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GEOMETRIC FEATURE-BASED MACHINE LEARNING FOR WILTING DETECTION IN *VINCA ROSEA*

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Early and reliable detection of plant wilting is crucial for maintaining crop productivity and ensuring sustainable agricultural practices. This study aimed to evaluate the effectiveness of machine learning models in detecting wilting in *Vinca rosea* plants using simple geometric features extracted from digital images. The extracted features included leaf width, length, area, aspect ratio, and area coverage. Four machine learning classifiers, Support Vector Machine (SVM), Decision Tree (DT), k-Nearest Neighbours (kNN), and Naive Bayes (NB) were trained and validated to classify plants as wilted or healthy. Results showed that SVM achieved the highest performance, with 0.98 accuracy, 0.99 precision, 0.95 recall, 0.97 F1 Score, and 0.99 area under the curve (AUC), outperforming the other models. DT and kNN achieved competitive accuracy (0.97 and 0.95, respectively) but exhibited weaker recall, while NB showed high recall (0.92) but reduced precision (0.87). The findings highlight the robustness of SVM and the potential of simple geometric features combined with machine learning for rapid and reliable wilting detection. Moreover, integrating such image-based wilting detection with irrigation control can optimise water use while sustaining plant health and yield.

Keywords: *Vinca rosea*; wilting; image processing; machine learning

Plant health monitoring is a critical component of sustainable agriculture, as early detection of stress symptoms allows timely intervention and improved crop management (Zhong et al., 2025). One of the most visible indicators of plant stress is wilting (Rascio et al., 2023; Zhang et al., 2024) when reduced turgor pressure causes non-woody tissues to lose firmness and droop. Plant wilting occurs due to insufficient water availability, disease, pests (Saadati et al., 2024), or unfavourable environmental conditions. Wilting directly affects plant physiology, photosynthetic efficiency, and ultimately yield (Flexas et al., 2009; Saglam et al., 2014; Zhu, 2016). Traditional methods for assessing plant wilting rely heavily on visual inspection by experts (Kuzhiyil et al., 2025) or manual measurement of physiological parameters such as leaf water potential (Engelbrecht et al., 2007; Jang et al., 2024; Rodriguez-Dominguez et al., 2022), stomatal conductance (Bartlett et al., 2016; Ramos-Fernández et al., 2024), or relative water content (Dong et al., 2025; Zhou et al., 2021). While effective, these approaches are often time-consuming, labour-intensive, and destructive, making them less practical for large-scale or continuous monitoring.

Recent advances in image processing and computer vision have opened new opportunities for non-destructive, automated, and real-time plant wilting monitoring (Huixian, 2020; Omari et al., 2020; Upadhyay et al., 2025). By leveraging digital images, researchers can extract morphological, colour, and texture-based features that reflect the structural

and physiological changes associated with wilting (Cai et al., 2013, 2018; Cen et al., 2022; Chopin et al., 2018; Das Choudhury et al., 2019; Dolatabadian et al., 2025; Font and Farkas, 2008; Maraveas, 2024; Munisami et al., 2015; Pisani et al., 2023; Wang et al., 2019; Xiong et al., 2019; Yang et al., 2023). Image-based techniques are particularly attractive due to their low cost, scalability, and ability to integrate with precision agriculture platforms such as unmanned aerial vehicles (UAVs) (Syifa et al., 2020; Yildiz et al., 2020), Internet of Things (IoT) systems, and greenhouse automation.

In this study, we propose an image processing-based framework for wilt detection in *Vinca rosea* using machine learning classifiers. The method employs image processing techniques to extract morphological features from plant leaf images, enabling automated discrimination between healthy and wilted plants. The approach provides a non-invasive and efficient alternative to conventional physiological measurements, with potential applications in smart agriculture, greenhouse monitoring, and automated irrigation systems.

We evaluate our system on one of the most popular ornamental and medicinal plants, *Vinca rosea* (*Catharanthus roseus*), commonly known as Madagascar periwinkle (Nejat et al., 2015). This species is of particular significance due to its dual importance in horticulture and pharmaceutical industries. *Vinca rosea* is widely cultivated as a decorative plant because of its hardiness, resilience

to harsh environmental conditions, and low maintenance requirements, making it highly adaptable to diverse landscapes. In addition, it produces attractive flowers in a wide range of colours, which further enhances its value as an ornamental species (Esringü et al., 2022). Beyond its horticultural appeal, *Vinca rosea* is highly valued in the pharmaceutical sector for its alkaloid compounds, notably vincristine and vinblastine, which are extensively used in anticancer therapies (Goswami et al., 2024). Due to its high demand, *Vinca rosea* is cultivated on a commercial scale by farmers and horticulturists. However, large-scale production often involves managing hundreds to thousands of pots, where manual irrigation becomes labour-intensive and inefficient. Figure 1 shows an example of *Vinca rosea* cultivated in pots, displayed as hanging, ground-placed, or rack-arranged from local nursery.

Current practices rely on timer-based triggers without accounting for soil requirements, which can lead to excessive water application. Over-irrigation not only wastes water but also promotes root diseases, while under-irrigation causes wilting and reduces plant quality (Lakhari et al., 2024). Therefore, an automatic method to detect wilting and trigger irrigation only when necessary is highly beneficial. Such a system helps to maintain plant health, conserve water, and ensure consistent quality, making the development of reliable image-based wilting detection

methods both timely and practically important. Although image processing and computer vision have been widely explored for general plant stress detection (Dolatabadian et al., 2025), limited studies have specifically focused on wilting detection in *Vinca rosea*. Thus, this study aims to detect wilting in *Vinca rosea* using features extracted from digital images with machine learning classifiers. The novelty of this work lies in developing a species-specific, image-

based wilting detection approach that integrates calibrated feature extraction with machine learning – an area that remains underexplored for *Vinca rosea*.

Material and Methods

Sample preparation

Six *Vinca rosea* (*Catharanthus roseus*) plants cultivated in individual pots were purchased from a local nursery

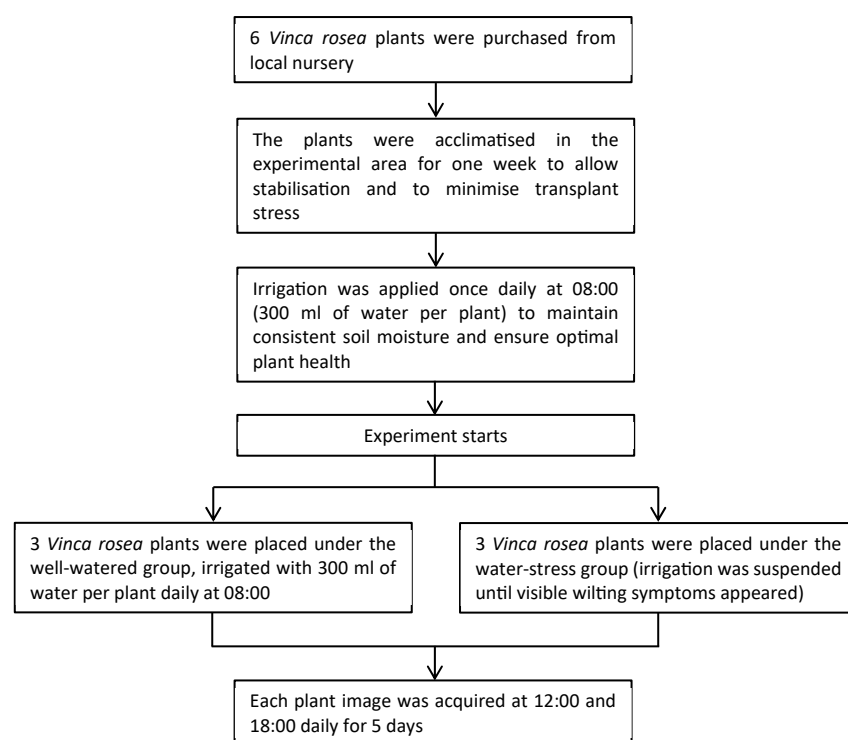


Fig. 2 Flow diagram process of the *Vinca rosea* plant preparation and experimental design



Fig. 1 Example of *Vinca rosea* cultivated in pots, displayed as hanging, ground-placed, or rack-arranged from a local nursery

in Selangor, Malaysia. The plants had an average stem diameter of 0.24 ± 0.03 cm, with mean height and canopy width of 13.97 ± 2.4 cm and 13.45 ± 1.3 cm, respectively. These measurements were obtained manually using a ruler, based on six repeated measurements. The average age of the plants at the time of acquisition was three months. Each plant was grown in a plastic pot (6.5 cm diameter $\times$ 7.5 cm height) filled with a standard potting medium composed of topsoil, sand, and organic compost in a 2 : 1 : 1 ratio. Prior to experimentation, the plants were acclimatised in the experimental area for one week to allow stabilisation and to minimise transplant stress. During this acclimatisation phase, irrigation was applied once daily at 08:00 (300 ml of water per plant) to maintain consistent soil moisture and ensure optimal plant health. Figure 2 shows the flow diagram process of the *Vinca rosea* plant preparation and experimental design.

Experimental design

The experiment was conducted in an outdoor shaded area to closely simulate typical horticultural growing conditions located at the Faculty of Mechanical Engineering & Technology, Universiti Malaysia Perlis, Malaysia (N 6.46152, E 100.35242). During the experimental period, the average ambient temperature and relative humidity were 28.5 °C (ranging from 24 °C to 35 °C) and 79.9% (ranging from 55% to 95%), respectively. These data were recorded daily at 6-hour intervals using our in-house data logger (Jusoh et al., 2024). All plants were grown in identical potting media and irrigated following a standardised schedule to

ensure consistent substrate temperature and humidity across samples. Following acclimatisation, the plants were subjected to controlled irrigation treatments to induce water stress, which served as the basis for wilting analysis. The treatments consisted of two groups:

- a) the control group (well-watered), irrigated with 300 ml of water per plant daily at 08:00;
- b) the water-stress group, in which irrigation was suspended until visible wilting symptoms appeared.

Each treatment group comprised three plants, arranged in a randomised complete block design (RCBD) to minimise environmental variation.

Image processing techniques

Image acquisition setup

Plant images were acquired daily using a smartphone camera (Apple iPhone XR, 12 MP) mounted on a tripod at a height of 1.2 m and positioned 60 cm from the plant to capture stable front view images with minimal distortion. One image for each sample was captured at front view angle under natural daylight conditions twice daily at 12:00 and 18:00 from 11 April 2025 (Day 1) until 15 April 2025 (Day 5). Figure 3 shows an example of *Vinca rosea* images captured at 12:00 for 5 days under control and water-stress group.

The captured images were saved in .jpeg format. Image acquisition was performed indoors against a white background under soft, diffused lighting to reduce shadows and ensure consistent illumination, providing reliable data for image analysis of *Vinca rosea* characteristics. A reference blue colour square (2×2 cm) was included in each image



Fig. 3 *Vinca rosea* plant images captured at 12:00 for 5 days under control and water-stress group

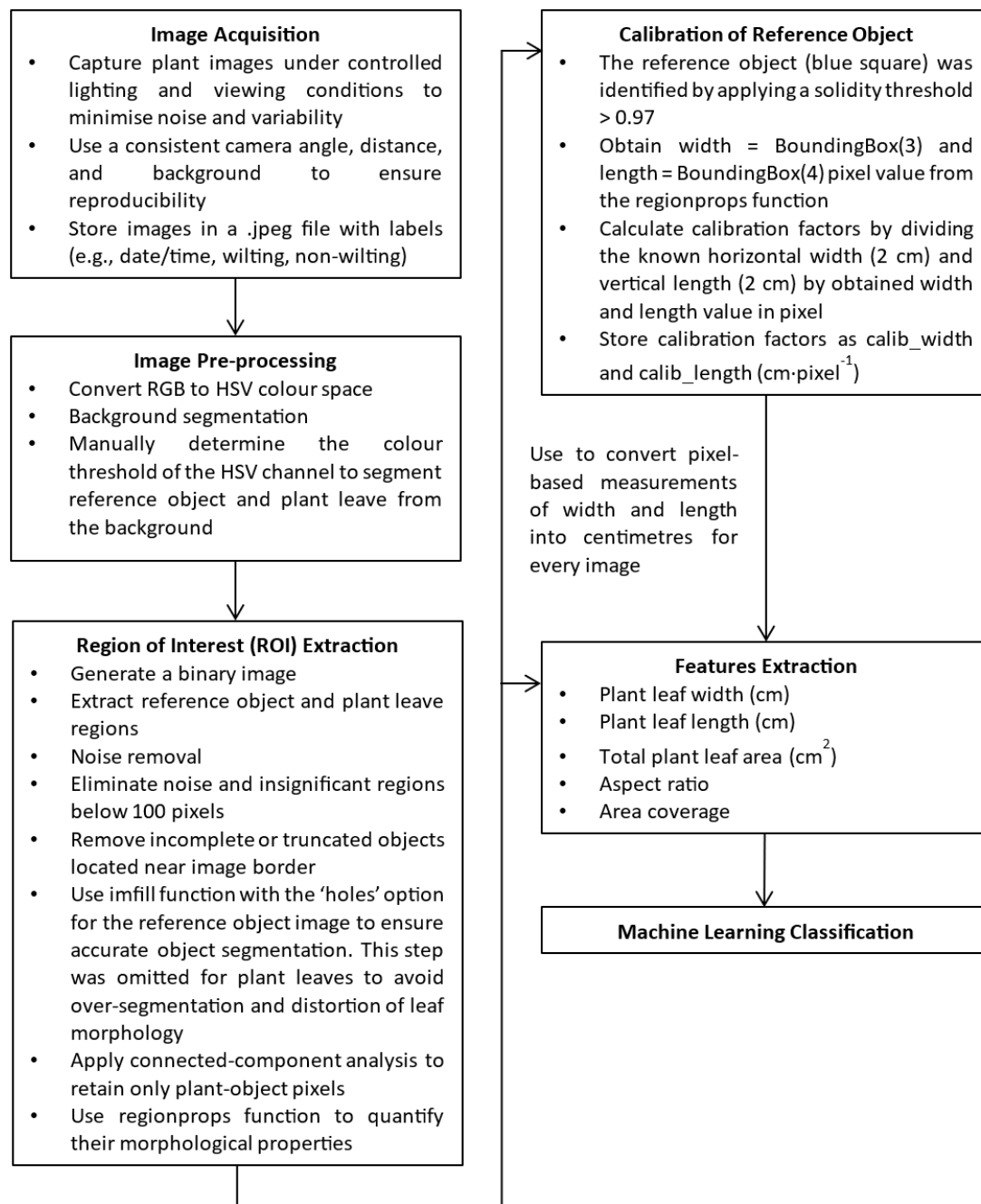


Fig. 4 Flow diagram of the process of image processing, calibration, and feature extraction in this work

to provide a calibration reference for converting pixel dimensions into centimetres. A square shape was selected because it provides distinct, well-defined edges that can be reliably detected during segmentation and is easy to position and capture consistently under field conditions. This simple geometry also minimises perspective distortion compared to more complex shapes, ensuring more stable and repeatable calibration across all images (Qin et al., 2024; Zulkifli et al., 2025). This calibration step is essential to ensure accuracy and reproducibility in subsequent morphological feature extraction, reducing potential errors caused by image scaling. Figure 4 shows the flow diagram of the process of image processing, calibration and feature extraction in this work.

Image segmentation and calibration

The acquired RGB (red, green, blue) image (2268×4032 pixels) was analysed using MATLAB (version 2018a, The MathWorks Inc). The RGB image shown in Fig. 5a was converted to HSV (hue, saturation, value) to separate colour from intensity which made it more robust to changes in lighting (Yang et al., 2015). The MATLAB Colour Thresholder app in the Image Processing and Computer Vision section was used to manually determine the colour threshold of the HSV channel to segment reference object and plant leave from the background (Pal and Pal, 1993). The identified HSV colour threshold value to segment the region of interest (ROI) used in this work is listed in Table 1.

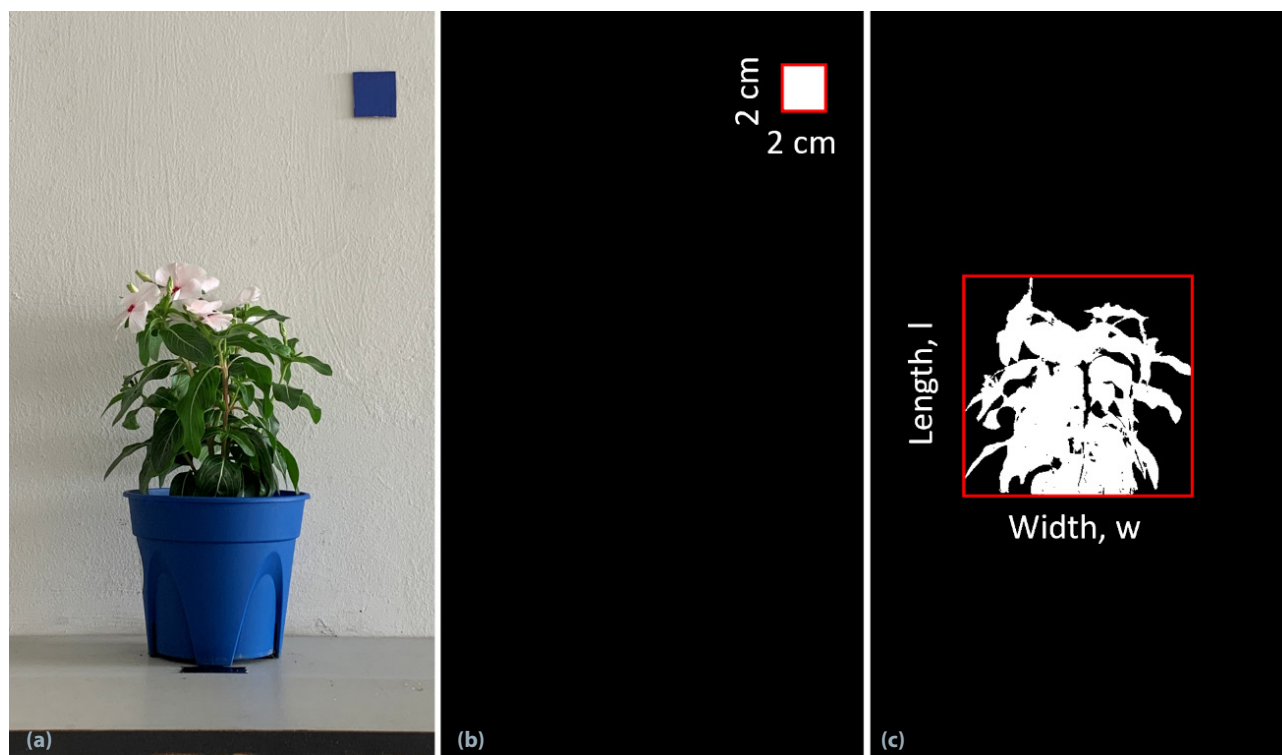


Fig. 5 (a) RGB image of image *Vinca rosea* plant; (b) BW mask of reference square object; (c) BW mask of identified plant leaf

To calibrate image pixel measurements in centimetres using the MATLAB, the first reference object (blue square) was segmented from the background using the created black and white (BW) mask based on chosen HSV colour thresholds (Table 1). To ensure the accuracy of segmentation, small artifacts and irrelevant objects were removed. Specifically, connected components with an area smaller than 100 pixels were discarded using `bwareaopen` to eliminate noise and insignificant regions. Additionally, partial blobs located along the image border were excluded using `imclearborder` to avoid incomplete or truncated objects that could bias subsequent feature extraction. To ensure accurate representation of segmented objects, the binary masks were post-processed using the `imfill` function with the 'holes' option in MATLAB. This procedure filled

any interior gaps within the detected regions, thereby converting hollow or fragmented objects into solid forms. By eliminating internal voids, the processed masks provided more consistent object boundaries, which improved the reliability of subsequent feature extraction such as area, solidity, and shape measurements.

Then, connected components within the binary images were first detected using the `bwconncomp` function, and their morphological properties were subsequently quantified using the `regionprops` function. The reference object (blue square) was identified by applying a solidity threshold, where only regions with solidity greater than 0.97 were retained. Solidity is defined as the ratio of the object area to the area of its convex hull, with values approaching 1 indicating highly compact and convex shapes. By setting the threshold above

0.97, only nearly perfect rectangular regions were preserved, ensuring that irregular or fragmented regions were excluded. This criterion was selected to reliably isolate the reference square while eliminating noise or non-square structures in the image. The segmented reference object is presented in Fig. 5b. The conversion of pixel measurements to real dimension units can be determined by dividing the known horizontal width (2 cm) and vertical length (2 cm) by the number of pixels spacing in horizontal and vertical direction obtained using the `width = BoundingBox(3)` and `length = BoundingBox(4)` from the `regionprops` function respectively. This procedure was applied to all images, and the calculated ratios were stored as `calib_width` and `calib_length` (cm-pixel⁻¹). These calibration factors were then used to convert the pixel-based measurements of width and length into centimetres, ensuring that all segmented regions were accurately scaled to known dimensions and enabling consistent analysis across the images of identical size and resolution (Wang et al., 2018; Yang et al., 2023).

Next, the plant leaf was segmented from the background using a binary

Table 1 Reference square object and plant leaf colour threshold of the HSV channel

Object	Parameters	Hue (H)	Saturation (S)	Value (V)
Reference square	min.	0.576	0.123	0.000
	max.	0.654	1.000	1.000
Plant leaf	min.	0.186	0.190	0.000
	max.	0.501	1.000	0.915

(BW) mask derived from the selected histogram thresholds, as summarised in Table 1. To improve segmentation accuracy, the same methods used for the reference object were applied: small artifacts (< 100 pixels) were removed from the binary mask using `bwareaopen`, and incomplete objects touching the image border were excluded using `imclearborder` to prevent bias in feature extraction. However, the `imfill` ('holes') step was intentionally omitted, as filling operations may artificially occupy natural voids within plant structures (e.g., spaces between leaves or within the canopy), which could lead to over-segmentation and misrepresentation of plant morphology. Then, the connected components were detected and their morphological properties quantified as described previously.

Feature extraction

In this study, the segmented plant leaf was extracted using geometric feature-based criteria (Mutlag et al., 2020). The leaf width (w) in pixel was calculated as the horizontal distance between the leftmost and rightmost pixels of the binary mask, corresponding to the BoundingBox (3) output of the `regionprops` function. The leaf length (l) in pixel was defined as the vertical distance between the topmost and bottommost pixels of the binary mask, extracted from BoundingBox (4). Real dimensions, including leaf width (cm), leaf length (cm), and leaf area (cm²), were calculated

using the predetermined calibration factors expressed in Eq. (1), Eq. (2), and Eq. (3), respectively.

$$LW = w \times \text{calib_width} \quad (1)$$

$$LL = l \times \text{calib_length} \quad (2)$$

$$LA = TP \times \text{calib_width} \times \text{calib_length} \quad (3)$$

where: LW – the real dimension leaf width (cm); w – the leaf width (pixel); LL – the real dimension leaf length (cm); l – the leaf length (pixel); LA – the total leaf area (cm²); TP – the total number of pixels within the binary mask

An example of leaf width, length, and area derived from the segmented mask image is presented in Fig. 5c. The aspect ratio of the plant leaf was computed as the ratio of its width to length $\frac{LW}{LL}$. The area coverage was defined as the ratio of the actual leaf area to the bounding rectangle area, expressed as $\frac{LA}{LW \times LL}$.

Machine learning classification

Figure 6 shows the flow diagram of the process for machine learning classification in this work.

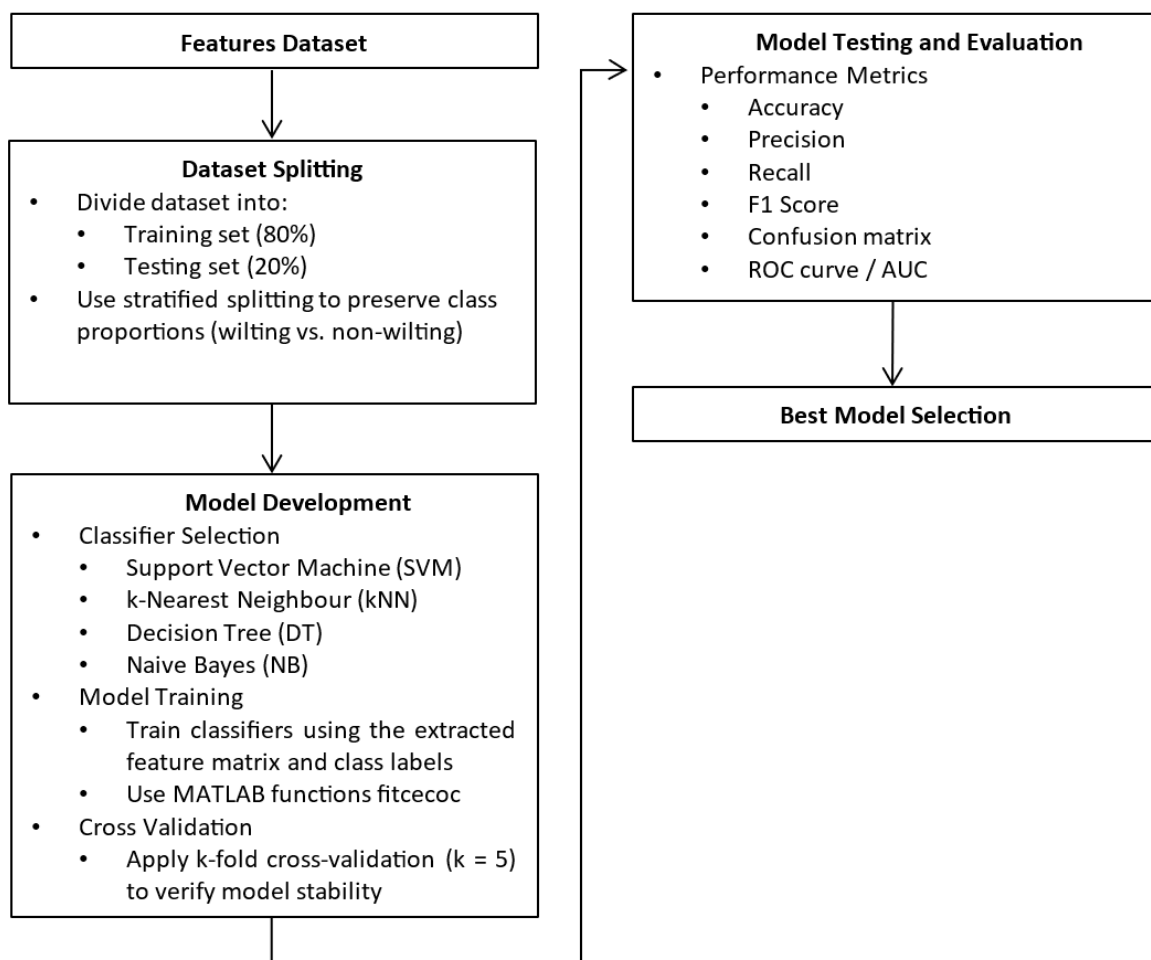


Fig. 6 Flow diagram of the process for machine learning classification in this work

Table 2 Machine learning classifiers model developed using MATLAB's error-correcting output codes (ECOC) fitcecoc function

Machine learning classifiers	Model
SVM	SVM model = fitcecoc (data, label, 'Learners', templateSVM ('KernelFunction', 'linear', 'Standardize', true))
DT	DT model = fitcecoc (data, label, 'Learners', template Tree ('MinLeafSize', 5))
kNN	kNN model = fitcecoc (data, label, 'Learners', template KNN ('NumNeighbors', 5, 'Standardize', true))
NB	NB model = fitcecoc (data, label, 'Learners', templateNaiveBayes)

The extracted features were summarised into data (60 observations $\times$ 5 features) and label (60 observations $\times$ 1 label). The plants condition was divided into two classes (label 0 = wilted plant, label 1 = healthy plant). The machine learning classifiers used in this study were Support Vector Machine (SVM), Decision Tree (DT), k-Nearest Neighbour (kNN), and Naive Bayes (NB). A multiclass classification model was developed using MATLAB's error-correcting output codes (ECOC) framework via the fitcecoc function, as summarised in Table 2.

Model evaluation was performed using stratified 5-fold cross-validation with the MATLAB function: `cv = cvpartition(label, 'KFold', 5, 'Stratify', true)`. The dataset was partitioned into five folds of approximately equal size, while maintaining class distribution through stratification. In each iteration, four folds were used for training and one for testing, ensuring all samples were tested once. Hyperparameter optimisation for each model was not conducted in this study because the classification task involved a low-dimensional feature set comprising only five input variables. For such compact feature spaces, the baseline configurations of common classifiers such as SVM, kNN, DT, and Naive Bayes are generally sufficient to achieve stable and reliable performance without extensive parameter tuning. Excessive optimisation in low-dimensional scenarios often yields minimal accuracy improvement while increasing computational overhead and the likelihood of overfitting, particularly when the dataset size is moderate. Final performance metrics were obtained by averaging results across the five folds, providing an unbiased estimate of generalisation. The accuracy of the machine learning classifiers model was evaluated using F1 Score, as formulated in Eq. (4), Eq. (5), and Eq. (6) (Yang et al., 2023):

$$precision = \frac{TP}{TP + FP} \quad (4)$$

$$recall = \frac{TP}{TP + FN} \quad (5)$$

$$F1\ score = \frac{2 \times precision \times recall}{precision + recall} \quad (6)$$

where: *TP*, *TN*, *FP*, and *FN* – true positive, true negative, false positive, and false negative, respectively
The F1 score was used due to the class imbalance in the dataset, where wilted plant samples were fewer than healthy ones. Unlike accuracy, the F1 score balances precision and recall, providing a fairer

evaluation of the classifier's ability to detect the minority (wilted) class. Furthermore, the area under the curve (AUC) of the receiver operating characteristic (ROC) was used as a metric for evaluating classification models. Unlike accuracy, which can be misleading in the presence of class imbalance, AUC measures the model's ability to discriminate between positive and negative classes across all classification thresholds.

Results and Discussion

Figure 3 illustrates that images captured on Day 1 differed slightly from those taken between Day 2 and Day 5 due to variations in camera-to-object distance and height, which resulted in larger images on the first day. These scaling differences were corrected using the reference blue square included in each image. The effectiveness of this calibration is evident in Fig. 7a and Fig. 7b, which show no significant differences in width and length between Day 1 and Day 2, as the plants remained healthy and water stress had not yet taken effect.

All images were acquired under a shaded and uniformly illuminated environment to minimise variability arising from ambient lighting. Image capture was performed at two fixed times each day (12:00 and 18:00), during which natural light levels were uniform and relatively stable, thereby further reducing illumination differences among samples. Moreover, the feature extraction process utilised only geometric-based descriptors, without incorporating any colour-derived indices. As these feature types are inherently less sensitive to lighting fluctuations, illumination variability did not exert a measurable influence on the resulting image data.

Figure 7 presents the trends of (a) plant leaf width, (b) plant leaf length, (c) total plant leaf area, (d) aspect ratio, and (e) area coverage in controlled and water-stressed plants over five days. Minimal changes were observed over time for plant leaf width (Fig. 7a), length (Fig. 7b), and aspect ratio (Fig. 7d), with percentage variations (Day 5 relative to Day 1) of -2.9%, -0.27%, and -2.2% in the well-watered group, and 4.16%, -8.11%, and 14.98% in the water-stressed group, respectively. The larger increase in aspect ratio under water-stressed may be attributed to the higher standard error on Day 5, reflecting increased sample variability. The leaf width and length of the *Vinca rosea* plant remained unchanged, likely because the main stem retained its structural rigidity and did not bend significantly during the five-day water stress period. This finding contrasts with previous reports (Yang et al., 2023), who documented decreases in soybean leaf length and width under water stress.

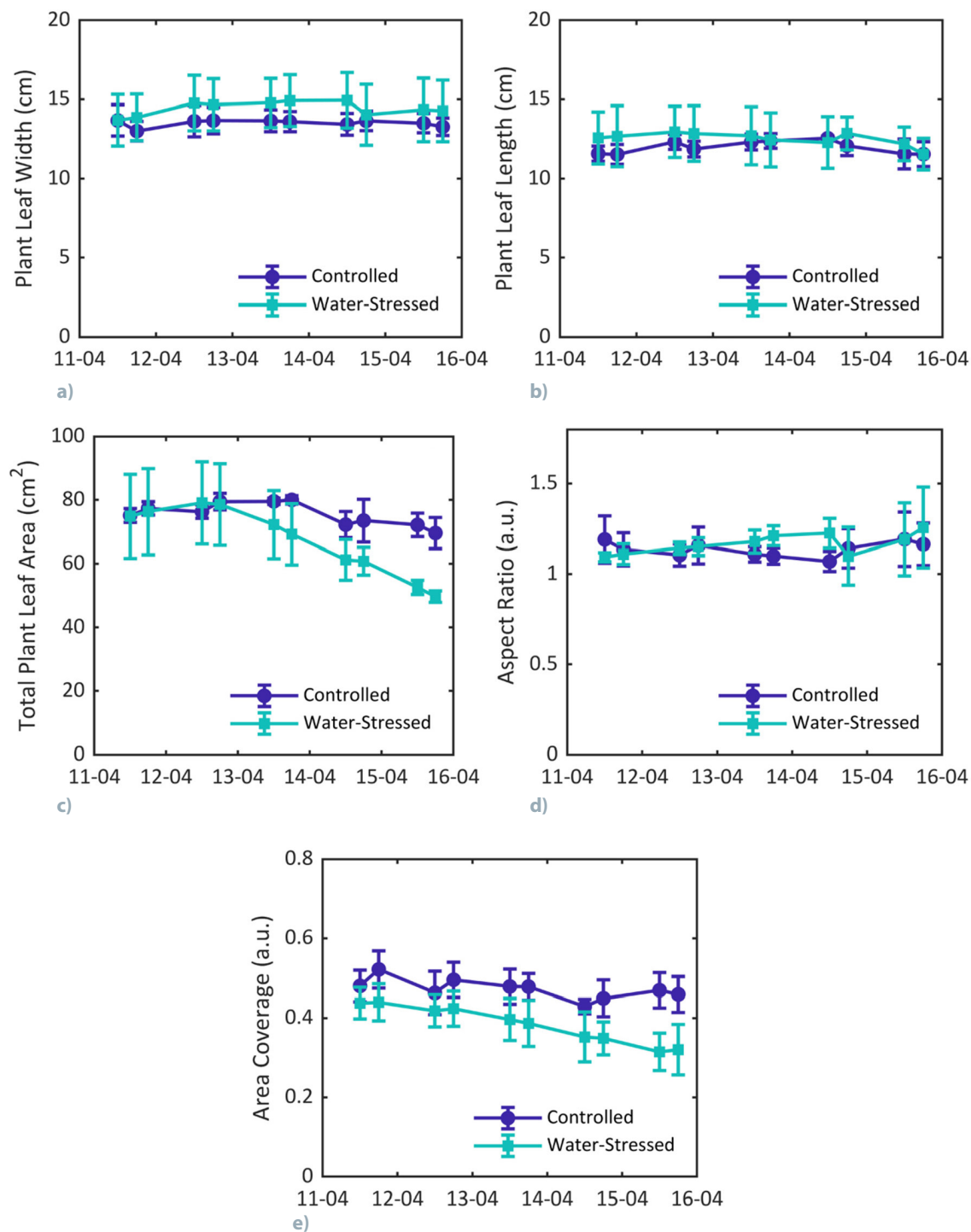


Fig. 7 Trends of (a) plant leaf width; (b) plant leaf length; (c) total plant leaf area; (d) aspect ratio; (e) area coverage in controlled and water-stressed plants over time from 11 April 2025 to 15 April 2025 (error bars indicate standard error; the a.u. denotes arbitrary units, representing a dimensionless normalised value)

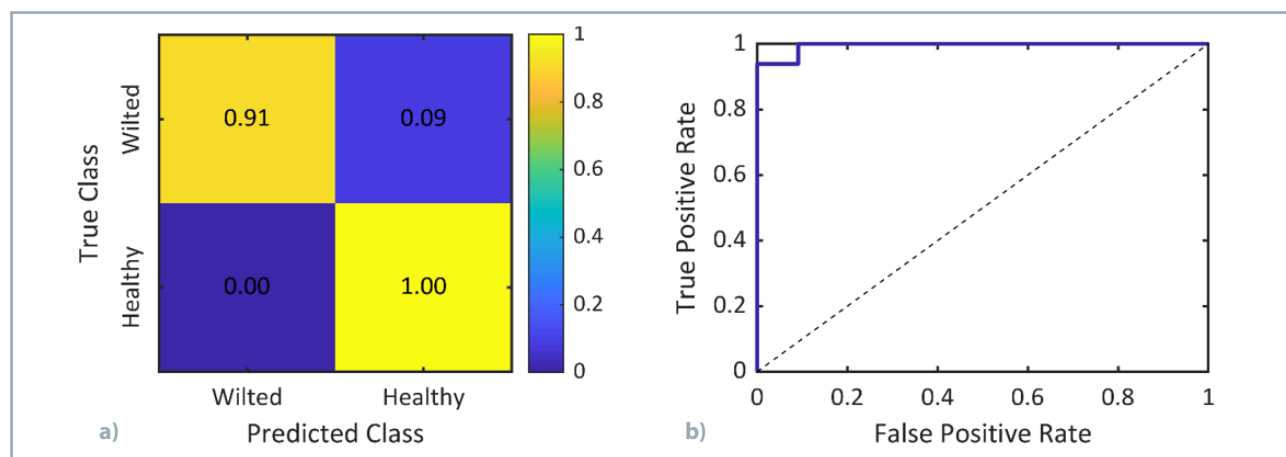
Conversely, total leaf area (Fig. 7c) and area coverage (Fig. 7e) declined significantly under water stress, decreasing by 33.7% and 26.7% by Day 5 relative to their Day 1 baselines (74.9 cm² and 0.44 a.u., where a.u. means arbitrary units). This indicates reduced canopy development compared to the controls. These findings agree with Yang et al. (2023), showing that under water stress, leaf wilting and curling reduce exposed surface area, lower transpiration, and

help plants maintain water balance for improved survival (Engelbrecht et al., 2007; Zhang et al., 2024).

Table 3 summarises the performance of four classifiers. The SVM outperformed all models with the highest accuracy (0.98), precision (0.99), recall (0.95), F1 Score (0.97), and AUC (0.99). The DT achieved competitive accuracy (0.97) but showed weaker recall (0.91), F1 Score (0.94), and AUC (0.88). The kNN reached 0.95 accuracy with high precision

Table 3 Classification results based on different machine learning models

Model	Accuracy	Precision	Recall	F1	AUC
SVM	0.98	0.99	0.95	0.97	0.99
DT	0.97	0.98	0.91	0.94	0.88
kNN	0.95	0.97	0.86	0.91	0.99
NB	0.93	0.87	0.92	0.90	0.99


Fig. 8 (a) Confusion matrix; (b) ROC curve of the SVM prediction model

(0.97) but the lowest recall (0.86), indicating a bias toward the majority class. The NB attained reasonable recall (0.92) and high AUC (0.99), but its lower precision (0.87) and F1 Score (0.90) reflected a higher false positive rate.

Notably, the models relied solely on five geometric features, avoiding colour and complex morphological traits, unlike the method reported by Yang et al. (2023). This simplicity enables straightforward and reliable feature extraction and reduces sensitivity to variations in light intensity during image acquisition, enhancing procedural robustness. Overall, the SVM outperformed other classifiers across nearly all metrics, establishing it as the most reliable model for plant leaf health classification in this study. The DT can be considered a strong alternative, whereas kNN and NB may be more prone to misclassification errors.

Figure 8 shows the confusion matrix and ROC curve of the best-performing prediction model, the SVM. The confusion matrix indicates minimal misclassification between classes, while the ROC curve confirms excellent discriminative power with an AUC of 0.99. SVM's superior performance stems from its ability to form optimal decision boundaries with limited features, demonstrating the effectiveness of simple geometric descriptors for reliable plant stress detection.

Conclusion

This study demonstrated that simple geometric features, when combined with machine learning, can reliably detect wilting in *Vinca rosea*. Among the four classifiers evaluated, the SVM achieved superior performance with near-perfect accuracy and discriminative capability. These results highlight the potential of image-based wilting detection as a practical approach for integration with irrigation control to

optimise water use and sustain crop health. Incorporating this method into horticultural practice could support efficient irrigation management, reduce water wastage, and preserve both the ornamental quality and medicinal value of *Vinca rosea*. Future work will involve acquiring images under uncontrolled field and nursery conditions to evaluate the robustness of the current machine learning model beyond controlled environments. In addition, the proposed framework will be extended for integration with an automated irrigation system in which irrigation events are triggered based on real-time wilt detection. This integration is expected to support precision water management and facilitate the practical deployment of the system in crop production.

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