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A Bayesian network-based approach to crop growth prediction and management in a digital agricultural environment

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Abstract Digital technology is accelerating the deep transformation of agriculture, and improving production efficiency has become the key to the high-quality development of agriculture. Crop growth prediction, as an important link in precision agriculture, can effectively guide agricultural production decisions and improve yield and quality through the integration of intelligent algorithms. In this paper, we constructed a BNM-PNN model combining Bayesian network and process neural network, and established a crop growth and development prediction model by collecting and analyzing the hyperspectral data, SPAD data and leaf area index of Italian shoot-tolerant lettuce under different nitrogen fertilizer application conditions. The study adopts the improved neural network initialization method and learning algorithm to solve the output locking problem of the Sigmoid-type excitation function and improve the convergence speed of the model. The results show that the BNM-PNN model has superior performance in crop growth prediction, with the coefficient of determination and regression estimation errors reaching 0.927 and 1.436 g/pl, respectively, with an average relative error of 3.24%. In the model performance evaluation, the accuracy of the BNM-PNN model reaches 96.15%, and the DICE score and sensitivity are 92.15% and 91.78%, which are significantly better than the traditional deep learning models such as GoogleNet and ResNet-50. The study shows that the fusion of Bayesian network and process neural network can effectively extract the key features of crop growth and provide technical support for accurate management of agricultural production.

Index Terms Digital agriculture; Bayesian network; Process neural network; Growth prediction; Crop management; Hyperspectral data

I. Introduction

The digitalization of agricultural production is located in the fundamental position of the digital construction of the whole agricultural industry chain, and it is also the focus point of the formation of new quality productivity to lead the high-quality development of agriculture [1], [2]. At present, China's agriculture is in a period of innovation-driven, new kinetic energy cultivation to generate advanced productivity of the depth of the transformation period, in the digitalization of rural revitalization of the wind, accelerate the digital butterfly of the agricultural production end as the key [3]-[5]. Digital agricultural technology is a specific application of digital technology in the field of agriculture, which is an important type of agricultural technology [6]. According to the endogenous growth theory of economics, it is known that technological progress is the core driving force to promote productivity enhancement, so digital agricultural technology is logically able to effectively promote agricultural production efficiency [7], [8]. Among them, the crop growth prediction method is mainly through the understanding of the physiological and ecological processes of crops, the use of scientific means to predict the state of crop growth, yield, quality and other indicators, so as to achieve the purpose of predicting its economic benefits [9]-[12]. Previous methods of describing the physiological processes of crops, although many, were limited to fitting static parameters of crops and failed to monitor and predict dynamically [13]. Based on this, modern agricultural technology proposes to integrate intelligent algorithms for management in the study of crop growth patterns to provide scientific guidance for agricultural production [14]. It can not only faithfully describe the various growth indicators of crops but also predict the relevant growth status of crops, so as to achieve the purpose of increasing production and income to improve economic efficiency [15]-[17].

The digitalization of agricultural production is located in the fundamental position of the digital construction of the whole agricultural industry chain, and it is also the focus point of the formation of new quality productivity to lead the high-quality development of agriculture. At present, China's agriculture is in a period of innovation-driven, new kinetic energy cultivation to generate advanced productivity in the depth of the transition, in the digitalization of rural revitalization of the wind, accelerate the digital butterfly of the agricultural production side is the key. Digital agricultural technology is a specific application of digital technology in the field of agriculture, which is an important type of agricultural technology. According to the endogenous growth theory of economics, it is known that technological progress is the core driving force to promote productivity enhancement, so digital agricultural technology can logically and effectively promote agricultural production efficiency. Among them, the crop growth prediction method is mainly through the understanding of the physiological and ecological processes of crops, using scientific means to predict the state of crop growth, yield, quality and other indicators, so as to achieve the purpose of predicting its economic benefits. In the past, although there are many methods of describing the physiological process of crops, they are only limited to fitting static parameters of crops, but fail to monitor and predict dynamically. Based on this, modern agricultural technology proposes to integrate intelligent algorithms for management in the study of crop growth patterns to provide scientific guidance for agricultural production. It can not only faithfully describe the various growth indicators of crops but also predict the relevant growth status of crops, so as to achieve the purpose of increasing production and income to improve economic efficiency.

As the world's largest agricultural developing countries, agricultural production has always been one of the important conditions affecting the overall development of the country, at the same time, our country's population is also the world's largest, how to utilize the limited arable land to meet the population's growing demand for food is one of the major problems faced by our country. During the growth process of crops, how to realize the growth and development prediction through intelligent technology has become an important research topic to improve the quality and yield of crops. In this study, the BNM-PNN crop growth and development prediction model was constructed by combining the Bayesian network model with the process neural network. The developmental prediction model for lettuce growth was established by collecting hyperspectral data, SPAD data, and leaf area index through experimental research on Italian twitch-resistant lettuce in the greenhouse greenhouse of a company in S city, J province. The model adopts Bayesian network to extract spatial features and process neural network to learn temporal features, which realizes the dynamic prediction of crop growth. To solve the output locking problem of the Sigmoid-type excitation function during model training, an improved initialization method and learning algorithm are proposed, which effectively improve the convergence speed and prediction accuracy of the model. The superior performance of the BNM-PNN model in the field of crop growth prediction is verified through comparison experiments with traditional deep learning models, which provides technical support for the accurate management of agricultural production.

II. Data acquisition processing and deep learning models

As the world's largest agricultural developing country, agricultural production has always been one of the important conditions affecting the overall development of the country, and at the same time, our country's population is the largest in the world, how to utilize the limited arable land to meet the population's growing demand for food is a major problem faced by our country. In the growing process of crops, how to realize the growth and development prediction through intelligent technology has become an important research topic to improve the quality and yield of crops.

II. A. Experimental environment and image acquisition and processing

II. A. 1) Design of crop growing environments

This study was conducted in a greenhouse of a company in S city, J province. A pot test was used, the test variety was Italian drawdown-resistant lettuce, the test soil was yellow-brown loam with 0.15% soil total nitrogen, and the second season planting soil total nitrogen content was 0.16%. The test fertilizer was urea with 45% nitrogen content, produced by WH. The type of phosphorus fertilizer applied was calcium superphosphate, with an application rate of 350 kg/ha, and an effective calcium superphosphate content of more than 13%, produced by WN Agricultural Products Co. The potash fertilizer was grass ash at the rate of (soil 16:1 grass ash). Choose a plastic pot with a caliber of 18cm and a height of 15cm, and fill it with 2.5kg of air-dried soil sifted through a 0.5cm sieve, and transplant the seedling to the pot when it grows to 4~5 leaves after sowing, and plant one plant in each bowl.

The field experiment was conducted in two times, respectively, sowing in March 2023 and planting on April 5, sowing in September 2023 and planting on September 25, 5 nitrogen fertilizer gradients were set up in April 2023, with 20 pots planted in each treatment, totaling 100 pots, and 5 nitrogen fertilizer gradients were set up in September 2023, with 20 pots planted in each treatment, totaling 100 pots. Nitrogen fertilizer application in the base fertilizer 70% and 30% of the follow-up fertilizer, field management of the same general lettuce field, different nitrogen application aimed at obtaining lettuce populations with different colors and nitrogen content. Sampling and image acquisition were carried out during the rosette stage and product formation stage of the main lettuce reproductive period, and four plants were sampled at different leaf ages for each nitrogen treatment.

II. A. 2) Image data acquisition methods

In this study, data were collected from March 2023 to October 2023 lettuce growing cycle. The main data required were 500nm~1000nm hyperspectral data, SPAD data and leaf area index data. The hyperspectral data were collected with a Field Spec portable feature spectrometer, and the leaf area index data were collected with a LAI2200 plant canopy analyzer.The Field Spec portable feature spectrometer is manufactured by ASD, and is capable of collecting visible, near-infrared, and short-wave infrared spectral information, with the main parameters of reflectance, transmittance, and radiance, and with the spectral wavelengths of 300nm~2500nm. 300nm~2500nm, acquisition time 0.2s. LAI2200 Plant Canopy Analyzer measures the light from 5 angles above and 5 angles below the canopy to calculate the transmittance of the 5 angles, from which the number of leaves, the leaf area index and the inclination angle of leaves are deduced, and the spatial values are usually taken from multiple canopies for averaging.

Hyperspectral data collection with the Field Spec Geophysical Spectrometer should be performed in clear, cloudless or less cloudy weather, with no wind or wind not exceeding level 3, and during the collection time period between 10:00 and 14:00 Beijing time, to ensure that the collected data reflect the spectral properties of the measurement target as much as possible. The instrument should be turned on and warmed up for about 15 minutes before use to stabilize the light source and electrical characteristics of the spectrometer. Dark current acquisition and whiteboard calibration should also be implemented before performing target feature measurements, and the dark current acquisition and whiteboard calibration operations should be repeated at 4-minute intervals during use. During the data acquisition process, the height of the probe and the canopy should be kept above 0.5m, and the field of view angle should be about 30°. Instrument operators should wear dark-colored clothes and hats, and face the sun during the measurement process to ensure that the sun shines from the front to avoid the resulting shadows affecting the accuracy of the spectral data.

The LAI2200 Plant Canopy Analyzer should collect the A value of the upper canopy and the B value of the lower canopy during the measurement, and the A and B values should be calculated after certain arithmetic operations in order to calculate the leaf area index LAI value. To obtain reliable LAI data, the light probe should be aimed at the same part of the sky when measuring A and B values with the LAI2200, and the time and place of measurement of the two values should be the same as far as possible. The operator should not be within the viewing angle of the instrument during data collection, otherwise the operator should wear a hood with a 260° viewing angle.

II. A. 3) Crop image data processing

When performing enhancement operations on an image, the quality of the image is improved according to the needs of the processing, highlighting useful information in the image and weakening the less useful information [18]. The result should be more conducive to computer processing, the method does not increase the information of the original image data, but only deepens the recognizability of a certain type of information so that the processed image is more conducive to a specific processing than the original image. According to the different domains of action, image enhancement can be categorized into two types: spatial domain operation and frequency domain operation. Spatial domain operation deals with the gray value of the pixel, and frequency domain operation deals with a certain frequency domain of the image, and then inverse transformation is performed to obtain the enhanced image.

Gray scale transformation is used to achieve the purpose of image enhancement by adjusting the range of gray scale value changes or contrast of the image, which uses a transformation function to transform the gray scale value of the original pixel into a new gray scale value, which can be described by the following formula:

$$g(x,y)=T(f(x,y)) \tag{1}$$

where $f(x,y)$ represents the gray value of the pixel in the original image, $g=T(f)$ is the transformation function, and $g(x,y)$ is the new gray value of the pixel obtained by the transformation.

Image averaging is the averaging of multiple images taken of the same scene, which can eliminate high frequency noise. This method is commonly used to process video images. Let $F(x,y)$ be the image with noise, $N(x,y)$ be the noise and $G(x,y)$ be the original image, then the relationship between the three image data can be expressed as:

$$F(x,y)=N(x,y)+G(x,y) \tag{2}$$

Image averaging superimposes and averages a series of $F(x,y)$'s; the greater the number of $F(x,y)$'s involved in the operation, the closer the average will be to $G(x,y)$.

Neighborhood averaging only processes the spatial domain locally in the image. Suppose there is an original image $G(x,y)$ of $n\times n$, on which a domain averaging smoothing is done to obtain an image $F(x,y)$, where the gray value of each pixel in the figure is determined by the average of the gray values of the pixels in the given neighborhood of that pixel. The relationship between $G(x,y)$ and $F(x,y)$ can be expressed as:

$$F(x,y)=\frac{1}{m}\sum_{i\in s,j\in s}G(i,j) \tag{3}$$

where x and y are integers from 1 to $n-1$, respectively, s is a set of positions of the center of mass of the domain of the currently manipulated pixel point, and m is the total number of position coordinates within the set s.

II. B.Bayesian Networks and Deep Learning Models

II. B. 1) Bayesian network modeling

The construction of a Bayesian network (BNM) is a complex task that requires the involvement of knowledge engineers and domain experts [19]. For a Bayesian network with variable set $X=\{x_1,x_2,\cdots x_n\}$, its composition is divided into two parts:

(1) The network structure of a Bayesian network, denoted by S. Each variable in the set of variables X is conditionally dependent on the network structure S.

(2) The local probability distribution associated with each variable in the variable set X, denoted by P.

By combining the two parts of the network topology S and the set of local probability distributions P, a Bayesian network structure is constructed, denoted by BN = <S, P>, and if expressed in graphical form, the Bayesian network is a directed acyclic graph that can be used to represent the joint probability distributions of X. Each node in the graph corresponds to the individual variables in the set of variables X, and the absence of arcs connecting two nodes denotes conditional independence. Accordingly, the learning of the Bayesian network is decomposed into two stages:

First, the learning of the network topology, i.e., the learning of directed acyclic graphs.

Second, the learning of the parameters of each variable in the network, i.e., the learning of the local conditional probability distribution.

If for a given network structure BN = <S, P>, the joint probability distribution of the set of variables X is:

$$P(x)=\prod p(x_i\mid Pa_i) \tag{4}$$

Pa_i denotes the parent node of x_i, and $p(x_i\mid Pa_i)$ are the individual terms in the product equation representing the local probabilities, which are sought for the purpose of finding the local probabilities:

(1) Since Bayesian networks are composed of multiple variables and the variables ask sparse interrelationships, finding local probability distributions can achieve the purpose of reducing the capacity of the joint distribution in an exponential manner.

(2) Many local probability distribution tables can be used in Bayesian inference algorithms.

(3) It is conducive to knowledge engineering for modeling quantitative and qualitative representations of variables in Bayesian networks.

With the data set D known, let the scoring function (conditional probability) of the Bayesian network structure S be:

$$p(S^h\mid D)=p(S^h)p(D\mid S^h)/p(D) \tag{5}$$

Assume that S^h denotes the "joint probability distribution of X" and $p(S^h)$ denotes the probability that the structure of a given Bayesian network is the likelihood of S, with a value specified by the user. $p(D)$ is a normalization constant that does not depend on S^h and is not considered, so only the value of $p(D\mid S^b)$ needs to be computed.

The formula proposed by Cooper and Herskovits to calculate the value of $p(D\mid S^h)$ is:

$$p(D\mid S^k)=\prod_{i=1}^{n}\prod_{j=1}^{q_i}\frac{\Gamma(\alpha_{ij})}{\Gamma(\alpha_{ij}+N_{ij})}\cdot\prod_{k=1}^{r_i}\frac{\Gamma(\alpha_{ijk}+N_{ijk})}{\Gamma(\alpha_{ijk})} \tag{6}$$

This is a metric based on maximum a posteriori probability. Where q_i represents the number of configurations in the parent node set of the i nd variable, n represents the number of variables per record in the dataset, N_{ij} is the sum of N_{ijk} over k, and N_{ijk} represents the number of records in the dataset where the parent node set of the i th variable is configured to be the j th and the value of the variable takes the k th value.

II. B. 2) Deep Learning Related Models

A process neuron network (PNN) can be formed by a number of process neurons and other types of neurons according to a certain topology [20]. Figure 1 shows the structure of a multi-input single-output system containing a hidden layer of process neurons.

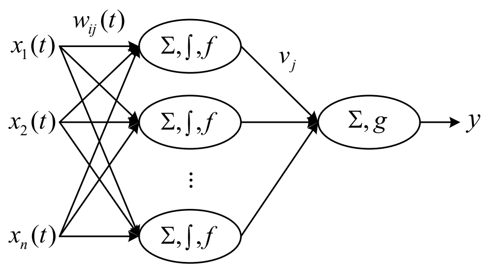


Figure 1: Process neural network

In the figure, the mapping relationship between the network inputs and outputs is:

$$y = g(\sum_{j=1}^{m} v_j f(\int_0^T (\sum_{i=1}^{n} w_{ij}(t)x_i(t))dt - \theta_j^{(1)}) - \theta) \tag{7}$$

where $w_{ij}(t)(i=1,2,\cdots,n; j=1,2,\cdots,m)$ is the connection weight function between the input layer node and the hidden layer node, $v_j(j=1,2,\cdots,m)$ is the connection weight from the hidden layer node to the output node, $[0,T]$ is the time-varying signal input process interval. f is the process neuron excitation function, $\theta_j^{(1)}$ is the excitation threshold of the hidden layer node, g is the output neuron excitation function, and θ is the output neuron threshold.

In the network, neurons of the same type have the same structure, share the same theory and learning algorithm, and perform the same aggregation operation. At the same time, the information transfer between the hidden layers of each neuron should satisfy the definition of the input and output signal types of each type of neuron in the network model.

In a process neural network where both the input and output are time-varying functions, $v_j(t)(j=1,2,\cdots,m)$ is the connection weight function from the hidden layer node to the output node, and $y(t)$ is the network output function. The mapping relationship between the network input and output is:

$$y(t) = \sum_{j=1}^{m} v_j(t) f(\int_0^t (\sum_{i=1}^{n} w_{ij}(\tau)x_i(\tau))d\tau - \theta_j(t)), t \in [0,T] \tag{8}$$

Where: $[0,T]$ is the time-varying signal input process interval, f is the process neuron excitation function, and $\theta_j(t)$ is the threshold function of the hidden layer process neuron node j.

III. Crop growth and development prediction modeling

Some crops take a long time to grow, and it usually takes 1 to 2 months from sowing to maturity, which greatly increases the cultivation time of crops. Crop growth modeling and prediction can reduce the experimental time and experimental cost, help physiologists and botanists to analyze the growth pattern of crops, and provide a reference for plant experiments and researches that are constrained by time and environment. Based on this, this paper combines a Bayesian network model with a process neural network to establish a prediction model for crop growth and development, aiming to further improve the product quality of crops.

III. A. Image preprocessing and dataset construction

III. A. 1) Crop phenotypic characterization

Lettuce phenotypic feature extraction is mainly based on preprocessed near-infrared (NIR) images with high spectral resolution (500nm~1000nm, 3nm), and digital image analysis and machine learning methods are used to obtain phenotypic parameters such as structure, color, texture, etc. of the target lettuce samples or single plants. Common features included plant height, canopy area, leaf area index (LAI) and other structural information.

The extraction methods include single-plant segmentation measurement based on semantic segmentation (SS), population growth assessment based on grid sample analysis, and quality prediction based on convolutional neural network (CNN). Specifically, SS utilizes models such as Mask R-CNN to achieve segmentation of single vegetable plants, obtaining an average IoU of 95% and an average Dice coefficient of 95%, and high-precision measurements to obtain single-plant LAI (based on the total pixel counting method) and Cab (based on the corrected derivation of the vegetation index). Based on the 8m×8m grid sample segmentation, the coefficient of variation and the range of deviation of the spatial and temporal distribution parameters of NDVI and Cab were counted to assess the homogeneity of the growth status in the region, which provided the basis for fertilizer application in the sub-region. Construct multi-source phenotypic features including Lab color values and food sensory characteristics, input the regular crop growth prediction model, and realize the classification prediction of fruit appearance quality grade.

III. A. 2) Crop image resizing

In this study, lettuce growth image dataset was enhanced using data enhancement techniques to improve the generalization ability of the model, mainly using the following methods:

(1) Random cropping. The lettuce growth images are cropped to a random size and aspect ratio, and then the images are scaled to a set size. In this study, the training set image scaling size was set to 256×256.

(2) Random flipping. The lettuce growth images were randomly flipped, and the probability of horizontal flipping was set to 0.5 in this study.

(3) Normalization. Normalization operation is performed on the dataset to accelerate model training.

The training set data of this study is enhanced, first cropped to 256×256, then randomly flipped, and finally normalized. The validation and test sets are first downsampled to adjust the image size to 512×512, later cropped to 256×256 in the middle, and finally normalized.

III. A. 3) Crop image dataset construction

For more accurate labeling of lettuce plants, the labeled maps of lettuce plants in this study were obtained by manually using Photoshop software for pixel-level labeling. The process of manual labeling using Photoshop software is as follows:

First, the original image of the lettuce plant to be labeled was opened, and then the pencil tool in Photoshop software was used to manually cover the part of the original image of the lettuce plant that needed to be labeled pixel by pixel with a set color (e.g., white), so as to obtain the primary labeled image of the original image of the lettuce plant. Then, the primary labeling map uses the threshold segmentation method to retain the part of the lettuce plant covered by the pencil tool and remove the noisy part not covered by the pencil tool to obtain the secondary labeling map of the lettuce plant. Finally, the pixel values of the pencil tool scribble covered lettuce plant part in the secondary labeling map (e.g., 255) are converted to the labeling pixel values required by the model (e.g., 1), and the pixel values of the background part in the secondary labeling map are converted to 0 to obtain the final lettuce plant labeling map.

In order to ensure a uniform number of images of various background types after cropping, this study gives a certain degree of screening and deletion of similar backgrounds in the experimental environment, and only retains a certain number of representative original background images as well as the corresponding labeled images. Thus, the number of similar images in the input model is reduced, avoiding the model only learning the segmentation of a large number of similar background images in the training process and neglecting to learn the segmentation of other types of images, thus improving the training effect of the model. After cropping and filtering the original images of lettuce plants at multiple time points, 1874 cropped original images of lettuce plants and their corresponding labeled maps were finally selected as the lettuce plant segmentation dataset in this study. These images cover lettuce plant images from different shooting angles and different time points to ensure the diversity of the lettuce plant segmentation dataset, which helps to improve the model's prediction of lettuce plant growth and development. The 1874 original images of lettuce plants and their corresponding labeled images produced were randomly divided into a training set and a validation set according to the ratio of 7:3, both of which contained 1311 and 563 original images of lettuce plants and their corresponding labeled images, respectively.

III. B. Growth and development prediction analysis modeling

III. B. 1) Growth and Development Prediction Modeling Framework

In order to realize the accurate prediction of crop growth and development, this paper combines the Bayesian network model with the process neural network to establish the BNM-PNN model, whose specific framework is shown in Fig. 2, which consists of two modules: encoder and decoder. The designed network model can specify the length N of the input image sequence used for training, or it can be defined to predict the growth image of lettuce after N days.

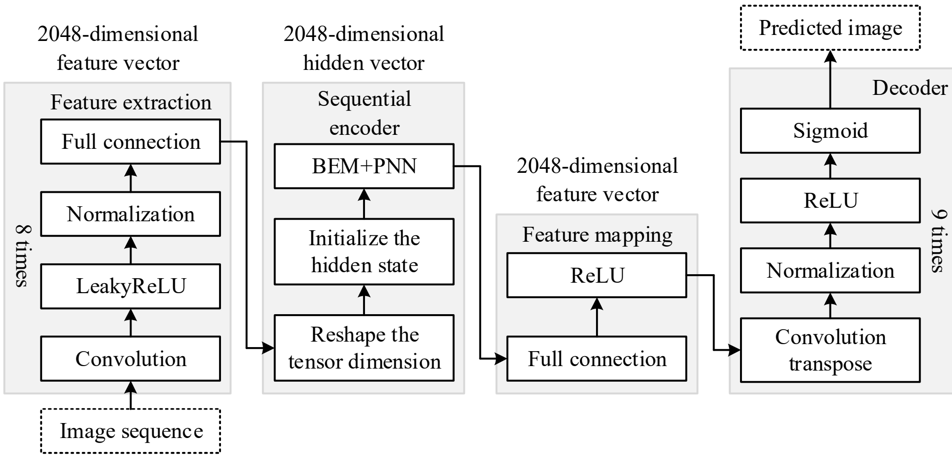


Figure 2: Growth and development prediction model

The BNM-PNN model adopts an end-to-end design, extracting spatial features through Bayesian networks and learning temporal features through process neural networks, which can model image sequences on the time axis for future image prediction. The structure incorporates Bayesian network's feature extraction of images and PNN's modeling of temporal sequences to form a crop growth and development prediction model for spatio-temporal prediction tasks. The encoder is responsible for extracting the feature representation of the input image, the decoder recovers these features into the image space, and the PNN module learns the temporal dependencies.

III. B. 2) Improving the initialization and learning algorithm

In order to solve the output locking problem of Sigmoid-type excitation function, based on the traditional neural network input value domain center initialization method, this paper proposes an initialization method and an improved learning algorithm for process neuron networks [21]. Specifically as follows:

(1) Initialization method for PNN networks. The connection weights v_{jp} and w_{ijt} of the hidden and output layers are initialized using the traditional neural network initialization method, while the excitation thresholds θ_j and φ_p of the hidden and output layers are initialized to μ_θ and μ_φ, respectively. where:

$$\theta_j = \mu_\theta = \frac{1}{K}\sum_{k=1}^{K}(\int_0^T(\sum_{i=1}^{n} w_{ij}(t)x_{ki}(t))dt) \tag{9}$$

$$\begin{aligned}\phi_p = \mu_\phi &= \frac{1}{K}\sum_{k=1}^{K}(\sum_{j=1}^{m} v_{jp} f(u_{kj}) - d_{kp}) \\ &= \frac{1}{K}\sum_{k=1}^{K}(\sum_{j=1}^{m} v_{jp} f(\int_0^T(\sum_{i=1}^{n} w_{ij}(t)x_{ki}(t))dt - \theta_j) - d_{kp})\end{aligned} \tag{10}$$

Using the above initialization method can inhibit to a certain extent the problem of excessive values of the independent variables of the excitation function caused by the summation and integration operations, reduce the risk of locking the output of the excitation function, and improve the convergence speed of the network.

(2) Improved learning algorithm for BEM-PNN network. The idea of the improved initialization method is introduced into the learning algorithm, retaining the correction method for the connection weights of the hidden layer and the output layer in the general learning algorithm, such as the gradient descent method. Instead, Eqs. (9) and (10) are used to correct the excitation thresholds θ_j and φ_p of the hidden and output layers. The specific algorithm is described as follows:

Step1 Given the error accuracy ε, accumulate the number of learning iterations $s = 0$ and learn the maximum number of iterations M.

Step2 Initialize connection weights v_{jp} and w_{ijt} with traditional neural network initialization method.

Step3 Initialize excitation thresholds θ_j and φ_p.

Step4 Calculate network training error E, if $E < \varepsilon$ or $s > M$, go to Step8.

Step5 Correct connection weights v_{jp} and w_{ijt}.

Step6 Correct the incentive thresholds θ_j and φ_p.

Step7 $s = s + 1$, turn to Step4.

Step8 Output learning results, end.

IV. Validation of crop growth and development prediction models

Crop growth and development is a complex process of varieties and environmental factors, so its prediction modeling is also a nonlinear and complex problem, and crop growth prediction is a key part of the precise management of agriculture. If a prediction model can be established to predict the corresponding crop growth according to the input environmental parameters before actual production, and then estimate the final yield, it will have positive significance in enhancing crop production potential and guiding farming.

IV. A. Growth prediction model training and testing

IV. A. 1) Growth prediction model training

The experimental data were collected from the greenhouse of a company in S city, J province, set up with natural environmental factors that are very favorable for the growth of the crop lettuce. Among the collected data, 200 sets of samples were extracted, and the first 60 sets of sample data were used for network training using gradient descent type network training method, and the training samples were used to calculate the gradient value of the network model, and to update the weights and thresholds of the network model. The training is stopped if overfitting occurs during training. The efficiency and generalization performance of the BNM-PNN model network training is improved by normalizing the sample data to the interval [-1,1] before training.

Using the “trial and error” method, the convergence rate and error of the BNM-PNN model can be obtained using the output values. The accuracy of the learning error of the neural network is set to be 10-5, the learning rate is 0.002, and the maximum number of iterations is set to be 500. The model was trained by combining the first 60 sets of samples, and Figure 3 shows the lettuce growth prediction learning error curve of the BNM-PNN model. Based on the training results of the learning error accuracy of the prediction model, it can be seen that the BNM-PNN model designed in this paper reaches convergence after 60 iterations, and its learning error accuracy is 10-5.

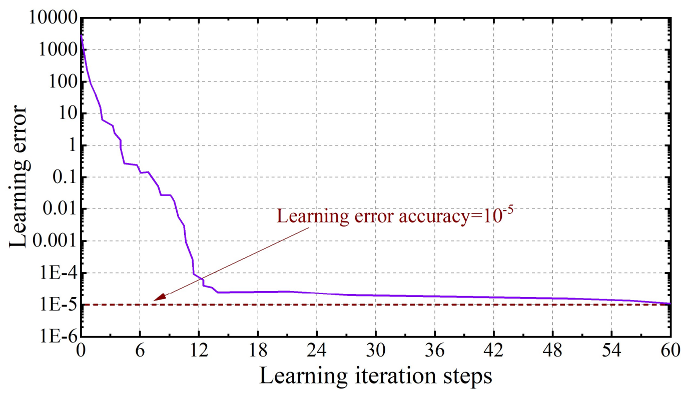


Figure 3: Growth prediction learning error curve

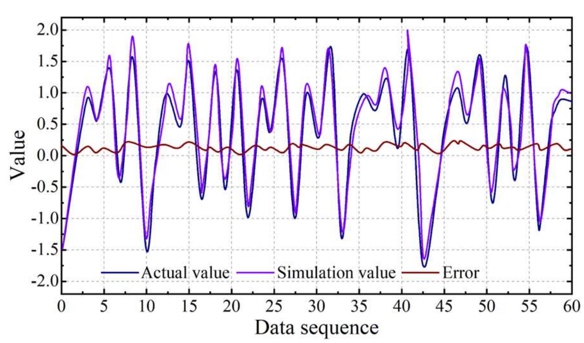


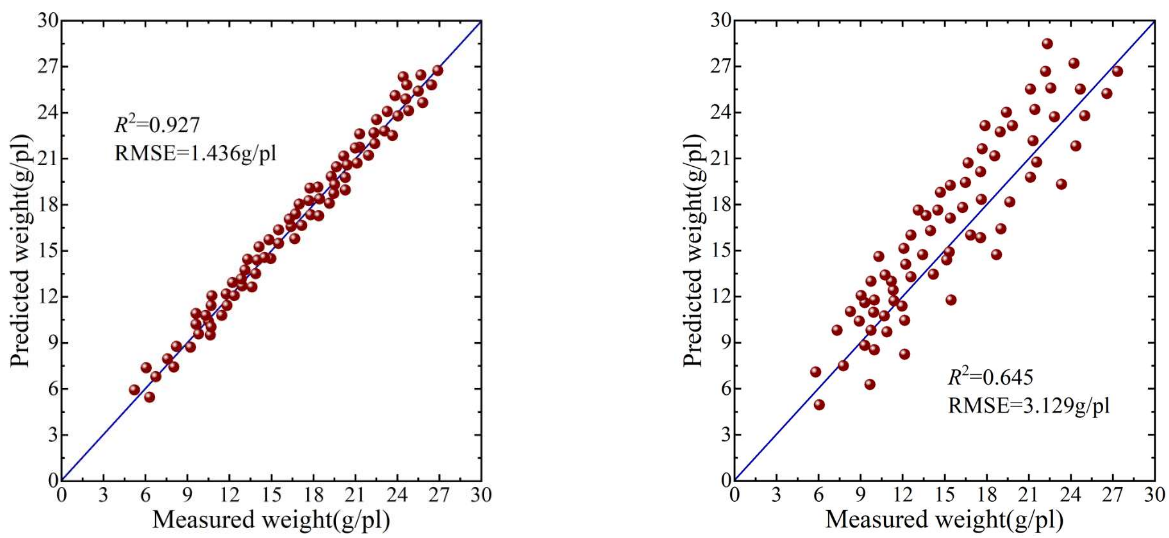
Figure 4: Simulation of crop growth prediction

The collected data samples were applied to be measured in the BNM-PNN model, and their measurement results are shown in Figure 4. As can be seen from the figure, the gap between the lettuce growth prediction value obtained by the BNM-PNN model and its actual value is relatively small, and its average relative error is calculated to be 3.24%. Therefore, the lettuce growth and development prediction model combining Bayesian network and process neural network in this paper has strong crop growth and development prediction effect, which can provide guidance for optimal cultivation and fertilization of crops.

IV. A. 2) Growth prediction model testing

In the BNM-PNN model established in this paper, after the model training was completed, the data of various indicators in the growth process of lettuce were selected to test the growth prediction effect of the BNM-PNN model. The indicators during lettuce growth including the predicted value of leaf area index, PAR above the canopy, planting density and other information were inputted into the BNM-PNN model and obtained to calculate the weight situation of lettuce per plant, which was further compared with the actual observation. The coefficient of determination (R2) and RMSE were used as evaluation indexes, and then the traditional PNN model was used as a comparison to obtain the different model test results of lettuce single plant weight as shown in Fig. 5. Among them, Fig. 5(a)~(b) shows the single plant weight test results of BNM-PNN and PNN models, respectively.

According to the inspection results of different models on the weight of individual lettuce plants, the BNM-PNN model, which combines Bayesian networks and Process Neural Networks, can predict the weight of individual lettuce plants in greenhouses relatively well, with a coefficient of determination and regression estimation error of 0.927 and 1.436g/plant, respectively. In contrast, the traditional PNN model has a coefficient of determination and RMSE of 0.645 and 3.129g/plant, respectively, when predicting the growth of individual lettuce plants. The comparison shows that the BNM-PNN model designed in this paper has a better predictive effect on crop growth, which can lay a solid foundation for optimizing lettuce yield and quality.



(a) BNM-PNN (b) PNN

Figure 5: Model test of individual plant weight

IV. B. Performance validation of growth prediction models

IV. B. 1) Comparative analysis of different models

For the performance of the BNM-PNN model designed in this paper in performing crop growth and development prediction, PNN, GoogleNet, ResNet-50, AlexNet and Inception are selected for comparative validation of the models. Accuracy, precision, recall and F1 value were used as evaluation metrics, and the previously constructed dataset was selected for model comparison. Table 1 shows the performance of different models on the self-constructed dataset.

As can be seen from the data in the table, the BNM-PNN model demonstrated superior performance in comparison with the traditional PNN model. The BNM-PNN model performed optimally in terms of accuracy, precision, recall and F1 value. In addition, the PNN model also outperformed the other four models in the accuracy of lettuce growth and development prediction, and the Inception model had the relatively lowest prediction performance. Among them, the ResNet50 model achieved an accuracy of 81.64% for lettuce growth and development prediction, which was 14.51% and 6.62% lower than that of the BNM-PNN and PNN models, respectively. Although the PNN model used the same process neuron network structure, the BNM-PNN model fused Bayesian network to extract lettuce growth-related parameter features and demonstrated superior classification ability on the dataset constructed in this paper. This is attributed to the fact that both methods employ process neural network techniques to enhance the detail information of the original image. However, the method in this study covers all images in the first stage of lettuce growth, in contrast to the PNN which only addresses the classification challenge under a single point in time. In addition, the images used in this study contain background information and are highly affected by external light and clarity, and these complications are beyond the processing capability of the PNN model. Therefore, this study taps into the deeper properties of feature learning through a Bayesian network model to achieve effective processing of lettuce growth data at different network depths. In addition, this model achieves accurate prediction of lettuce growth and development by fusing the features extracted from the process neural network, which proves its excellent performance and efficiency in processing complex crop image data.

Table 1: Performance of different models (%)

Model	Accuracy	Precision	Recall	F1 value
BNM-PNN	96.15	96.38	96.72	96.41
PNN	88.26	87.56	85.63	87.57
GoogleNet	79.82	79.63	79.45	77.63
ResNet-50	81.64	82.08	82.37	82.15
AlexNet	73.37	74.41	73.91	73.28
Inception	66.51	66.19	65.28	65.96

IV. B. 2) Analysis of model ablation experiments

The ablation experiment was used to study the effect of different treatments on the results of the BNM-PNN model in performing lettuce growth and development prediction, and the modules in the model were gradually removed to observe the changes in the BNM-PNN model. To make a better understanding of how the model works, as well as to demonstrate the efficiency of each module. DICE score and sensitivity were chosen as evaluation indexes, and the results of the ablation experiments of the BNM-PNN model are shown in Table 2.

The baseline model (Baseline) in this paper is the traditional basic network model of process neurons. Firstly, the PNN network with time-varying functions for both inputs and outputs is introduced separately, secondly, the Bayesian network module is introduced separately, and finally, the complete model of PNN and BNM is introduced. The changes of DICE score and sensitivity in the table show that the scores of DICE score and sensitivity index are getting higher and higher, which indicates that the introduction of different improvement methods enhances the robustness of the BNM-PNN model, and improves the prediction performance and efficiency of the BNM-PNN model for lettuce growth and development. The incorporation of different modules can extract the features in crop images layer by layer to effectively represent the key information in the images and use them to accurately predict crop growth and development. The baseline model has a high probability of false negatives and low accuracy. When PNN is introduced alone, the model tends to lose some of the feature images, and when BNM is introduced alone, the prediction accuracy of the model for target edges needs to be improved. The introduction of the complete innovative method enables the growth and development prediction model to have good feature extraction capability of crop images, to adapt to different types of crop images and predict them accurately, and to capture the spatial relationship between different regions in the image effectively.

Table 2: Model ablation experiment results

Model	PNN	BNM	DICE score/%	Sensitivity/%
Baseline	×	×	82.46±5.73	84.95±3.47
Baseline+PNN	√	×	87.58±4.69	86.52±3.38
Baseline+ BNM	×	√	89.71±4.37	88.39±4.26
BNM-PNN	√	√	92.15±4.05	91.78±3.79

V. Conclusion

In this study, a BNM-PNN crop growth and development prediction model integrating Bayesian network and process neural network was constructed to realize the accurate prediction of the growth status of Italian shoot-resistant lettuce. The results show that the designed BNM-PNN model reaches convergence after 60 iterations, with a learning error accuracy of 10-5, and the average relative error between the predicted and actual values is only 3.24%. Compared with the traditional PNN model, the BNM-PNN model performed excellently in lettuce monocot weight prediction, with an improved coefficient of determination of 0.282 and a reduced regression estimation error of 1.693 g/pl. In the comparison of the performance of the different models, the BNM-PNN model achieved an accuracy of 96.15% with an F1 value of 96.41%, which was higher than that of the closest-performing PNN model by respectively 7.89% and 8.84%, and 29.64% and 30.45% higher than the worst performing Inception model. The model ablation experiments further validated the fusion effect of Bayesian networks and process neural networks, with the complete BNM-PNN model achieving a DICE score of 92.15 ± 4.05% and a sensitivity of 91.78 ± 3.79%, which were 9.69% and 6.83% higher than the baseline model, respectively. The study proved that the crop growth prediction model integrating Bayesian network and process neural network can effectively capture the spatial and temporal characteristics of the crop growth process, which provides a powerful tool for precision management in agriculture, and is of great practical significance for improving crop yield and quality and guiding agricultural production.

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