

Article

Modeling the Mechanical Properties of Root–Substrate Interaction with a Transplanter Using Artificial Neural Networks

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Abstract: The mechanical properties of a plug seedling substrate determine whether it will crush during the transplantation, thereby affecting the integrity of the root system and the survival rate of transplanted seedlings. In this study, we measured eight morphological parameters of pepper seedlings using machine vision and physical methods, and the corresponding substrate mechanical parameters of the plug seedlings were tested using a texture analyzer. Based on the experimental data, a BPNN framework was constructed to predict the substrate mechanical properties of plug seedlings at different growth stages. The results indicate that the BPNN with a framework of [8, 15, 15, 1] exhibits higher R^2 and lower errors. The mean absolute error (MAE), mean squared error (MSE), and mean absolute percentage error (MAPE) values are 7.669, 88.842, and 9.076%, respectively, with an R^2 of 0.867. The average prediction accuracy of 20 test data set is 90.472%. Finally, predictions and experimental validations were conducted on the substrate mechanical properties of seedlings grown for 47 days. The results revealed that the BPNN achieved an average prediction accuracy of 93.282%. Additionally, it exhibited faster speed and lower computational costs. This study provides a reference for the non-intrusive estimation of substrate mechanical properties in plug seedlings and the design and optimization of transplanting an end-effector.

Keywords: plug seedling; mechanical properties; BPNN; prediction



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1. Introduction

Manual transplanting is more labor-intensive and spacing between adjacent seedlings is uneven; this non-uniformity causes difficulties in subsequent agricultural operations. So, mechanical transplantation is adopted by farmers for efficient vegetable seedlings transplantation and to decrease the operating cost and time [1,2]. The integrity of raising medium during the transplantation process is crucial for protecting the seedling roots and improving the survival rate of transplanted seedlings. The raising medium is inherently discrete, and although it can take on a fixed shape when bound in plug trays, the original stable form of the substrate is easily disrupted during the process of using a transplanting gripper.

In recent years, the study of mechanical properties such as compressive strength, tensile strength, and creep of substrate blocks has aroused interest. These studies on

mechanical properties provide a basis for the design and manufacturing of automated transplanting machinery and systems for plug seedlings [3]. Sami Mohamed et al. carried out an investigation into the effect of different soil moisture content and pickup speeds on the pickup force, balance, resistance, and lump damage during the transplanting of seedlings [4]. In Jiang Z et al.'s research, a force measure system with tension and pressure transducers was installed on the designed end-effector [5]. The adhesive force FL between the root plug and the cell of seedling trays and the extrusion force FK on the root plug were measured and analyzed. Some studies believe that compressive force is the main factor causing the plug seedlings substrate to be broken. Liu Jiaodi used a TA-XT2i texture analyzer to investigate the variation patterns between compressive resistance and compression quantity at different stages of the growing medium [6]. Ren Zhirui believes that compression speed is also a factor worth considering; he found that the most suitable picking condition is the gripper moving at a speed of 3 to 5 mm/s [7].

Although obtaining the mechanical properties of seedling substrate through sensors and instruments is more accurate and reliable, it is less efficient. Some researchers have applied the discrete element method (DEM) to complete this research, and results show that the DEM is suitable for solving nonlinear problems in seedling substrate research [8,9]. Hongbin Bai et al. simulated the seedlings grasping process of transplanting the end-effector and optimized the design of the seedling gripper [10]. Gao Guohua et al. utilized the ECM adhesive force elastoplastic contact model as the particle contact model and established a complex particle model with various material properties; this model allows for the interaction investigation between steel needles and the seedling substrate [11]. The DEM has clear advantages in terms of efficiency, but before simulating seedling substrate mechanical properties it is necessary to establish geometric models for particles of different materials and define their properties. Additionally, it is crucial to choose an appropriate physical model for particle contact. Some of these parameters are unknown and need to be obtained through preliminary experiments. Errors in experimentation and modeling may lead to misleading test results.

Numerous factors influence the damage to seedlings substrate in transplanting; these factors exhibit a high degree of complexity, strong interdependence, and considerable uncertainty [12]. Artificial neural networks (ANNs) have been widely employed in establishing mathematical models for complex relationships. They possess significant advantages in handling fuzzy, stochastic, and nonlinear data [13–15]. In predicting and optimizing agricultural equipment parameters, ANNs also show great promise. Some researchers predict the optimal values of the seeder forward speed, seed metering plate inclination and the seed level in the hopper based on ANN-PSO, obtained 100% cell fill of seed metering machine [16]. Kumar, S.P. et al. proved the potential of the ANN as an efficient technique for modeling soil–tool interactions under specific experimental conditions [17]. In this study, the mechanical properties of the seedling substrate are regarded as a nonlinear problem influenced by multiple factors; a back propagation neural network (BPNN) framework is proposed to describe the relationship between parameters (seedling age, plant height, leaf area, etc.) and the mechanical properties of the substrate. This facilitates the prediction of substrate mechanical properties under different parameter conditions, thereby reducing the research time cycle and manpower costs.

2. Materials and Methods

2.1. Experimental Materials and Instruments

The experiment was conducted from June to August 2023 in the Key Laboratory of Intelligent Horticultural Equipment of the Ministry of Agriculture and Rural Affairs. The experimental subjects were pepper seedlings, and they were sowed on May 12 in indoor conditions. The seedling tray used had 200 cells, and the cell shape approximated a frustum. The upper dimensions of the cell were 20 mm × 20 mm, the lower dimensions were 10 mm × 10 mm, and the depth was 38 mm. The substrate was prepared by uniformly mixing peat, vermiculite, and perlite in a conventional ratio of 3:1:1. The particle sizes

of perlite and vermiculite were 1–3 mm, while peat had a particle size of 1–5 mm. After sowing and watering the seedlings every 2 days, a handheld soil moisture meter (YGY-TRY type) was used to collect soil moisture content data. To maintain consistent substrate moisture during the experiment, the seedling was thoroughly watered 2 days before testing, ensuring that the moisture content remained in the range of 69.38% to 72.14%.

The mechanical properties of the substrate were tested via a CTA texture analyzer (Tianjin Chuangxing Electronic Equipment Manufacturing Co., Ltd., Tianjin, China). The load force range of the analyzer is 0–50 kg, with a load force accuracy of 0.01–0.0001 g. It has a deformation displacement range of 0–310 mm, with a displacement resolution accuracy of 0.0001 mm. The detection speed ranges from 0.0001 mm/s to 40 mm/s, and the speed resolution accuracy is 0.1–0.001 mm/s. The data acquisition rate is between 200 sps and 25,000 sps. This machine is capable of measuring parameters such as puncture resistance, yield strength, tensile (compression, bending) strength, and elastic modulus according to standards such as GB, ASTM, and JISDIN, among others; it is controlled by a small computer, and automatically completes loading, unloading, and data collection and analysis.

2.2. Test Methods for Plant Morphological Parameters

Under conditions where water content, substrate volume density, and component ratios remain constant, the density of the plug seedling root systems influences the cohesion of the substrate. The degree of root development exhibits a significant correlation with the stem and leaf parameters of the plant [18]. Therefore, morphological parameter data were collected separately for pepper seedlings at 22 days, 27 days, 32 days, 37 days, and on the 42nd day. As shown in Figure 1, these parameters include plant height (distance from the growing surface to the tip of the bud), leaf length (measured using the longest dimension), leaf width (measured using the widest dimension), leaf quantity (excluding those with a length less than 3 mm), root length (measured using the longest dimension), and root quantity (counting only those roots with a length exceeding 5 mm).

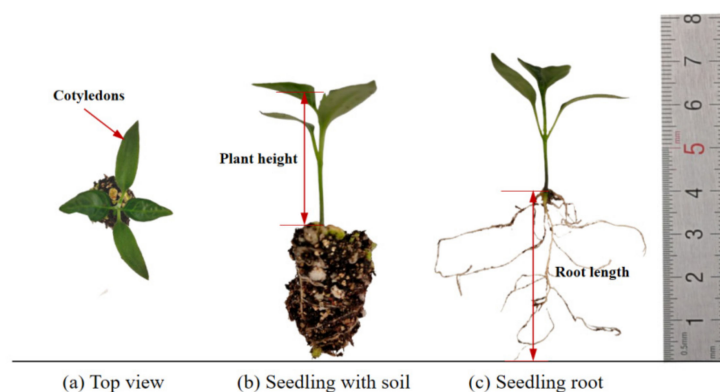


Figure 1. Plug seedling morphological parameters measurement.

The leaf area is considered one of the optimal indicators for assessing seedling quality. Conventional leaf area measurement relies primarily on leaf area meters, which incur high equipment costs and may also cause damage to plants. Some researchers have explored methods for testing the leaf area of potted seedlings based on machine vision, achieving high accuracy [19]. In this study, a CCD camera was used to capture an image at a distance of 20 cm directly above the seedlings; a square reference object measuring 10 × 10 mm was placed in a position level with the canopy. The image processing procedure, as shown in Figure 2, includes pre-processing, target segmentation, edge detection, and leaf area calculation. When the seedlings grow to the stage of having four cotyledons, the leaf tips tilt downward slightly. To ensure the accuracy of the leaf area calculation, before collecting photos, the leaves are gently curled in the opposite direction manually to keep

them in as horizontal a state as possible. To validate the accuracy of the leaf area obtained through the machine vision method, a AM350 portable leaf area meter was also used to test the corresponding seedlings. The results indicated an error ranging between 1.89% and 3.54%. This discrepancy arises because the visual method provides the leaf projection area, whereas the actual leaf is not a perfectly flat plane. If such an error is present in each individual seedling, its impact on the entire system can be ignored.

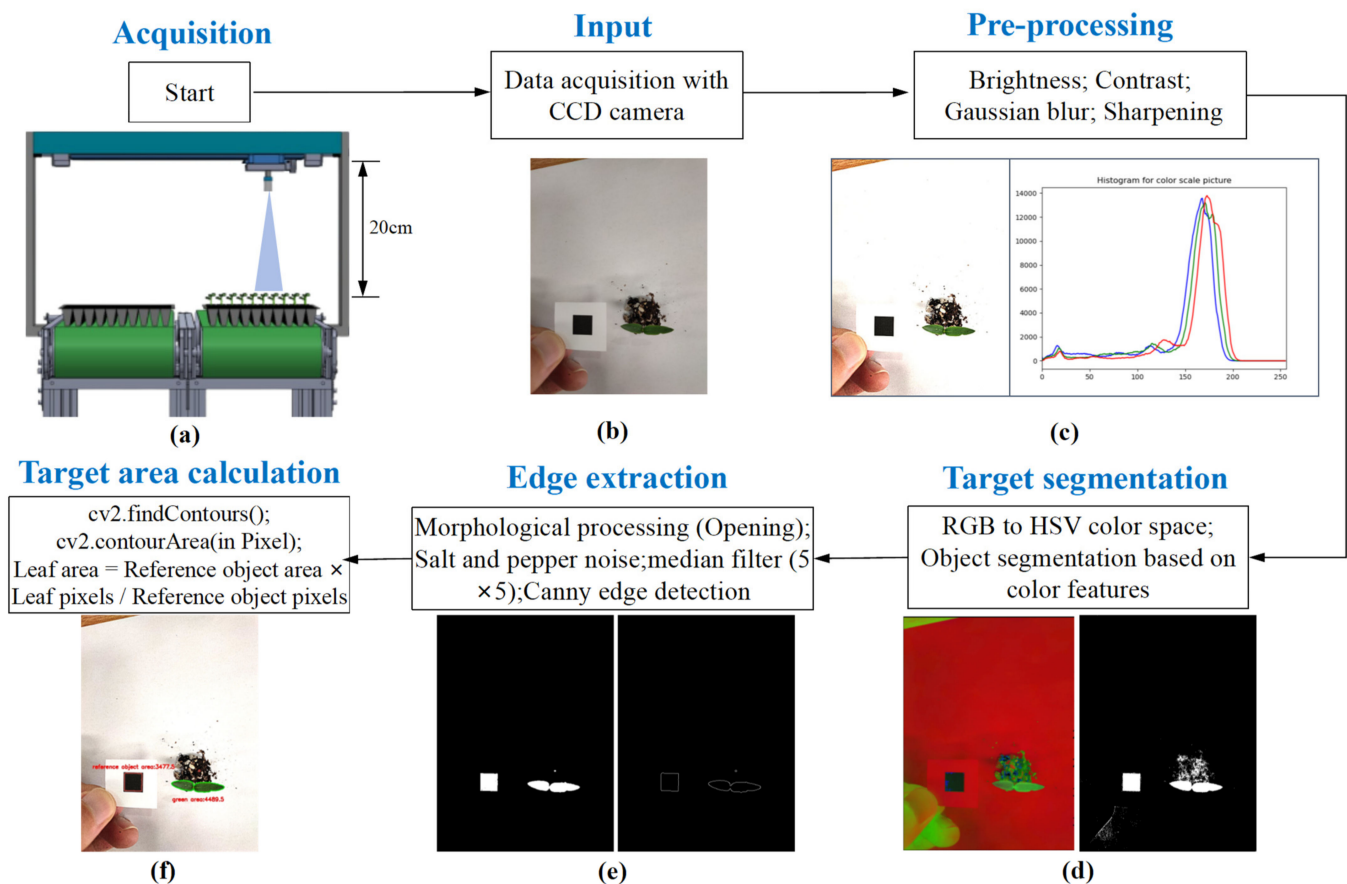


Figure 2. Process of obtaining leaf area of seedlings based on machine vision. Note. (a) is the method of image acquisition; (b) is the images have captured; (c) is the image pre-processing, including brightness, contrast, Gaussian blur and sharpening; (d) is target segmentation based on its color feature; (e) is the process of morphological processing and target edge extraction and (f) is leaf area calculation.

2.3. Test Methods for Mechanical Properties

The mechanical properties of the substrate for plug seedlings mainly include tensile, compressive, and puncture forces. Tensile force is the sum of the adhesive force between the substrate and the cell walls, together with their gravitational forces. It determines the pulling force exerted by the end-effector during transplanting. Compressive and puncture forces can assess the intrinsic mechanical characteristics of the substrate. Each test was repeated 12 times.

The method for tensile force testing is as follows: knotting cotton threads with a diameter of 0.05 mm into a symmetrical “cross” shape and putting it at the bottom of the cells before fill substrate and sowing. This approach reduced the impact of tensile materials on the force results and avoided issues such as direct seedling pulling that lead to damage to young seedlings. During the experiment, the plug seedlings are placed directly beneath the probe. As shown in Figure 3, four cotton threads are clamped using a designed fixture, and the seedlings are vertically pulled upward at a speed of 1 mm/s to assess the

tensile load variation curve. A flat plate probe is used to test the substrate compression resistance. The substrate block was placed on the experimental platform, and the flat plate descended vertically at a loading speed of 1 mm/s. The changes in the compressive load on the substrate were recorded. Research indicates that the intact rate of the substrate is highest when using a needle-type end-effector with a diameter of 3 mm [20]. Therefore, in the puncture test, a steel needle with a diameter of 3 mm was used to puncture along the four edges of the cell. During this process, a portion of the circular surface of the steel needle came into contact with the cell wall made of PVC material, while another portion came into contact with the substrate. The insertion depth was consistent with the depth of the cell (3.8 mm), and the loading speed was also set at 1 mm/s.

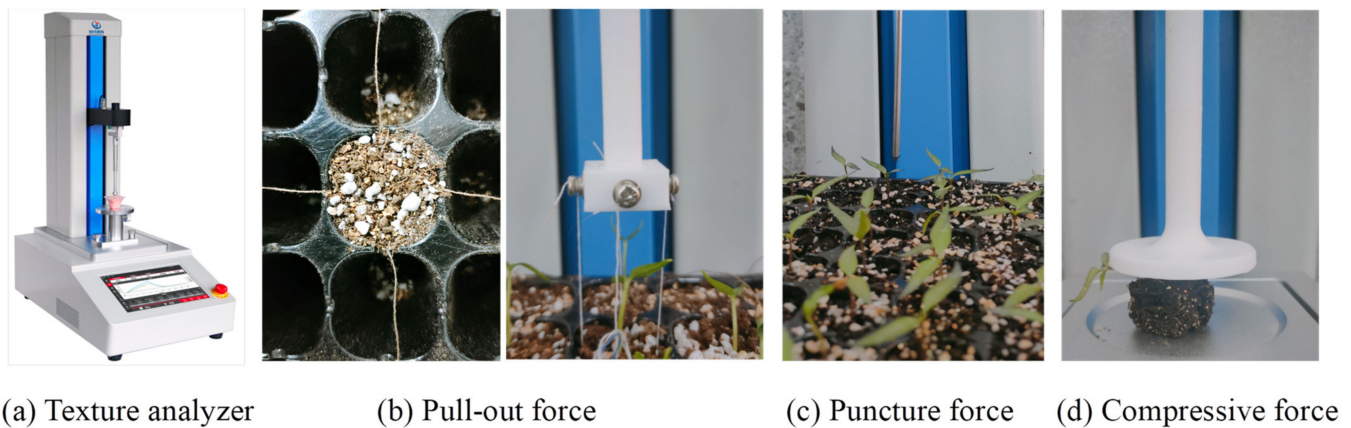


Figure 3. Test method of mechanical properties of plug seedlings. Note. (a) is the TCA texture analyzer used in the experiment; (b) is the test process of the pullout force of the substrate; the substrate is pulled out by holding and stretching the thin wires buried in the holes before sowing to obtain the maximum pulling force; (c) is the testing process on the force required for the steel needle of the transplanter puncture into the substrate and (d) uses the flat-plate compression method to test the maximum compression force when the substrate is broken.

2.4. BPNN Construction

The construction process of the BPNN is as follows: The input data consist of eight variables related to the pepper seedling growth, including the growth stage (days), canopy height (mm), leaf length (mm), leaf width (mm), leaf quantity (number of leaves), root length (mm), root quantity (number of roots) and leaf area (cm²). Therefore, the input layer comprises eight neurons. During the transplanting, the end-effector steel needle pierces into the substrate and then pulls upwards to remove the seedling. The primary mechanical characteristics in this process are the puncture force and pull-out force; the lateral compression load on the substrate is limited. To simplify the model, a weighting of the puncture force, compression force, and pull-out force output is performed using weights of 0.3, 0.1, and 0.6, respectively; at the same time, min-max normalization is used to linearly scale the data to the range of [0, 1] to avoid errors, and denormalization is performed when displaying predicted values. The output layer of the network consists of only one neuron, referred to as the comprehensive mechanical characteristic of the substrate. The network is trained on a datasets including 60 data and tested on a separate datasets having 20 sets of data to evaluate its performance.

The lower number of hidden layers has a significant impact on the accuracy of the network. Conversely, exceeding the optimal number of hidden layers results in a magnitude increase in training time and network complexity [21]. Experiments conducted by Karsoliy indicate that the number of neurons in the first hidden layer should be nearly equal to that in the second hidden layer, facilitating ease of training [22]. At the same time, two hidden layers are generally sufficient to address nonlinear complex problems, with the option of adding a third hidden layer if precision is the primary criterion for network design.

Two principles guide the determination of the number of neurons in the hidden layers: (i) the number of neurons should be two-thirds (or 70–90%) of the size of the input layer, and (ii) the number of neurons in the hidden layers should be less than twice the number of neurons in the input layer. Adhering to these principles, the recommended configuration includes two to three hidden layers with 5 to 15 neurons. A full factorial design method is applied for the test and a total of 22 experiments were conducted to select the optimal hidden layer structure.

Lenovo computers are used for online training. The system is Windows 10, the processor is Intel Core i7-14700, 2.5 GHz, the memory is 16 GB, the hard disk capacity is 1024 GB, and the graphics chip is NVIDIA GeForce RTX3060. We utilized a Sigmoid as the activation function for both the hidden layer and the output layer, with a learning rate of 0.25, training target error of 0.001, and a total of 60,000 iterations. Commonly employed evaluation metrics including mean square error (*MSE*), mean absolute error (*MAE*), mean absolute percentage error (*MAPE*), and coefficient of determination (R^2) are selected to assess the predictive performance of the network. The calculation formulas for these four statistics are provided below:

- Mean square error (*MSE*):

$$MSE = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad (1)$$

- Mean absolute error (*MAE*):

$$MAE = \frac{1}{n} \sum_{i=1}^n |Y_i - \hat{Y}_i| \quad (2)$$

- Mean absolute percentage error (*MAPE*):

$$MAPE = \frac{100\%}{n} \sum_{i=1}^n \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \quad (3)$$

- Coefficient of determination (R^2):

$$R^2 = 1 - \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{\sum_{i=1}^n (Y_i - \bar{Y})^2} \quad (4)$$

Here, n represents the total number of observations, Y_i is the actual value, $\hat{Y}_i$ is the predicted value, and $\bar{Y}$ is the mean of the actual values. *MSE* and *MAE* provide information on the magnitude of errors, *MAPE* emphasizes the relative percentage errors. Larger values of them suggest a higher variability in the errors. R^2 assesses the overall explanatory power of the model and ranges from 0 to 1; a higher R^2 value suggests a better ability of the model to explain the variance in the data.

3. Results and Discussion

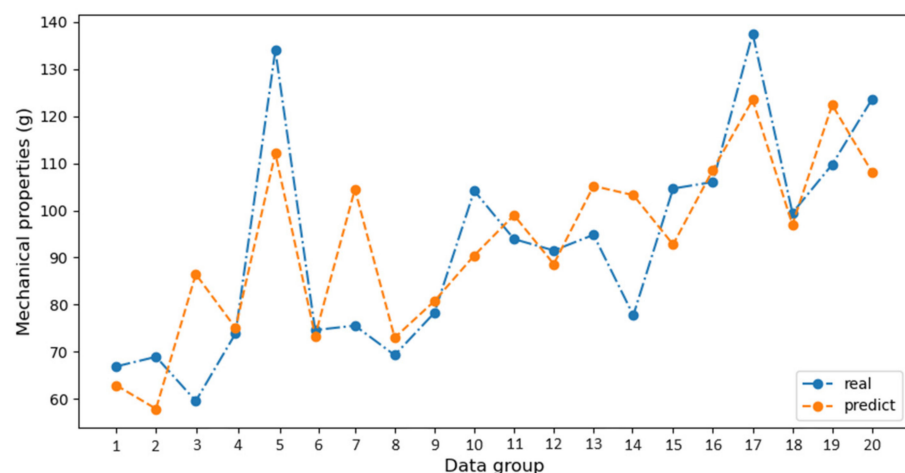
3.1. Neural Network Framework Results

As for the BPNN framework, the results of 22 orthogonal experiments are presented in Table 1. The neural network demonstrates the minimum *MAE*, *MSE*, and *MAPE* values when configured with two hidden layers, each containing 15 neurons. Specifically, the corresponding values are 7.669 for *MAE*, 88.842 for *MSE*, and 9.076% for *MAPE*. Additionally, the R^2 achieves its maximum value of 0.867, indicating the highest predictive accuracy of the network. Therefore, the optimal architecture for the BPNN in predicting the mechanical properties of the substrate is determined as [8, 15, 15, 1].

Table 1. Comparison of results of different hidden layer network structures.

No.	Number of Hidden Layers	Hidden Layer 1	Hidden Layer 2	Hidden Layer 3	MAE	MSE	MAPE (%)	R ²
1	2	5	5	0	11.289	191.325	12.350%	0.607
2	2	6	6	0	12.023	231.834	13.924%	0.524
3	2	7	7	0	11.761	231.280	13.727%	0.525
4	2	8	8	0	13.637	268.522	15.624%	0.448
5	2	9	9	0	13.550	257.552	15.164%	0.471
6	2	10	10	0	12.867	228.178	14.509%	0.531
7	2	11	11	0	12.189	224.697	13.687%	0.539
8	2	12	12	0	9.327	143.817	11.132%	0.705
9	2	13	13	0	11.710	218.793	13.588%	0.551
10	2	14	14	0	9.527	157.982	10.935%	0.676
11	2	15	15	0	7.669	88.842	9.076%	0.867
12	3	5	5	2	12.155	239.242	13.654%	0.509
13	3	6	6	3	11.876	206.582	13.571%	0.576
14	3	7	7	3	13.495	283.368	15.416%	0.418
15	3	8	8	4	13.942	289.851	15.917%	0.405
16	3	9	9	4	13.497	258.325	15.250%	0.471
17	3	10	10	5	9.117	138.587	10.582%	0.715
18	3	11	11	5	11.715	191.551	13.375%	0.607
19	3	12	12	6	12.847	233.136	14.804%	0.521
20	3	13	13	6	12.998	252.724	14.989%	0.481
21	3	14	14	7	12.572	229.730	14.844%	0.528
22	3	15	15	7	9.191	141.258	10.884%	0.710

Figure 4 presents the prediction results and ground truth comparison of the neural network framework [8, 15, 15, 1] on a test set comprising 20 groups. The actual value of the seedling mechanical properties is tested by the texture analyzer, including the maximum load (g) of puncture, compression and pull-out of the seedling substrate. These three are weighted to form the comprehensive mechanical properties (g) of the substrate, and the value show by the ordinate. It is evident that the BPNN model exhibits effective training and demonstrates a high degree of fitting. Notably, the seventh group exhibits the largest prediction error, with a ground truth of 76.824 g and a predicted value of 105.442 g, resulting in a prediction accuracy of 71.698%. The fourth group demonstrates the best prediction performance, with a ground truth of 71.703 g and a predicted value of 74.224 g, yielding a prediction accuracy of 96.631%. The average prediction accuracy across the 20 data sets is 90.472%.

**Figure 4.** Comparison of the predicted and real values of the test set.

A regression analysis between the network output and the corresponding targets was carried out. There were 60 training and 20 testing data. Figure 5 demonstrates the correlation of experimental and BPNN predicted values for seedling substrate mechanical properties on training and testing datasets, respectively. It shows a good fit of BPNN predicted values to the actual measured data, and with $R^2 = 0.867$ for the training data and $R^2 = 0.804$ for the testing data.

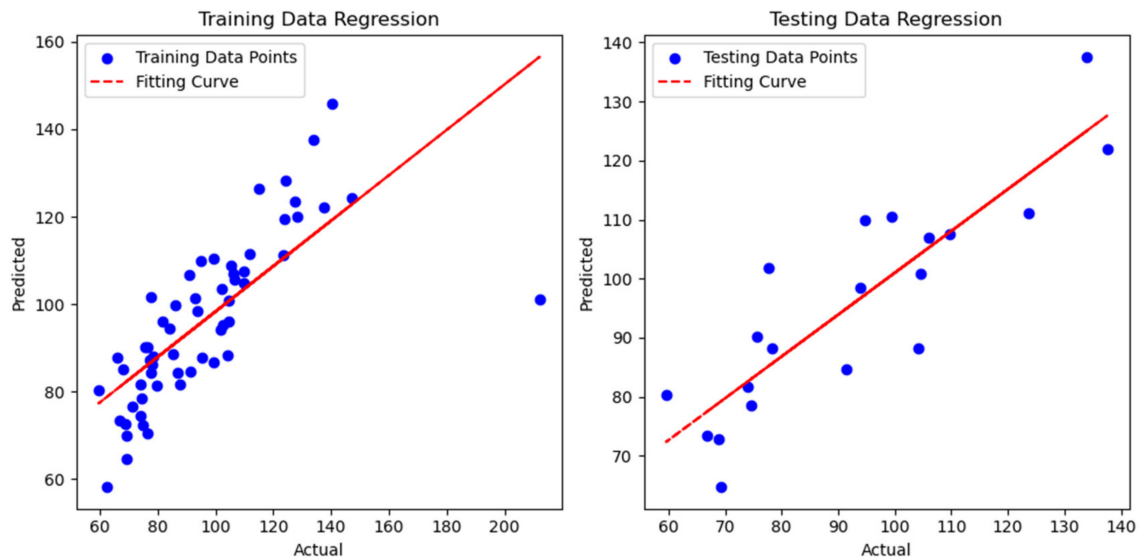


Figure 5. Regression plots of BPNN during training and testing.

3.2. Prediction Verification Test

To further validate the prediction accuracy of the BPNN, predictions and experimental verification of the substrate mechanical properties of 47-day-old pepper seedlings were conducted. Nine seedlings were randomly selected from the tray, and eight parameters were measured as input for the neural network trained in the previous section to predict their mechanical properties. Subsequently, the mechanical properties of the seedling substrate cultivated under the same conditions were experimentally tested using a texture analyzer, including puncture load, compression load, and tensile load peaks. Each test was repeated nine times. Figure 6 illustrates the puncture test load curve. After the steel needle made contact with the surface of the growing substrate, the force continuously increased until reaching a peak. After penetrating the substrate, the force decreased. The maximum load peak among the nine repetitions was 143.848 g, the minimum was 75.592 g, and the average of the puncture load peaks for the steel needle was 117.586 g.

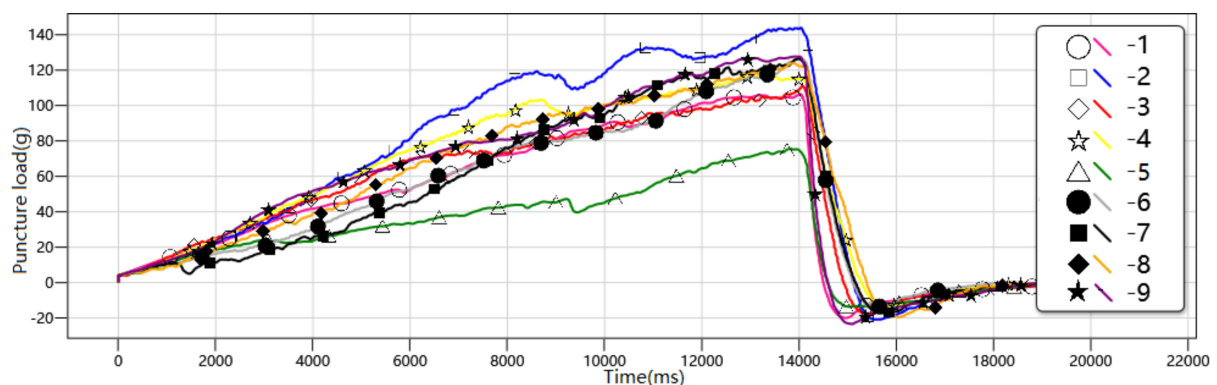


Figure 6. Puncture load curve.

Figure 7 shows the tensile load curve; the load steadily increases over time during the tensile test, reaching a peak before decreasing. The minimum peak tensile load is recorded at 82.102 g, the maximum at 157.738 g, with an average of 120.957 g. Inconsistent tension in the cotton thread fixation, leading to variations in the initiation of force application by the textural analyzer probe, results in a significant variation in the time taken to reach the peak among different experimental groups. However, this variation does not impact the ultimate experimental outcomes.

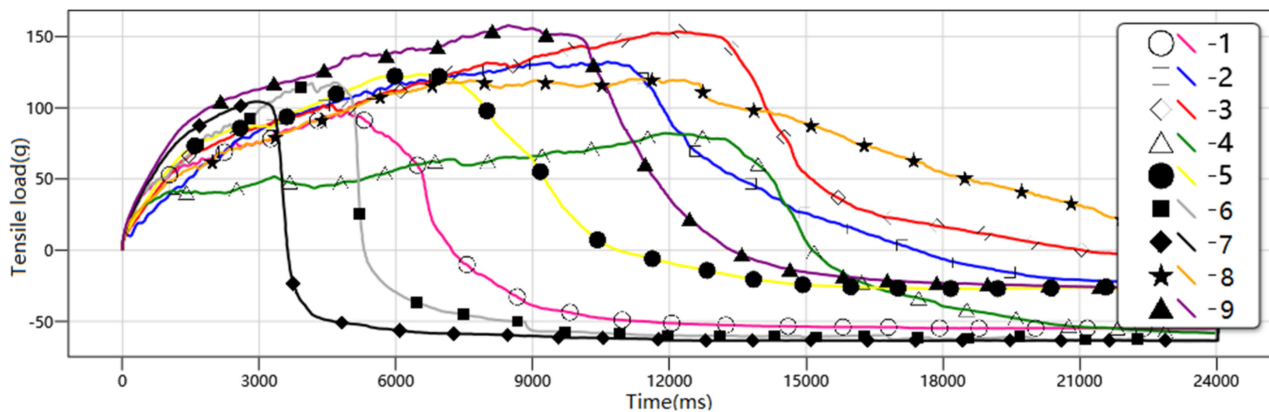


Figure 7. Curve of tensile load.

Similarly, due to differences in substrate sizes, there are variations in the time the probe is subjected to force during compression testing, resulting in different peak load arrival times in the compression load curve (Figure 8). The maximum peaks are concentrated around 150 g, which is the maximum target load of the experiments, because there is no phenomenon of sudden collapse of the solid substrate. In the course of the plate compression, there is no distinct yielding failure point observed in the substrate. Additionally, the compression failure of the substrate initiates from areas with fewer roots, gradually expanding the extent of fragmentation.

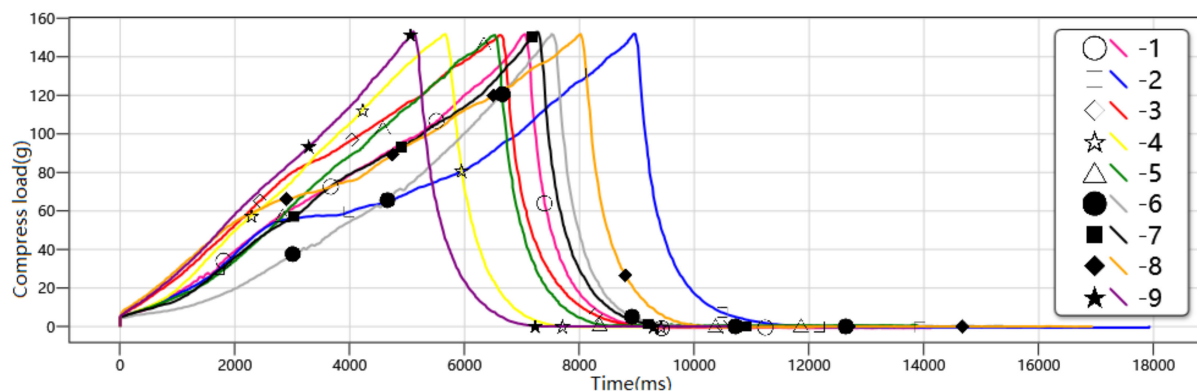


Figure 8. Curve of compressive load.

Using weights of 0.3, 0.1, and 0.6, the peak values of puncture, compression, and tensile loads were weighted and integrated for comparison with the predicted results. The comprehensive mechanical property values of the nine groups of seedling substrates predicted based on the BPNN ranged from smallest to largest: 81.697 g, 92.384 g, 104.368 g, 110.522 g, 112.258 g, 121.867 g, 127.981 g, 130.621 g, and 150.346 g, with an average of 114.672 g. In contrast, the experimentally obtained true values were 99.465 g, 105.189 g, 111.908 g, 115.731 g, 123.678 g, 124.365 g, 137.548 g, 140.385 g, and 148.103 g, with an average of 122.933 g. The average prediction accuracy of the BPNN reached 93.282%, a

level deemed acceptable for agricultural applications. This indicates that the model has good predictive performance, and using the neural network method for predicting the mechanical properties of plug seedling substrates is feasible.

Mechanical property tests revealed that the load peak of the compress test remained relatively stable, showing no significant variation in the growth time of seedlings. The compressive load primarily depended on the substrate ratio and moisture content, both of which remained consistent, thereby accounting for the aforementioned results. Load peak values of puncture and tensile exhibited a continuous increase over time. Due to the robust fiber structure present in the root system, this ensures a high cohesion force within the substrate.

Plug seedlings substrate block consists of a plant root and growing medium with different solid materials, and its mechanical properties are closely related to the success rate of transplanting and the degree of damage, playing an important role in key components design such as the end-effector mechanism. Currently, researchers focus on the following three aspects: (i) the characteristics of the substrate block itself, including compressive properties, creep properties, tensile properties, etc. [23]; (ii) the adhesiveness between the substrate and tray cell wall, such as the bonding force between the root system and pore wall and the influence of substrate moisture content on the success rate of seedling picking; and (iii) the interaction process between the substrate and the transplanting manipulator, involving factors such as the friction coefficient between the substrate and the seedling needle, and the broken pattern of the substrate caused by the steel needle [24]. These methods require the use of mechanical instruments and sensors, etc.; although they can obtain more accurate information, they are invasive and destructive to the experimental objects and are unsustainable. This process is also very time-consuming.

The artificial neural network (ANN) is a mathematical model that mimics the physiological structure and function of the human brain's neural network. By training on known data, it learns to identify underlying patterns and utilizes its strong generalization ability to predict future data. This method has found wide applications in the field of agriculture. S Pohan et al. applied the backpropagation algorithm of neural networks to predict the growth of greenhouse plant seedlings, achieving an accuracy of 92.79%, which closely approximates actual data [25]. Marvellous M demonstrated the potential of ANN models as tools for selecting high-yielding sugarcane seedlings by predicting the stem count, stem height, and stem diameter [26]. Researchers also examined the performance of predicting pea seed yield using both linear (MLR) and non-linear (ANN) models, achieving highly accurate predictions with a correlation coefficient of 0.936. These studies explored the mapping relationship between seedling growth status and yield, showcasing the powerful potential of ANNs [27]. However, there is limited literature on the study of mechanical properties of plug seedling substrates.

In fact, the factors that influence the mechanical properties of the substrate are limited, including the substrate material, material ratio, moisture content, and seedling growth stage (degree of root system development), etc. Therefore, it is theoretically feasible to predict the mechanical properties of the substrate through these parameters. Our research results also confirm this view. However, the relationship between these factors and the target exhibits strong nonlinearity and uncertainty, constituting a multi-parameter coupled problem. The ANN has the ability to learn and build models of nonlinear complex relationships, which is very important because the relationship between input and output faced in our study is nonlinear and complex. After learning, an ANN can infer unknown relationships between unknown data. At the same time, the ANN network structure is simple and the computing cost is low. Given the advantages of artificial neural networks in rapidly simulating complex nonlinear problems, this study employed an ANN to establish a predictive model for the mechanical properties of plug seedling substrates. The average prediction accuracy reached 93.282%, which is a remarkably surprising result. It significantly reduces the traditional research time cycle and saves on expensive equipment costs.

There is still a need for some work to improve this research. The moisture content and the material ratio of the substrate are also variable, influencing the mechanical properties of the bowl seedling substrate blocks [28]. Considering that current seedlings are cultivated on a large scale in a controlled indoor environment, the moisture content of seedlings in different trays remains relatively constant. Therefore, in this study, the conventional moisture content values during the transplantation period of plug seedlings were referenced and set as a constant, maintaining within the range of 69.38% to 72.14% and investigating the substrate mechanical properties. The material ratio of the matrix only uses conventional parameters. An ideal neural network prediction model should accurately forecast the mechanical properties of different targets in various environments. Hence, the subsequent work will explore the prediction of substrate mechanical properties considering additional factors, including the moisture content and material ratio.

4. Conclusions

This study utilizes eight parameters, namely plant height, leaf length, leaf width, leaf number, root length, root number, and leaf area, measured at different growth stages of pepper seedlings, as inputs to construct a BPNN for predicting substrate mechanical properties. The optimal hidden layer and neuron numbers of the network were determined through orthogonal experiments, revealing that the optimal network architecture is [8, 15, 15, 1]. At this configuration, the network achieves the minimum values for MAE, MSE, and MAPE, which are 7.669, 88.842, and 9.076%, respectively. The R^2 is 0.867. The average prediction accuracy for the 20 test set data is 90.472%.

To further validate the prediction accuracy of the BPNN, predictions and experimental verifications were conducted on the mechanical properties of the substrate for pepper seedlings with a growth period of 47 days. The average value of the peak load obtained from the steel needle penetration was 117.586 g, and the average tensile load was 120.957 g. During the plate compression process, there was no apparent yield point observed in the substrate block. Comparing the results with the nine sets of values measured by the texture analyzer, the BPNN achieved an average prediction accuracy of 93.282% for the comprehensive mechanical properties. This level of accuracy indicates that predicting the mechanical properties of the substrate for pepper seedlings based on neural network methods is feasible.

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