Retrieval of horticultural crop morphology from color based on Elman neural network

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Abstract: The quantification of the relationship between morphological and color indicators in various organs of horticultural crops is of great significance for crop digital visualization research using computer vision technology. To study this relationship, observational data from a six-year experiment were collected, focusing on seven kinds of color component values of different organs including root, stem, and leaf. Using the collected color data as input, a simulation model was established based on the Elman neural network for six horticultural crops including zizania, cucumber, celery, spinach, parsley, and tea. Results indicated that the horticultural crop morphology model based on the Elman neural network exhibited high simulation accuracy with root mean square error (RMSE) ranging from 0.14 to 1.05 cm and normalized root mean square error (NRMSE) ranging from 2.02% to 11.34% for the maximum root length simulation model. The simulation model for stem length and diameter had an RMSE ranging from 1.42 to 4.96 cm and 0.25 to 1.17 mm, respectively, with NRMSE ranging from 18.19% to 25.65% and 15.13% to 27.25%, respectively. Similarly, chlorophyll content, leaf length, leaf width, and leaf area simulation models exhibited RMSE ranging from 2.80 to 8.22 SPAD, 0.44 to 18.04 cm, 0.22 to 3.49 cm, and 0.25 to 36.39 cm^2, respectively, with NRMSE ranging from 8.63% to 21.04%, 15.00% to 22.87%, 15.12% to 33.58%, and 6.88% to 24.90%, respectively. These findings provide essential theoretical support for precision agriculture in areas of water and fertilizer management, plant growth diagnosis, and yield prediction.

Keywords: horticultural crop, morphology, color, Elman neural network, root, stem and leaf

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1 Introduction

The importance of plant organ color cannot be underestimated when it comes to understanding different aspects of plant growth. Factors such as nutrition, diseases, pests, and organ maturity can all be reflected through the color of plant organs[1,2]. Thanks to the rapid development of computer vision technology, the color of crops has now become a valuable source of physiological and ecological information[3]. However, accurately analyzing organ morphology using color data from horticultural crops still poses a significant challenge.

The variation of plant leaf color is mainly due to the fluctuation of three pigments, namely chlorophyll, carotenoid, and anthocyanin. The green color is attributed to chlorophyll, while yellow and red colors correspond to carotenoid and anthocyanin pigments, respectively[4]. Recent research studies have employed colorimeters to evaluate the association between soil-plant analyzer development (SPAD) and the color of different crops, including wheat, rice, and cucumber, through the analysis of LAB color feature parameters[5,6]. Moreover, monitoring color feature parameters can present various conditions regarding plant growth, such as the height of the plant, the leaf area index, biomass, disease, pest, and nitrogen levels[2,7,8]. Although drone multispectral, hyperspectral, and LiDAR technologies have been employed to collect plant growth data and images, these methods are costly, and the data processing procedures are complicated, which restricts their widespread adoption[9]. As an alternative, laser scanners offer an inexpensive option to create high-resolution images and measure organ color

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characteristic traits. These analyses typically use the RGB and LAB color spaces[5,10]. Moreover, incorporating additional color spaces, such as LCH, YUV, YCbCr, HSV, and HSL, in comprehensive organ color analysis can enhance the visual realism of image analysis[11]. However, existing studies have mainly concentrated on overall or scene scale leaf color analysis, disregarding the quantitative correlation between color spaces on the organ level and various types of horticultural crop morphology[3,12].

In current research on leaf color, physical material models that rely on Bidirectional Reflectance Distribution Function (BRDF) combined with Bidirectional Transmission Distribution Function (BTDF) or Bidirectional Surface Scattering Distribution Function (BSSDF) have been widely used[13,14]. However, these models lack important input parameters that are biologically significant, which can have a negative impact on the accuracy and universality of the simulations. To address this challenge, an integration of leaf color image processing technology with regression analysis and neural networks has been proposed as a potential solution for simulating crop morphology and phenotypic characteristics. Several regression methods, including support vector machine[15] and regression methods[5], have been explored in this area. Additionally, neural network approaches, such as the Back Propagation (BP) neural network[16], the fuzzy neural network[17], the probabilistic neural network[18], and the radial basis function neural network[19], have shown promising results. Combining these new methods can improve the accuracy and stability of phenotypic characteristics models retrieved from images, while enhancing the objective settings of neuron counts. The Elman neural network is known for its high accuracy in prediction, rapid convergence, stable learning and memory, and good dynamic characteristics. It has been successfully applied in the research of greenhouse environment microclimate[16]. Further exploration of its application in image retrieval of plant growth based on the Elman neural network is warranted, given the potential benefits of this approach. By leveraging the power of neural networks in conjunction with new image processing techniques, it may be possible to more accurately simulate crop morphology and better understand plant phenotypic characteristics.

The color of plant organs plays a crucial role in comprehending plant growth and development. Through the utilization of computer vision technology and the incorporation of diverse color spaces, a deeper understanding of organ morphology in horticultural crops could be gained. By combining regression analysis, neural network techniques, and employing the Elman neural network, the precision and consistency of plant phenotypic characteristic models derived from images could be enhanced. In summary, these advancements contribute significantly to the knowledge of plant biology and offer valuable insights for improving crop cultivation practices.

2 Materials and methods

2.1 Experimental design

Table 1 shows the experimental varieties of horticultural crops, experiment sites, and duration in this study. Each sowing date was set with three replicates, using a random block design. The sampling plan for this experiment was to take three representative experiment samples for each treatment, and complete the sample determination on the same day. The sample determination process involves washing the sample, separating the organs and laying them flat on the scanner in order, setting the scanning parameters, scanning to generate images, and measuring the corresponding indicators of the organs in order, which ensures correspondence between each indicator. The sampling frequency for leafy and melon crops was 10 d, for zizania was once at harvest, and for tea was 30 d. Cucumber (*Cucumis sativus* L.), spinach (*Spinacia oleracea* Linn.), parsley (*Libanotis seseloides* Turcz.), and celery (*Apium graveolens* L.) were grown in greenhouses, while zizania (*Zizania caduciflora* Turcz.) and tea (*Camellia sinensis* L.) were grown in the fields. According to the local conventional cultivation management methods, this experiment ensured the agricultural resources such as light, temperature, water, and nutrients required for the development and growth of various horticultural crops. Please refer to the preliminary work of the research team for specific cultivation management methods[20-24]. The varieties of tea trees were yellow tea, white tea, and green tea. This study regularly scanned images of crop roots, stems, and leaves separately throughout the entire growth period, and measured their colors.

Table 1 Experimental crop varieties and overview of this study

Crop	Variety name	Experiment position	Experiment time
Zizania	Lijiao (LJ)	Lishui, Zhejiang, China	2021-2022
Cucumber	Jinsheng 206 (JS)	Wuqing, Tianjin, China	2018-2020
Celery	Juventus (J)	Wuqing, Tianjin, China and Lishui, Zhejiang, China	2018-2023
Spinach	Daye (DY)	Lishui, Zhejiang, China	2021-2023
Parsley	Siji (SJ)	Lishui, Zhejiang, China	2021-2023
Tea	Yellow tea: Zhonghuang (Y1), Huangjinya (Y2), Huangjinyu (Y3) Green tea: Longjing (G1), Yingshuang (G2) White tea: Zaonaibai (W1), Anji (W2)	Lishui, Zhejiang, China	2021-2023

Organ color was determined by picture recognition, which used EPSON Expression 11 000 XL scanner (Epson Co., Ltd., China) to scan individual plants, which used six-line alternating matrix CCD to scan the original and xenon light source tubes as the scanning light source, with a scanning range of 310×437 mm on a flat plate. Color image scanning speed could reach 16 ms per line (2400 dpi) and generate 720 pixel high-definition pictures. Then, this study used ImageJ software to determine the morphology of various organs[25]. This study randomly selected three parts (top, middle, and bottom) of the organ, and measured with a color recognizer to obtain RGB, LAB, LCH, YUV, YCbCr, HSV, and HSL color model parameters[5,10,11,26], and the average value was taken as the color measurement result of each organ.

The leaves selected in the experiment were free of any disease and insect pest, physiological disease spots, and mechanical damage. SPAD-502plus chlorophyll meter (Konica Minolta, Inc., Japan) was used to select at least three points from the top, middle, and bottom of the leaves (avoiding the vein) for chlorophyll content measurement, and the average value was taken as the chlorophyll content measurement result of organ leaves. In order to avoid errors, it was necessary to properly block the direct sunlight and gently wipe the dust or other impurities from the plant leaves during the measurement. At the same time, it was necessary to try to avoid the position where the leaf veins are concentrated to ensure the accuracy of measurement[27]. The distance from the bottom of the root to the bottom of the stem was the root length, cm. The distance from the bottom of stems to the bottom of leaves was the stem length, cm.

2.2 Model validation statistical variables

Statistical criteria mainly include average value ($\bar{X}$), standard deviation (SD) and linear regression coefficient (α), intercept (β), determination coefficient (R^2), root mean square error (RMSE), normalized root mean square error (NRMSE), and compliance index (D). RMSE and NRMSE[20-23] are used to measure the deviation between the observed value and the measured value, and can also well reflect the measurement precision. If NRMSE is less than 10%, it indicates the very high accuracy of model simulation effect. If NRMSE is at 10%-20%, it indicates the high accuracy of model simulation effect. If NRMSE is 20%-30%, it indicates the medium accuracy of model simulation effect. If NRMSE is greater than 30%, it indicates poor accuracy of model simulation effect. D[24] is a normalized metric index. The closer the value is to 1, the higher the consistency of the distribution trend between the simulated value and the observed value, and the better the model simulation effect.

3 Model description

3.1 Modeling factor

This study established different horticultural crop morphology simulation models based on BP and Elman neural network methods, which take into account RGB, LAB, LCH, YUV, YCbCr, HSV, and HSL color model parameters of organ root, stem, and leaf, with a total of 21 modeling factors. This study established a simulation model of leaf area of different horticultural crops based on stepwise regression method, which takes into account leaf length, leaf width, (leaf length)^2, (leaf width)^2, and (leaf length×leaf width), with a total of five modeling factors.

3.2 Elman neural network

Elman neural network is a two-layer BP network structure with feedback, which is composed of input layer, hidden layer (middle layer), receiving layer, and output layer[16]. The function of the input layer unit is to transmit signals. The function of the output layer unit is linear weighting. The hidden layer unit will perform nonlinear transformation on the input signal through an activation function. This feedback mode enables Elman neural network to detect and identify time-varying patterns. As a one-step delay operator, the receiving layer returns the output value of the intermediate layer unit at the last moment to the input. This special two-layer network can approximate any function with any precision, and the only requirement is that the hidden layer must have enough neurons. The nonlinear state space expression describes the Elman neural network[16].

In order to avoid neuron saturation, the input data was normalized at the input layer, each value was converted to [0,1] interval, and the predicted results were normalized at the output layer[28]. In this study, the number of hidden layer neurons of BP neural network and Elman neural network was set as $\sqrt{n+m}+a$ (a was a constant between 1 and 10)[28,29]. In order to improve the training efficiency and network generalization performance, the normalized method was used to preprocess the sample data.

In this study, the simulation effect of Elman neural network based on image inversion plant morphology simulation model was compared with that of the classical BP neural network method. In order to reflect the comparability of algorithms, the algorithm parameters (training function, number of hidden layer neurons, maximum training times, initial learning rate, and target error) of the two neural networks were consistent for the simulation of the same plant appearance.

4 Model validation and result analysis

4.1 Validation of root morphology simulation model

The maximum root length model was validated by using the mutually independent data of the root color. The solid line represents a 1:1 line, and the dotted line represents the error control range. It could be seen that the simulated value and the measured value were close to the 1:1 line, and close to the error range. The results showed that the simulated values were in good agreement with the measured values. Figure 1 indicates that the RMSE of the observation value (X_{obs}±SD=10.14±4.40 cm) and simulation value (X_{sim}±SD=10.08±4.50 cm) of the maximum root length simulation model was 0.88 cm, NRMSE was 8.67%, R^2 was 0.96, and D was 0.99.

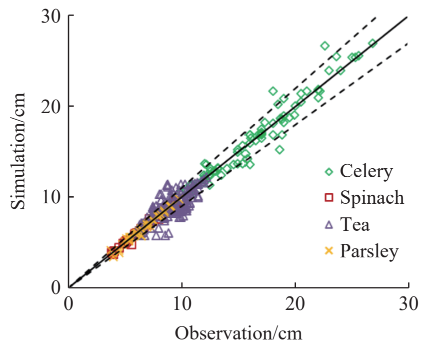


Figure 1 Validation of maximum root length simulation model based on Elman neural network with color indicators

Table 2 denotes that the RMSE of the maximum root length simulation model of different crops was 0.79-2.19 cm, and the NRMSE was 11.93%-13.42%. It could be seen from the NRMSE that the optimal horticultural crop maximum of root length

Table 2 Statistics for the comparisons between the simulated and measured maximum root length of different horticultural crops using BP and Elman neural network

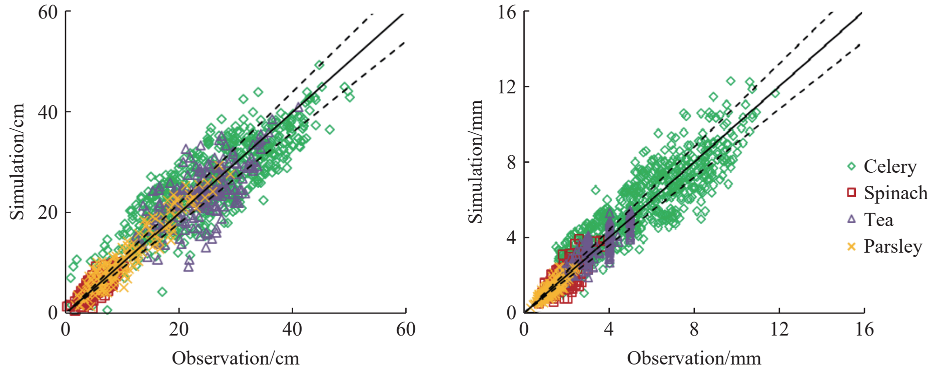
Indicators		$\bar{X}_{obs}$±SD/cm	$\bar{X}_{sim}$±SD/cm	N	α	β	R^2	CV	RMSE/cm	NRMSE/%	D
BP neural network	Celery	16.27±4.34	16.89±2.88	82	−0.37	0.99	0.43	0.03	3.32	20.39	0.76
	Spinach	6.76±1.61	7.01±0.28	51	−8.82	2.22	0.15	0.03	1.53	22.68	0.34
	Parsley	6.61±1.51	6.66±0.91	45	1.54	0.76	0.21	0.03	1.34	20.31	0.63
	Tea	9.06±1.41	9.11±0.18	157	−3.29	1.36	0.03	0.01	1.39	15.36	0.19
Elman neural network	Celery	16.27±4.34	16.29±4.57	82	1.23	0.92	0.95	0.03	1.05	6.44	0.99
	Spinach	6.76±1.61	6.74±1.63	51	0.13	0.98	0.99	0.03	0.14	2.02	1.00
	Parsley	6.61±1.51	6.54±1.56	45	0.34	0.96	0.98	0.03	0.23	3.54	0.99
	Tea	9.06±1.41	8.93±1.44	157	2.55	0.73	0.55	0.01	1.03	11.34	0.86

$\bar{X}_{obs}$ represents the average of observed values, $\bar{X}_{sim}$ represents the average of the simulated values, SD represents the standard deviation, and N represents the number of samples. α, β, and R^2 respectively represent the regression coefficient, regression constant, and coefficient of determination. CV represents the coefficient of variation, RMSE represents the root mean square error, NRMSE represents the normalized root mean square error, and D represents the compliance index. The following table is the same.

simulation model was parsley. The RMSE of the maximum root length simulation model based on BP neural network method was 1.34-3.32 cm, the NRMSE was 15.36%-22.68%, the RMSE of the maximum root length simulation model based on Elman neural network method was 0.14-1.05 cm, and the NRMSE was 2.02%-11.34%. It could be seen from the NRMSE that the optimal modeling method of the maximum root length simulation model was Elman neural network method. To sum up, the optimal maximum root length simulation model was spinach simulation model based on Elman neural network.

4.2 Validation of stem morphology simulation model

The stem length and diameter model were validated by the mutually independent data of the stem color. It could be seen that the simulated value and the measured value were close to the 1:1 line, and close to the error range. The results expressed that the simulated values were in good agreement with the measured values. Figure 2a states that the RMSE of the observation value (X_{obs}±SD=20.30±10.74 cm) and simulation value (X_{sim}±SD=20.44±10.38 cm) of the stem length simulation model was 4.21 cm, NRMSE was 20.73%, R^2 was 0.85, and D was 0.96. Figure 2b states that the RMSE of the observed value (X_{obs}±SD=4.02±2.48 mm) and the simulated value (X_{sim}±SD=4.16±2.48 mm) of the stem diameter simulation model was 0.91 mm, NRMSE was 22.65%, R^2 was 0.87, and D was 0.97.



a. Stem length simulation model b. Stem diameter simulation model

Figure 2 Validation of stem length and diameter simulation model based on Elman neural network with color indicators

Table 3 shows that the RMSE of different crop stem length simulation models was 1.74-5.67 cm, and the NRMSE was 19.67%-31.36%. The NRMSE expressed that the optimal horticultural crop stem length simulation model was tea. The RMSE of stem length simulation model based on BP neural network method was 2.05-6.38 cm, and the NRMSE was 21.15%-37.06%. The RMSE of stem length simulation model based on Elman neural network method was 1.42-4.96 cm, and the NRMSE was 18.19%-25.65%. It could be seen from the NRMSE that the optimal modeling method stem length simulation model was Elman neural network method. The RMSE of different crop stem diameter simulation models was 0.34-1.30 mm, and the NRMSE was 18.83%-30.91%. The NRMSE indicated that the optimal horticultural crop stem diameter simulation model was tea. The RMSE of the stem diameter simulation model based on BP neural network method was 0.43-1.43 mm, the NRMSE was 22.53%-36.63%, the RMSE of the stem diameter simulation model based on Elman neural network method was 0.25-1.17 mm, and the NRMSE was 15.13%-27.25%. It could be seen from the NRMSE that the optimal modeling method stem diameter simulation model was Elman neural network method. In general, the optimal stem length and stem diameter simulation model was tea simulation model based on Elman neural network.

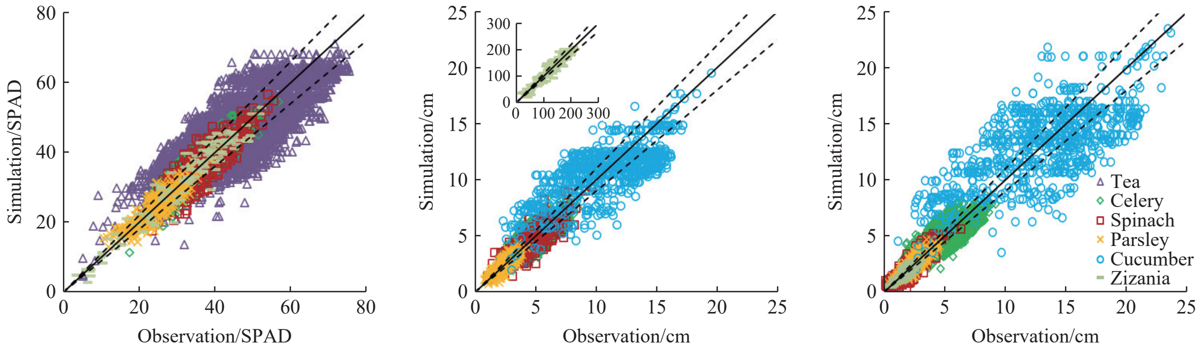
Table 3 Statistics for the comparisons between the simulated and measured stem length and diameter of different horticultural crops using BP and Elman neural network

Indicators (Stem length)		$\bar{X}_{obs}$±SD/cm	$\bar{X}_{sim}$±SD/cm	N	α	β	R^2	CV	RMSE/cm	NRMSE/%	D
BP neural network	Celery	24.99±9.48	25.43±6.66	615	–1.89	1.06	0.55	0.02	6.38	25.52	0.83
	Spinach	5.53±2.19	5.71±0.88	140	0.53	0.88	0.13	0.03	2.05	37.06	0.49
	Parsley	10.85±5.98	11.16±5.44	173	–0.03	0.97	0.79	0.04	2.77	25.54	0.94
	Tea	24.20±5.47	23.27±1.94	209	–1.21	1.09	0.15	0.02	5.12	21.15	0.49
Elman neural network	Celery	24.99±9.48	25.39±8.43	615	0.61	0.96	0.73	0.02	4.96	19.84	0.92
	Spinach	5.53±2.19	5.30±2.15	140	1.26	0.80	0.62	0.03	1.42	25.65	0.88
	Parsley	10.85±5.98	11.11±6.32	173	0.86	0.90	0.90	0.04	1.98	18.25	0.97
	Tea	24.20±5.47	23.71±5.59	209	8.30	0.67	0.47	0.02	4.40	18.19	0.82
Indicators (Stem diameter)		$\bar{X}_{obs}$±SD/mm	$\bar{X}_{sim}$±SD/mm	N	α	β	R^2	CV	RMSE/mm	NRMSE/%	D
BP neural network	Celery	5.50±2.32	5.87±1.62	615	–1.36	1.17	0.66	0.02	1.43	25.94	0.86
	Spinach	1.87±0.55	2.26±0.39	140	0.47	0.62	0.19	0.02	0.65	34.57	0.58
	Parsley	1.17±0.40	1.40±0.13	173	–0.64	1.30	0.17	0.03	0.43	36.63	0.51
	Tea	3.47±0.89	3.47±0.36	209	–0.61	1.18	0.22	0.02	0.78	22.53	0.56
Elman neural network	Celery	5.50±2.32	5.75±2.14	615	0.04	0.95	0.76	0.02	1.17	21.23	0.93
	Spinach	1.87±0.55	1.86±0.69	140	0.86	0.54	0.46	0.02	0.51	27.25	0.81
	Parsley	1.17±0.40	1.18±0.42	173	0.27	0.77	0.66	0.03	0.25	21.70	0.90
	Tea	3.47±0.89	3.52±0.84	209	0.43	0.86	0.67	0.02	0.52	15.13	0.90

4.3 Validation of leaf morphology simulation model

The leaf chlorophyll content, length, and width model were validated by using the mutually independent data of the leaf color. It could be seen that the simulated value and the measured value were close to the 1:1 line, and close to the error range. Figure 3a expresses that the RMSE of the observed value (X_{obs}±SD= 41.22±12.32 SPAD) and the simulated value (X_{sim}±SD= 40.98±11.22 SPAD) of the chlorophyll content simulation model was 6.04 SPAD, NRMSE was 14.66%, R^2 was 0.76, and D was 0.93. Figure 3b expresses that the RMSE of the observed value (X_{obs}±SD=6.23±12.63 cm) and the simulated value (X_{sim}±SD= 6.32±12.67 cm) of leaf length simulation model was 1.73 cm, NRMSE was 27.81%, R^2 was 0.98, and D was 1.00. Figure 3c expresses that the RMSE of the observed value (X_{obs}±SD=4.52± 3.30 cm) and the simulated value (X_{sim}±SD=4.59±3.14 cm) of leaf width simulation model was 1.15 cm, NRMSE was 25.45%, R^2 was 0.88, and D was 0.97.

Table 4 denotes that the RMSE of chlorophyll content simulation models for different crops was 2.80-8.22 SPAD, and the NRMSE was 8.63%-21.04%. The NRMSE explained that the optimal horticultural crop chlorophyll content simulation model was celery. The RMSE of chlorophyll content simulation model based on BP neural network method was 3.14-8.66 SPAD, the NRMSE was 9.27%-22.51%, the RMSE of chlorophyll content simulation model based on Elman neural network method was 2.45-7.77 SPAD, and the NRMSE was 7.98%-19.56%. The NRMSE illustrated that the optimal modeling method chlorophyll content simulation model was Elman neural network method. In a word, the optimal chlorophyll content simulation model was celery simulation model based on Elman neural network.



a. Leaf chlorophyll content simulation model b. Leaf length simulation model c. Leaf width simulation model

Figure 3 Validation of leaf chlorophyll content, length, and width simulation model based on Elman neural network with color indicators

Table 4 Statistics for the comparisons between the simulated and measured leaf chlorophyll content of different horticultural crops using BP and Elman neural network

Indicators		$\bar{X}_{obs}$±SD/SPAD	$\bar{X}_{sim}$±SD/SPAD	N	α	β	R^2	CV	RMSE/SPAD	NRMSE/%	D
BP neural network	Zizania	33.36±11.65	33.14±9.20	123	1.08	–2.57	0.73	0.03	6.04	18.10	0.91
	Celery	34.19±5.07	33.89±4.14	2193	1.71	0.96	0.61	0.00	3.17	9.27	0.87
	Spinach	37.16±6.65	37.06±4.4	300	–1.81	1.05	0.48	0.01	4.77	12.83	0.79
	Parsley	25.32±5.43	25.35±4.38	392	–0.34	1.01	0.66	0.01	3.14	12.42	0.89
	Tea	47.85±12.11	46.73±7.45	3594	–6.18	1.16	0.51	0.00	8.66	18.09	0.78
	White tea	57.36±8.97	57.52±5.24	696	–7.86	1.13	0.44	0.01	6.75	11.77	0.75
	Yellow tea	46.51±14.16	47.23±10.5	986	–6.46	1.12	0.69	0.01	7.99	17.18	0.89
	Green tea	64.45±7.17	63.57±3.14	602	–5.49	1.10	0.23	0.00	6.35	9.85	0.59
	Green tea - Harvesting	35.48±9.33	35.59±3.91	1310	–9.35	1.26	0.28	0.01	7.99	22.51	0.59
Elman neural network	Zizania	33.36±11.65	33.35±11.85	123	0.95	1.74	0.93	0.03	3.10	9.30	0.98
	Celery	34.19±5.07	34.02±4.91	2193	4.32	0.88	0.72	0.00	2.73	7.98	0.92
	Spinach	37.16±6.65	36.94±6.92	300	7.10	0.81	0.72	0.01	3.76	10.13	0.92
	Parsley	25.32±5.43	25.18±5.30	392	2.18	0.92	0.80	0.01	2.45	9.68	0.95
	Tea	47.85±12.11	47.54±10.09	3594	3.90	0.92	0.59	0.00	7.77	16.24	0.87
	White tea	57.36±8.97	56.84±8.12	696	8.50	0.86	0.61	0.01	5.76	10.05	0.88
	Yellow tea	46.51±14.16	46.43±12.18	986	0.22	1.00	0.74	0.01	7.28	15.64	0.92
	Green tea	64.45±7.17	64.14±5.54	602	14.16	0.78	0.37	0.00	5.84	9.06	0.76
	Green tea - Harvesting	35.48±9.33	35.11±7.01	1310	3.99	0.90	0.45	0.01	6.94	19.56	0.80

Table 5 shows that the RMSE of different crop leaf length simulation models was 0.44-18.04 cm, and the NRMSE was 15.00%-22.87%. The NRMSE expressed that the optimal horticultural crop leaf length simulation model was zizania. The RMSE of the leaf length simulation model based on BP neural network method was 0.46-21.65 cm, the NRMSE was 15.92%-23.99%, the RMSE of the leaf length simulation model based on Elman neural network method was 0.41-14.42 cm, and the NRMSE was 11.99%-21.74%. It could be seen from the NRMSE that the optimal modeling method leaf length simulation model was Elman neural network method. The RMSE of different crop leaf width simulation models was 0.22-3.49 cm, and the NRMSE was 15.12%-33.58%. The NRMSE indicated that the optimal horticultural crop leaf width simulation model was green tea. The RMSE of the leaf width simulation model based on the BP neural network method was 0.23-3.61 cm, and the NRMSE was 15.78%-36.52%. The RMSE of the leaf width simulation model based on the Elman neural network method was 0.21-3.36 cm, and the NRMSE was 13.32%-30.64%. It could be seen from the NRMSE that the optimal modeling method leaf width simulation model was Elman neural network method. On the whole, the optimal stem leaf length simulation model was zizania simulation model based on Elman neural network, and the optimal stem leaf width simulation model was green tea simulation model based on Elman neural network.

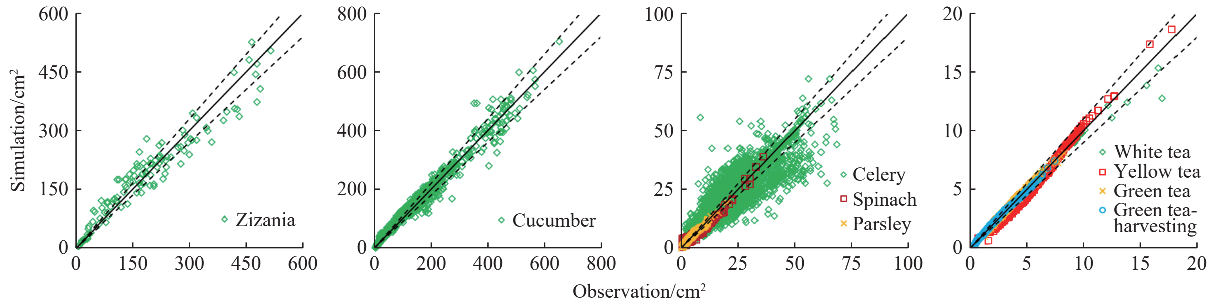
Table 5 Statistics for the comparisons between the simulated and measured leaf length and width of different horticultural crops using BP and Elman neural network

Indicators (Leaf length)		$\bar{X}_{obs}$±SD/cm	$\bar{X}_{sim}$±SD/cm	N	α	β	R^2	CV	RMSE/cm	NRMSE/%	D
BP neural network	Zizania	120.23±48.72	121.48±42.66	117	1.02	–4.01	0.80	0.04	21.65	18.01	0.94
	Cucumber	10.78±3.44	10.57±1.82	803	1.29	–2.81	0.46	0.01	2.59	23.99	0.74
	Celery	5.32±1.07	5.42±0.53	6487	1.12	–0.76	0.31	0.00	0.90	16.86	0.65
	Spinach	4.90±1.59	5.14±1.08	251	1.08	–0.63	0.54	0.02	1.11	22.66	0.81
	Parsley	2.45±0.68	2.52±0.44	449	1.02	–0.10	0.44	0.01	0.51	20.81	0.77
	Tea	3.72±0.68	3.87±0.05	3604	0.95	0.05	0.00	0.00	0.69	18.65	0.27
	White tea	4.4±0.82	4.46±0.23	708	1.63	–2.84	0.20	0.01	0.75	17.01	0.45
	Yellow tea	4.61±0.80	4.64±0.11	1039	1.93	–4.34	0.07	0.01	0.78	16.94	0.23
	Green tea	3.84±0.70	3.92±0.15	604	1.56	–2.27	0.12	0.01	0.67	17.46	0.36
	Green tea - Harvesting	2.86±0.61	2.91±0.39	1671	1.04	–0.18	0.45	0.01	0.46	15.92	0.77
Elman neural network	Zizania	120.23±48.72	120.83±49.66	117	0.94	6.79	0.92	0.04	14.42	11.99	0.98
	Cucumber	10.78±3.44	10.75±2.40	803	1.05	–0.53	0.54	0.01	2.34	21.74	0.82
	Celery	5.32±1.07	5.41±0.73	6487	0.91	0.40	0.38	0.00	0.85	15.98	0.75
	Spinach	4.90±1.59	4.83±1.53	251	0.87	0.70	0.70	0.02	0.89	18.16	0.91
	Parsley	2.45±0.68	2.49±0.67	449	0.80	0.46	0.63	0.01	0.44	17.74	0.89
	Tea	3.72±0.68	3.84±0.42	3604	0.71	0.98	0.19	0.00	0.63	16.96	0.64
	White tea	4.40±0.82	4.48±0.65	708	0.78	0.93	0.38	0.01	0.67	15.22	0.77
	Yellow tea	4.61±0.80	4.64±0.50	1039	0.81	0.87	0.25	0.01	0.70	15.25	0.67
	Green tea	3.84±0.70	3.89±0.57	604	0.77	0.83	0.39	0.01	0.56	14.71	0.78
	Green tea - Harvesting	2.86±0.61	2.90±0.49	1671	0.91	0.21	0.55	0.01	0.41	14.36	0.85
Indicators (Leaf width)		$\bar{X}_{obs}$±SD/cm	$\bar{X}_{sim}$±SD/cm	N	α	β	R^2	CV	RMSE/cm	NRMSE/%	D
BP neural network	Zizania	1.86±0.43	1.86±0.24	117	1.20	–0.36	0.42	0.02	0.33	17.71	0.73
	Cucumber	13.02±4.6	13.14±2.38	803	1.22	–2.99	0.40	0.01	3.61	27.69	0.70
	Celery	5.41±1.24	5.52±0.68	6487	1.08	–0.55	0.36	0.00	1.00	18.50	0.70
	Spinach	2.07±1.20	2.32±0.85	251	1.14	–0.57	0.65	0.04	0.76	36.52	0.85
	Parsley	2.64±0.81	2.70±0.51	449	1.10	–0.31	0.48	0.01	0.59	22.18	0.78
	Tea	1.50±0.28	1.55±0.05	3604	0.93	0.06	0.03	0.00	0.28	18.58	0.30
	White tea	1.76±0.31	1.81±0.07	708	1.85	–1.58	0.19	0.01	0.29	16.50	0.41
	Yellow tea	1.86±0.32	1.87±0.05	1039	1.27	–0.52	0.04	0.01	0.31	16.67	0.25
	Green tea	1.59±0.25	1.64±0.05	604	1.30	–0.55	0.07	0.01	0.25	15.78	0.33
	Green tea - Harvesting	1.11±0.32	1.12±0.21	1671	1.03	–0.06	0.48	0.01	0.23	20.55	0.79
Elman neural network	Zizania	1.86±0.43	1.88±0.49	117	0.76	0.44	0.74	0.02	0.25	13.32	0.92
	Cucumber	13.02±4.60	13.10±3.45	803	0.91	1.04	0.47	0.01	3.36	25.77	0.81
	Celery	5.41±1.24	5.49±0.83	6487	0.95	0.20	0.41	0.00	0.96	17.72	0.76
	Spinach	2.07±1.20	2.16±1.24	251	0.84	0.27	0.75	0.04	0.64	30.64	0.93
	Parsley	2.64±0.81	2.72±0.82	449	0.81	0.44	0.68	0.01	0.49	18.64	0.90
	Tea	1.50±0.28	1.55±0.17	3604	0.68	0.46	0.16	0.00	0.27	17.65	0.60
	White tea	1.76±0.31	1.79±0.24	708	0.77	0.39	0.36	0.01	0.26	14.65	0.76
	Yellow tea	1.86±0.32	1.88±0.21	1039	0.79	0.37	0.27	0.01	0.27	14.78	0.69
	Green tea	1.59±0.25	1.61±0.20	604	0.65	0.55	0.26	0.01	0.23	14.46	0.71
	Green tea - Harvesting	1.11±0.32	1.12±0.27	1671	0.88	0.13	0.55	0.01	0.21	19.37	0.85

This study solved the model parameters between leaf area and morphology (leaf length and width) by stepwise regression method according to the principle of least square method (Table 6). The leaf area simulation model was validated by using the mutually independent leaf morphology data. It could be seen that the simulation value and the measured value are close to the 1:1 line, and close to the error range, that is, the simulation value and the measured value were relatively consistent. Figure 4 implies that the RMSE of leaf area simulation models for different horticulture crops was 0.25-36.39 cm^2, NRMSE was 6.88%-24.90%, R^2 was 0.83-0.99, and D was 0.95-1.00. The optimal leaf area simulation model was tea simulation model based on stepwise regression.

Table 6 Stepwise Regression parameters between leaf area and leaf morphology of different horticultural crops

Crop name	N	Leaf length	Leaf width	(Leaf length)^2	(Leaf width)^2	Leaf length×Leaf width	Intercept	R^2
Zizania	100	-	20.3143	0.0028	-	0.4492	–5.1664	0.9101
Cucumber	690	4.8279	-	0.2946	0.6548	–0.382	–16.9482	0.9840
Celery	5779	0.41	–1.4402	0.1341	0.2242	0.4049	1.4709	0.9250
Spinach	341	0.9584	–3.1510	–0.0897	0.3218	0.6593	1.4418	0.9743
Parsley	320	0.4197	-	–0.096	–0.0568	0.8613	–0.6576	0.9951
White tea	653	0.0927	0.5021	–0.0168	–0.199	0.6134	–0.4713	0.9994
Yellow tea	874	–1.0553	–0.9807	0.0541	0.0422	0.9037	2.4367	0.9855
Green tea	546	0.06	0.6753	–0.0286	–0.3332	0.6725	–0.5042	0.9968
Green tea - Harvesting	1032	-	–0.5426	–0.0052	0.1201	0.7565	0.2143	0.9985



a. Gramineae leaf area simulation model
b. Melons and fruits leaf area simulation model
c. Leafy vegetables leaf area simulation model
d. Shrubs leaf area simulation model

Figure 4 Validation and statistics of leaf area simulation model based on Stepwise Regression with morphology indicators

5 Discussion

This study established Elman neural network simulation model of horticultural crops physiological and ecological indicators based on the six-years sowing date variety experiment observed data and used independent experiment data to validate the model. This research overcomes the problems of model universality, such as the high price of equipment like UAV multi spectral, hyperspectral, and lidar sensors, and the complex data processing process[9]. Meanwhile, Elman neural network makes up for the limitation of BP neural network, which is only applicable to obtain the local optimal solution and cannot obtain the global optimal solution[16,30]. The results can provide scientific basis for crop digital visualization, and theoretical support for precision agriculture. The research features were as follows: 1) considered RGB, LAB, LCH, YUV, YCbCr, HSV, HSL, and other color spaces to comprehensively analyze the colors of different organs (roots, stems, leaves), which enhanced the visual effect realism of image analysis and improved the model accuracy; 2) set the number of hidden layer neurons as $\sqrt{n+m}+a$[28,29], which avoided the decline of model accuracy caused by subjective experience setting, and used the normalization method to preprocess the sample data which improved the training efficiency and network generalization performance.

A large number of studies have shown that the color feature parameters of plant organ images can accurately reflect the plant growth status[7,8,31]. These studies are in good agreement with the results of this study. However, this study supplemented the quantitative relationship between the spatial distribution of color on the scale of single leaf and other organs and the growth of different types of horticultural crops. This study established different horticultural crop morphology simulation models based on BP and Elman neural network methods by using color feature parameters inversion of plant organ images (Tables 2-5). The simulation effect was as follows: maximum root length (average RMSE was 0.61 cm, average NRMSE was 5.84%, excellent simulation effect) > chlorophyll content (average RMSE was 5.07 SPAD, average NRMSE was 11.96%, good simulation effect) > leaf length (average RMSE was 2.19 cm, average NRMSE was 16.21%, good simulation effect) > leaf width (average RMSE was 0.69 cm, average NRMSE was 18.70%, good simulation effect)>stem length (average RMSE was 3.19 cm, average NRMSE was 20.48%, general simulation effect) > stem diameter (average RMSE was 0.61 mm, average NRMSE was 21.33%, general simulation effect). This study established simulation model of leaf area of different horticultural crops based on stepwise regression method using leaf morphology feature. The simulation effect was as follows: shrubs (average RMSE was 0.25 cm^2, average NRMSE was 6.88%, excellent simulation effect)>gramineous (average RMSE was 36.39 cm^2, average NRMSE was 19.26%, good simulation effect) > melons and fruits (average RMSE was 21.62 cm^2, average NRMSE was 14.14%, good simulation effect) > leafy vegetables (average RMSE was 4.36 cm^2, average NRMSE was 24.90%, general simulation effect). To sum up, the simulation model of physiological and ecological indicators of horticultural crop organs based on Elman neural network algorithm had good simulation effect, in which the leaf length and leaf width are retrieved from leaf color, and the leaf area is retrieved through stepwise regression parameters.

The simulation model developed in this study has successfully utilized organ color component data to extract organ physiological and ecological indicators. This innovative approach demonstrates the simplicity of input data and the high accuracy of simulation results. However, it is crucial to acknowledge that this study did not account for morphological changes, such as leaf folds and curls, which may occur simultaneously with color changes during the aging process. At the same time, it is necessary to increase the sampling frequency to explore the differences in crop color status at different growth stages. The expression of color in plant organs involves a highly complex process affected by various external climatic conditions, including light, temperature, and humidity, as well as internal factors such as plant nutrition, diseases, and pests.

This study integrated as many different crop types as possible through the current horticultural crop data, in order to explore the universal research ideas for retrieval morphology from color. Therefore, it is essential to establish a dynamic database of crop characteristics at different growth stages and varieties. Elman neural networks all use gradient descent-based BP algorithm for weight and threshold optimization. This method is simple and easy to implement, but the randomness of initial weights and thresholds can increase the output error of the network, reduce the recognition and classification accuracy of the network, and also decrease the stability of the network. The network is prone to falling into local extremum and other disadvantages. Therefore, in order to enhance the global search capability of the algorithm, genetic algorithms with variable population size can be used in the future to optimize the initial weights and thresholds of the network. Meanwhile, in the future, it is possible to integrate comprehensive databases[32,33] and compare various machine learning algorithms[5,17-19] with the aim of improving the accuracy and universality of the model. The model will provide a reliable foundation for agricultural research and high-yield cultivation.

6 Conclusions

1) The root morphology simulation model based on Elman neural network has a high simulation effect. The RMSE of maximum root length simulation model was 0.14-1.05 cm, and the NRMSE was 2.02%-11.34%.

2) The stem morphology (length and diameter) simulation model based on Elman neural network has a high simulation effect. The RMSE respectively was 1.42-4.96 cm and 0.25-1.17 mm, and the NRMSE respectively was 18.19%-25.65% and 15.13%-27.25%.

3) The leaf morphology (chlorophyll content, length, and width) simulation model based on Elman neural network and leaf area simulation model based on stepwise regression method have a high simulation effect. The RMSE respectively was 2.80-8.22 SPAD, 0.44-18.04 cm, 0.22-3.49 cm, and 0.25-36.39 cm^2, and the NRMSE respectively was 8.63%-21.04%, 15.00%-22.87%, 15.12%-33.58%, and 6.88%-24.90%.

Data availability

The data presented in this study are available on request from the corresponding author. The data are not publicly available because the data need to be used in future work.

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