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RESEARCH ARTICLE

High-throughput Morphological Phenotyping of Tomato Seedlings Using Computer Vision and Machine Learning

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ABSTRACT

Monitoring the early-stage vegetative growth is particularly critical for determining the plant's vigour, stress tolerance, and yield potential. Accurate and timely phenotyping of these traits is essential for informed decision-making in cultivation. However, traditional phenotyping methods are labour-intensive and time-consuming since most of them rely on manual inspection and subjective criteria. This study presents an automated, image-based approach integrated with artificial intelligence to monitor morphological traits of early growth stages of tomato plants. In this study, images of the seedlings of the tomato variety called "Thilina" were used, and an Excess Green (ExG) based segmentation method was employed for image preprocessing. The K-nearest neighbour machine learning model has gained the highest accuracy of 89% out of all machine learning models, and the convolutional neural network was utilised in identifying the plant timelines with prominent growth. The results of seedling evaluation through image-based phenotyping reveal that early vegetative parameters are reliable predictors of transplant readiness and vigour.

***Keywords**: Image processing, Machine learning, Morphological phenotyping, Plant propagation, Tomato*

INTRODUCTION

Tomato (*Solanum lycopersicum* L.) belongs to the family Solanaceae and is regarded as one of the most significant vegetables produced in commercial agriculture. Phenotyping can reveal plenty of information on traits of a crop during different stages of growth (Jin *et al*., 2022). It is important to evaluate the phenotypic traits of tomato plants and explore their variation during different growth stages to understand the relationship between tomato plant growth (Fentik, 2017). Specifically, morphological phenotyping of tomato seedlings involves the observation and analysis of physical characteristics exhibited by young tomato plants at the early stages of growth. These characteristics can provide valuable insights into the plant's genetics, health, vigour, and potential performance. It aids in selecting seedlings with desired traits for further cultivation, whether that's for improving yield, disease resistance, or other factors important for successful tomato production.

Traditional morphological phenotyping methods have been integral to the selection and improvement of plant varieties. Visual assessment remains a cornerstone in phenotyping, allowing cultivators to evaluate various morphological traits. Characteristics such as plant height, leaf shape, colour, and disease resistance are routinely assessed through visual inspection (Blazakis and Kalaitzis, 2023). Morphometric measurements involve quantification of plant features, such as leaf area, stem diameter, and seed size. Callipers, rulers, and other measuring tools are used to obtain accurate data (Blazakis and Kalaitzis, 2023). While providing quantitative data, these traditional methods are mostly time-consuming and may not capture the complexity of certain traits. Further, these methods inherently suffer from limitations regarding precision, scalability, and adaptability to diverse environments.

In recent years, the integration of autonomous technologies into phenotyping processes has revolutionised plant cultivation practices, offering unprecedented capabilities for non-invasive, high-throughput data collection (Silva *et al.*, 2024). Autonomous phenotyping technologies represent a paradigm shift in plant cultivation, enabling researchers to collect precise and real-time data on plant traits at unprecedented scales. The integration of drones, sensors, imaging techniques, and robotics offers immense potential for advancing planting programs, ultimately contributing to global food security and sustainable agriculture. High-throughput imaging platforms have been used to capture seedling traits under controlled environments, allowing non-invasive tracking of growth over time (Samiei *et al.*, 2020).

Advanced imaging techniques, coupled with computer vision algorithms, play a crucial role in autonomous phenotyping. RGB imaging, fluorescence imaging, and 3D imaging technologies allow for non-destructive and highly detailed assessments of plant morphology and traits. Visible-light cameras are commonly used for acquiring plant leaf morphological traits, while spectral imaging technology is preferred for physiological and biochemical traits (Zhang *et al.*, 2023). Studies combining image data with machine learning algorithms have shown promising results in predicting biomass and early vigour, improving transplant selection accuracy (Xu *et al.*, 2023).

Recent literature has undertaken machine learning for the purpose of phenotyping (Sheikh *et al.*, 2023). Jáquez-Gutiérrez and his team aimed to develop a faster and more reliable method for screening tomato mutants with altered leaf morphology (Jáquez-Gutiérrez *et al.*, 2019). This approach saved significant time and space while identifying mutants with various leaf developmental abnormalities. Furthermore, potential links between leaf development and agronomic traits were uncovered, expanding the understanding of tomato genetics. A low-cost and open-access 3D phenotyping pipeline called "3DPhenoMVS" was introduced for tomato plants (Wang *et al.*, 2022). It is capable of calculating 17 phenotypic traits throughout the plants' life cycle using structure from motion algorithms. Six traits were evaluated for accuracy against manual measurements, showing strong correlations. The study also explored the impact of environmental factors on tomato growth and yield, revealing that stronger light intensity and moderate temperature and humidity lead to increased biomass and yield. The main objective of the study was to evaluate the accuracy of a photogrammetric method based on structure from motion and multi-view stereo for plant phenotyping at the organ level (Rose *et al.*, 2015). This study compared the measurements obtained from the photogrammetric method with high-accuracy reference data obtained from a close-up laser scanner. The parameters focused on were leaf area, main stem height, and the convex hull of the complete plant, which was important for current phenotyping scenarios. This study demonstrated that the photogrammetric approach is highly suitable for the monitoring scenario, providing accurate measurements that correlate well with the reference data.

The literature on planting and phenotyping shows a growing interest in automating the screening process to improve efficiency and accuracy. Although existing research papers have made significant progress in automated phenotyping, there are still limitations in monitoring phenotypic characteristics of early growth stages of plants such as difficulty in measuring traits like leaf accurately since seedlings are tiny and missing of critical stages of the plants since phenotypes can change within hours or days. Therefore, the main objective of this research is to assess tomato seedling growth by evaluating morphological traits, facilitating the identification of the most vigorous seedlings for transplantation and improving overall field performance.

MATERIALS AND METHODS

The seedling sorting process was divided into three stages: image acquisition, feature extraction, and model development and evaluation.

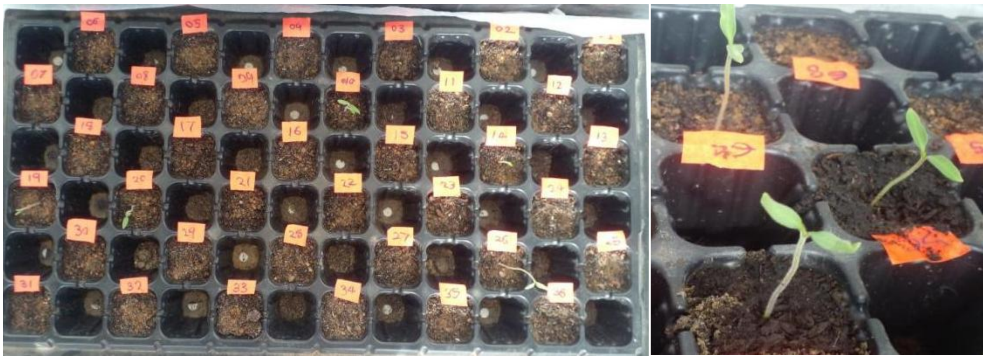

Figure 1: Seeds were planted in a bubble tray and the cells are numbered to identify each plant

Preparation of dataset

This research has used the seeds of a tomato variety called "Thilina", which is one of the most famous varieties, in Sri Lanka. Tomato is a popular cash crop among farmers (Hensman, 2021). Plants were grown in a bubble tray as shown in Figure 1, placed in a outdoor location with temperatures around 21–27°C and adequate light for seed germination.

The dataset used for tomato plant growth prediction was systematically constructed by capturing top-view images of the resolution 640×640 of 80 individual plants over an 11-day period, with two images taken daily (one in the morning and one in the evening). The images were acquired using Raspbery Pi 3B+ camera with a 5-megapixel Omnivision OV5647 sensor.

Image preprocessing and feature extraction

An enhanced ExG-based segmentation method was employed to isolate green plant regions from background noise. Each RGB image was first converted to float format, and the ExG index was calculated as in the following Equation.

$$\mathrm{ExG} = 2\mathrm{G} - \mathrm{R} - \mathrm{B}$$

A binary mask was created by thresholding the ExG values and further refined through morphological opening (5×5 elliptical kernel) to remove small artefacts. To suppress non-vegetative blue regions, the image was converted to HSV space, and a hue-based filter was applied to exclude blue pixels. The clean green mask was obtained by combining the ExG and non-blue masks, as shown in Figure 2. Each individual tomato plant's performance was automatically measured by extracting features such as leaf area, number of leaves and leaf area index (LAI). These features were extracted from a total of 1920 images of tomato seedlings.

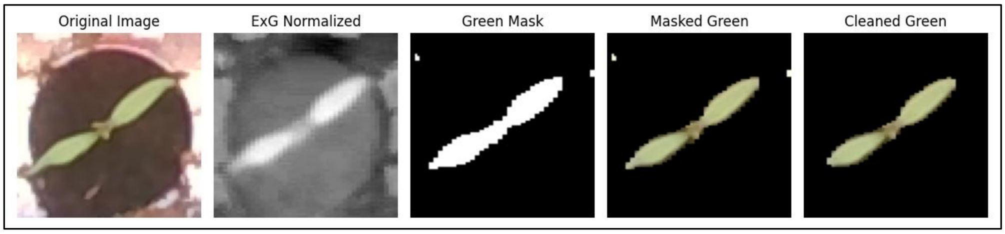

Figure 2: Preprocessing and isolating the green area of the seedlings in each cell of the bubble tray

Model development and training

The dataset was divided into training (80%) and testing (20%) portions. Then, data were trained with different classifiers such as decision trees, random forest, support vector machine (SVM), k-nearest neighbour (k-NN), and deep neural network (DNN). Every model was trained on the training set and evaluated on the test set. Then the top-performing model was selected after being ranked highest in accuracy. Valuable feedback was provided for the supervised learning process through manual annotation, by ensuring that the machine learning models were trained on data that represented real-world outcomes.

Performance evaluation

Performance was gauged using accuracy, support, F1-score, precision, and recall. Precision represented the percentage of positive forecasts that were true, while recall represented the percentage of true positives that were accurately classified as positives. The F1-score was a harmonic mean of recall and precision, while accuracy represented the percentage of accurate forecasts overall.

RESULTS AND DISCUSSION

As shown in Table 1, the best result was achieved by k-NN, with an accuracy of 0.89. Random forest and SVM had slightly lower accuracies of 0.85, respectively. Decision tree and DNN had the lowest accuracies of 0.70 and 0.57, respectively.

Table 1: Performance scores of each model

Classifier	Precision	Recall	F1-score	Accuracy
Random forest	0.93	0.67	0.81	0.85
Support vector machine (SVM)	1	0.67	0.8	0.85
k-nearest neighbour (k-NN)	1	0.79	0.83	0.89
Decision tree	0.72	0.67	0.73	0.7
Deep neural network (DNN)	1	0.11	0.21	0.57

Additionally, the timeline images were used to identify the best timeline using CNN. Once all 11-day images of plant timelines were entered into the system, they can be categorised as good, weak, or average timelines as shown in Figure 3 (a,b,c).

(a)

(b)

(c)

Figure 3: Timeline of the (a) weak growth of the plant, (b) average growth of the plant, and (c) good growth of the plant

Table 2 details each layer type, its output shape, and the number of trainable parameters involved in the CNN model.

Table 2: Summary of the CNN architecture

Layer (type)	Output shape	Parameters
conv2d_8	(None, 62, 126, 32)	896
max_pooling2d_8	(None, 31, 63, 32)	0
flatten_8	(None, 62496)	0
dense_16	(None, 128)	7999616
dropout_1	(None, 128)	0
dense_17	(None, 3)	387

In this classification task, varying performance was exhibited by the k-NN model across different classes, as shown in Table 3. Perfect precision (1.00) was showcased by class 0, implying that when this class was predicted by the model, it was invariably correct. However, missed instances were suggested by its lower recall (0.73) and F1-score (0.50). Conversely, consistent precision, recall, and F1-scores around 0.60, 0.75, and 0.72, respectively, were displayed by classes 1 and 2, indicating a more balanced prediction pattern. The overall accuracy of 0.72 signified that the classes for 72% of the dataset were accurately predicted by the model. While precise predictions for class 0 were excelled in and stability was maintained in predicting other classes, there was an opportunity for improvement, particularly in enhancing the model's ability to capture more instances of class 0 without compromising its precision.

There is one similar research in the literature on early identification and localisation for weak seedlings based on phenotype detection to determine the early growth condition of seedlings, aiming to replace inefficient and subjective manual culling and replenishment in factory nurseries (Xu *et al.*, 2023). They have used an Azure Kinect sensor to collect top-view data (images and point clouds) of watermelon plug seedlings and collected phenotypic features such as plant height and leaf area for each seedling. Six machine learning classification methods were compared (including logistic regression, SVM, GBDT, XGBoost, LightGBM, and Random Forest). Random forest was identified as the optimal classification model, achieving the highest accuracy of 84%. However, the proposed method in this paper is more accurate (89%) than this in seedling sorting.

Table 3: CNN model accuracy

	Precision	Recall	F1-score	Support
0	1.00	0.73	0.50	3
1	0.60	0.75	0.72	4
2	0.60	0.75	0.72	4
Accuracy			0.72	11
Macro average	0.77	0.78	0.71	11
Weighted average	0.62	0.67	0.60	11

CONCLUSION

The determination of the best plants among the samples is heavily dependent on their phenotyping traits. Early-stage seedling vigour is a crucial determinant of crop establishment and final yield. Image-based phenotyping has emerged as an efficient tool for assessing morphological characteristics. An autonomous screening approach was proposed in this research, which combined imaging technologies, and machine learning algorithms to provide non-invasive phenotypic analyses on tomato seedlings. The study employed machine learning-based models such as random forest, k-nearest neighbour (k-NN), Support vector machine (SVM), decision tree, and Deep neural network (DNN). The system has shown promising results in selecting healthy seedlings for further growth. Further, CNN was capable of classifying timelines of seedlings into the categories of weak, average and good based on their growth. As part of future work, the proposed approach can be extended to monitor vegetative growth, flowering, and yield stages of the plants. This ongoing phenotypic tracking is expected to combine with a hardware setup with vision sensors that can autonomously provide valuable insights into the dynamic changes in plant traits with minimal human intervention.

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