Intelligent Control System of Water and Fertilizer in Greenhouse Based on Tomato Phenotype Discrimination and Growth Environment Prediction

Qin Qiu¹, Shanshan Cao², Fantao Kong³, Xiangyang Zhou⁴, Shuqing Han⁵,
Wei Sun*

¹Agricultural Information Institute Chinese Academy of Agricultural Sciences Beijing, China
²College of Computer and Information Engineering Xinjiang Agricultural University Urumqi, China

*Corresponding author e-mail: maplesunw@163.com, aqiuqin_qq@163.com,
²caoshanshan@caas.cn, ³kongfantao@caas.cn, ⁴zhouxiangyang01@caas.cn,
⁵hanshuqing@caas.cn.

Abstract. In this paper, the real-time greenhouse tomato phenotypic parameters data were obtained, and the current tomato growth and growth status were identified based on the in-depth learning method. Combined with the tomato phenotypic parameters data under the optimal water and fertilizer conditions, the comparative analysis was carried out. According to the difference of phenotypic parameter data of tomato, the deficiency status of water and fertilizer was identified, and the target scheme of water and fertilizer was determined. Based on LSTM neural network model, the predicted value of environmental parameters was obtained, and compared with the standard value of environmental parameters for the purpose of stopping irrigation and fertilization.

1. Introduction
With the development of agricultural modernization, the intelligent control system of water and fertilizer plays an increasingly important role in the development of facility agriculture, water-saving agriculture and ecological agriculture. There are many researches on irrigation and fertilization of greenhouse tomatoes, but most of them focus on the water-fertilizer coupling research aiming at tomato yield and quality [1]-[5]. There are few reports on the intelligent regulation of water and fertilizer requirements in different growing seasons based on the phenotypic status and growth environment of tomatoes. Therefore, the research based on crop growth model combined with water and fertilizer regulation has become the focus of people's attention. At present, most of them are based on crop experience model, that is, to determine the formula of water and fertilizer according to artificial experience. Because of strong subjective initiative and great individual differences, it is easy to create the status quo of "high input and low output", which can not really meet the needs of crop water and fertilizer. With the development of the Internet of Things, there are many studies on the regulation of water and fertilizer according to the changes of greenhouse environment, but most
models fail to monitor crop growth information. The disadvantage is that water and fertilizer deficiency cannot be judged until the symptoms of crops are obvious, but at this time the damage to crops has caused [6], which leads to the problem of low water use efficiency. The existing water and fertilizer control technology has low timeliness, scientificity and intelligence, low water and fertilizer utilization efficiency, and cannot maximize economic benefits. Therefore, this paper designs a dynamic control system for the amount of basic irrigation and fertilizer application in real time according to tomato phenotype and greenhouse growth environment, so as to effectively save water and fertilizer resources and facilitate the rapid and efficient growth and development of tomatoes.

2. Architecture

The greenhouse water and fertilizer intelligent control system based on tomato phenotypic discrimination and growth environment prediction is composed of tomato phenotypic discrimination module, greenhouse growth environment prediction module and water and fertilizer intelligent control module. The architecture is shown in Fig. 1.

The phenotypic characteristics of tomato were different in different growth stages, and the phenotypic characteristics could reflect the growth status and lack of water and fertilizer of tomato. Therefore, after determining the growth cycle of tomato, the phenotypic data of tomato under the condition of optimal water and fertilizer content in greenhouse were compared with the phenotypic data collected by real-time monitoring to determine whether greenhouse tomato was in the state of water and fertilizer deficiency at present. When the water and fertilizer are missing, the lack of water and fertilizer is further analyzed, according to the analysis results, the corresponding solenoid valve is opened, and the water and fertilizer irrigation is realized through the control instruction of water and fertilizer irrigation. During the operation of watering and fertilizing, the environmental parameters of greenhouse will be affected. Through acquiring historical growth environment parameters and real-time acquisition of current growth environment parameters, environmental parameters can be predicted. By comparing and analyzing the obtained environmental predicted value with the reference value of environmental parameters under the condition of optimal water and fertilizer content. When the predicted value is consistent with the reference value, the solenoid valve is closed, the control command is stopped, and the corresponding watering and fertilizing operation is terminated.

Figure 1. Architecture diagram
3. Key Technologies

3.1. Tomato Phenotype Recognition Technology
Tomato phenotype recognition technology is based on ResNet50 convolution neural network, and its flow chart is shown in Fig. 2.

Data preprocessing. The training data set and test data set of tomato phenotypic parameter data were preprocessed and enhanced to expand the data set and enhance the data characteristics.

Model training. Initialization of weights, feature extraction of training data set by convolution layer, generation of feature map, forward transfer through pooling layer and full connection layer to get output value. Then the error between the output value and the target value is calculated and transmitted in reverse. According to the error, the weight is updated. Finally, the trained classification model is obtained.

Image recognition. The trained classification model was used to predict the phenotypic parameters of unknown tomatoes, and the output value was obtained to identify the growth and growth status of tomatoes.

![Flow chart based on ResNet50 convolution neural network](image)

Figure 2. Flow chart based on ResNet50 convolution neural network

3.2. Growth Environment Prediction Technology

3.2.1. Technical Process of Growth Environment Prediction. The growth environment prediction technology is based on LSTM neural network. The steps are as follows:

- Historical data acquisition and preprocessing.
- After processing the data, it is divided into training data and test data according to the proportion.
- Construction of LSTM Neural Network Model.
- Training of LSTM Neural Network Model Using Training Data Set.
- Prediction of greenhouse environment based on completed training LSTM neural network model.

3.2.2. LSTM Neural Network Model Framework. The LSTM neural network model includes: an input layer, an LSTM cell layer, and an output layer. The framework of greenhouse environmental variables prediction model based on LSTM neural network model is shown in Fig.3.
Figure 3. Framework of greenhouse environmental variables prediction model based on LSTM neural network model

The forward propagation function of the LSTM recursive cyclic neural network is as follows[7]:

\[ i^{<t>} = \sigma(W_i x^{<t>} + W_{hi} h^{<t-1>} + W_{ci} c^{<t-1>} + b_i) \]  
\[ f^{<t>} = \sigma(W_f x^{<t>} + W_{hf} h^{<t-1>} + W_{cf} c^{<t-1>} + b_f) \]  
\[ c^{<t>} = f^{<t>} \odot c^{<t-1>} + i^{<t>} \odot \tanh(W_c x^{<t>} + W_{hc} h^{<t-1>} + b_c) \]  
\[ o^{<t>} = \sigma(W_o x^{<t>} + W_{ho} h^{<t-1>} + W_{co} c^{<t>} + b_o) \]  
\[ h^{<t>} = o^{<t>} \odot \tanh(c^{<t>}) \]

Among them, \( i^{<t>} \) denotes the input gate, \( f^{<t>} \) denotes the forgetting gate, \( c^{<t>} \) denotes the cell state after the input gate and the forgetting gate at \( t \) time, \( o^{<t>} \) denotes the cell state of the output gate at \( t \) time, and \( h^{<t>} \) denotes all the output states of the LSTM unit at \( t \) time. \( W \) denotes the weight matrix; \( b \) denotes the bias term; \( \sigma \) denotes the activation function, which maps variables to intervals \([0, 1]\). The internal cell structure of LSTM cell layer is shown in Fig. 4.

Figure 4. Internal cell structure of LSTM cell layer

### 3.2.3. LSTM Neural Network Model Training

The training data set is used to train LSTM neural network model, which includes the following steps:
Calculate the output value of LSTM cells according to the forward calculation formula as in claim 5.

Calculate the error items of each LSTM cell in two directions of time and network level, including two back propagation directions according to time and network level, and the root mean square error RMSE is used as the error calculation formula to update the model parameters.

\[
RMSE = \sqrt{\frac{1}{L(m-L)} \sum_{i=m-L}^{L} (P_i - Y_i)^2}
\]  

Among them: L (m-L) is the total number of training samples; Pi is the predicted value; Yi is the true value.

According to the corresponding error terms, the gradient of each weight is calculated. The weight is updated by gradient-based optimization algorithm, and the weight and bias in LSTM model are updated by Adam gradient descent algorithm to minimize network loss.

4. System Implementation

The greenhouse water and fertilizer intelligent control system device based on Tomato phenotype discrimination and growth environment prediction includes tomato phenotype parameter acquisition module, tomato phenotype parameter acquisition module and water and fertilizer intelligent control module. The system structure diagram is shown in Fig. 5.

Figure 5. Structure chart of greenhouse water and fertilizer intelligent control device based on Tomato phenotype discrimination and growth environment prediction

5. Conclusion

In this paper, by detecting the direct reaction of phenotypic physiological characteristics of greenhouse tomato, combined with the changes of growth environment data, we can understand the demand of tomato for water and fertilizer in real time, assist in the optimization and regulation of water and fertilizer, to a certain extent, perfect the time lag of water and fertilizer model, effectively save water and fertilizer resources, improve the utilization rate of water and fertilizer, which can solve the problems that vegetable farmers are difficult to master and save manpower and material resources. It is of great significance to guide farmers to irrigate and fertilize scientifically.

This work was financially supported by CAAS-ASTIP 2016-AII Intelligent Agriculture Key Technologies and System Integration,Y2018ZK46 West Agriculture and Animal Husbandry Internet of Things Technology.

References

[1] H. B. Wang, H. X. Cao, et al., “Responses of Plant Nutrient and Photosynthesis in Greenhouse Tomato to Water-Fertilizer Coupling and Their Relationship with Yield,” *Scientia Agricultura Sinica*, vol. 52, no. 10, 2019, pp.1761-1771.

[2] X. Hong, T. T. Hu, et al., “Construction of comprehensive evaluation model for tomato nutrition quality based on method set and its response to water and fertilizer supply,” *Agricultural Research in the Arid Areas*, vol. 37, no. 03, 2019, pp. 129-138+148.

[3] D. Liu, J. Y. Wang, et al., “Greenhouse furrow irrigation under the condition of different water and nitrogen dosage on tomato yield, quality and the influence of water and nitrogen utilization,” *Soil and Fertilizer Sciences*, 2018, pp. 112-117.

[4] X. Gao, S. X. Zhang, et al., “Stable water and fertilizer supply by negative pressure irrigation improve tomato production and soil bacterial communities,” *SN Applied Sciences*, vol.1, no.
[5] H. M. Kong, R. H. Lu, et al., “Application Effect of Integrated Water and Fertilizer Technology for Tomato,” *Asian Agricultural Research, United States of America*, vol. 9, no. 11, 2017, pp. 62-65.

[6] T. Y. Lv. Research on Water and Fertilization Supply Decision for Tomato Vegetative Growth Stage Based on Stem Diameter and Plant Height. Jiangsu University, 2017.

[7] L. Chen, X. H. Pei, et al., “Prediction of Greenhouse Environment Variable Based on LSTM,” *Journal of Shenyang Ligong University*, vol. 37, no. 05, 2018, pp. 13-19.