7. Conclusion

This paper presented a multimodal model of predicting the growth of vegetation through thermal imaging and canopy structure that applies a convolutional neural network to fuse the two data types. In order to consider both the structural and physiological aspects of plant development, a new formulation of growth index including temperature and canopy coverage was developed. The effectiveness of the feature fusion method was confirmed by the experiment outcomes, which indicate that the proposed model can preserve high rates of compliance with the observed data and predict the growth patterns in a proper manner.

The framework presents an automated, non-destructive system of monitoring plant development with possible applications in yield forecasting, stress identification and accurate agricultural decision-making. The proposed approach is more reliable than the traditional single-sensor approaches because it provides a more comprehensive picture of the plant conditions.

The future research will focus on the real-time application in agricultural monitoring systems, the inclusion of other sensors and large-scale testing under different environmental conditions. The positive results demonstrate that the proposed approach can be an effective tool to use in sustainable agricultural practices and intelligent management of crops.

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