Research on Plant Growth State Classification Based on CNN-LSTM

Liguo Tian¹,², Yu Sun¹, Meng Li¹, Yuesong Wang¹, Jinqi Liu¹ and Chuang Liu¹

¹Tianjin Key Laboratory of Information Sensing & Intelligent Control, School of Automation and Electrical Engineering, Tianjin University of Technology and Education, Tianjin 300222
²E-mail: tlg1234@163.com

Abstract. The plant electrical signal is a physiological signal that reflects the growth state of plants affected by the external environment. Online monitoring of plant growth states is realized by studying the electrical signal changes of plants in different growth states. In this paper, a Convolutional Neural Network (CNN) based and Convolutional Neural Network and Long Short-Term Memory Neural Network (CNN-LSTM) based classification model of plant growth state is built to realize feature extraction and training and classification studies of Aloe Vera electrical signals in different growth states. The short-time Fourier transform (STFT) is used to convert the de-noised aloe electrical signal into a signal energy map, which is used as the input of the classification model, and the different growth states of the aloe are used as the output of the classifier. It is concluded that the CNN-LSTM neural network model has high accuracy in the classification of aloe electrical signals in different growth states when training, and the plant electrical signals can be used as an effective evaluation index for plant growth state detection.

1. Introduction

Plant electrical signal is a physiological signal that have the function of transmitting information in plants [1]. They can reflect the physiological state of plants in real time, including metabolism material transportation and other physiological changes. The electrical signals of plants in different growth states show significantly different characteristics [2]. Because there is a close relationship between plant electrical signal and its growth state, people can monitor the growth state of plants by monitoring the characteristic law of plant electrical signal.

Under the condition that the external environmental conditions remain the same, two groups of aloes with different health status are selected as the experimental objects, the electrical signals are collected regularly. The collected electrical signals are subjected to wavelet packet de-noising, and the short-time Fourier transform is used to convert the one-dimensional signal into a two-dimensional signal energy map, used as the input of the classification model. Based on the study of environmental changes in plant electrical signals. The CNN and CNN-LSTM neural network were used to explore the characteristic rules between electrical signals and plant growth state, and the plant growth state was classified and recognized, which laid a foundation for the online diagnosis of plant growth state [3].

2. Convolutional neural network

2.1. Convolutional layer
In the Convolutional Neural Network, the Convolutional layer uses convolution operations to extract the features of each part of the two-dimensional or three-dimensional image data, and then they can be integrated to obtain all the feature information [4]. In the process of convolution operation, when the convolution kernel calculated by the model convolution is different, the corresponding output feature values are different. Convolution kernels of different sizes are used to extract different feature information of the image [5]. Compared with the fully connected neural network, the convolutional layer has two characteristics: local connection and weight sharing. Both local connection and weight sharing can speed up the learning rate of the network. The local connection mode is shown in figure 1.

![Local connection diagram.](image)

**Figure 1.** Local connection diagram.

2.2. Activation function

In a multi-layer neural network, there is an activation function between the output of the upper node and the input of the lower node [6]. The activation function is also called the nonlinear mapping layer, that is, the activation function can transform the nonlinear problem into a state that the CNN can handle. Nair and Hinton introduced the ReLU function into the neural network. The mathematical form is as follows:

\[
rectifier(x) = \begin{cases} 
  x & x > 0 \\
  0 & x \leq 0 
\end{cases}
\]  

(1)

It can be seen from the mathematical model that the ReLU function solves the problem of the disappearance of the gradient, and the model converges quickly, which improves the efficiency of the model operation. But with the gradual deepening of training, when the occurrence of \(x<0\), the neural gradient remains at 0, resulting in the weights cannot be updated normally. But if a suitable learning rate is set for the model in advance, this situation can also be well alleviated.

3. Long and short-term memory neural network

The growth state of the plant is not only related to the temperature, humidity and light intensity of the environment in which the plant is located, but also has a certain correlation in the time series. Recurrent Neural Network (RNN) is a kind of neural network that contains time cycle structure, which can solve problems with time series [7]. Therefore, the cycle neural network is used to classify plant electrical signals. LSTM is mainly used to solve the long-term dependence problem in RNN. The LSTM neural network is mainly controlled based on the unit turntable. A unit is divided into forget gate, input and output gate [8]. The forgetting gate determines the information passage problem of the electrical signal of the plant body, and the input gate determines the input electrical signal at the time of frying [9]. The output gate completes the selective memory and update of the information, and outputs the information. The calculation diagram of forgetting gate, input and output gate in LSTM neural network is shown in figure 2.
4. Electrical signal data processing

4.1. Data collection
In this study, the electrical signals of aloe were collected by BL-420 biological function experimental device. TM_WAVE biological signal analysis software displays waveforms and extracts plant electrical signal data. Before collecting plant electrical signals, aloe was removed from the signal acquisition test box to ensure that the interference signal inside the experimental device was within the normal range [10]. Place the two groups of aloe A and B with different growth states (one group is in good growth state and the other is in poor growth state) in a plant growth incubator. The temperature in the box is maintained at the optimal temperature of 25°C and the humidity is set to 45%. The light intensity is set to 4500 Lux.

Two groups of positive and negative platinum electrodes A and B are inserted into the leaves of aloe vera respectively. The distance between the positive and negative electrodes is 2 cm, and the electrode C is grounded as the reference electrode. In order to avoid measurement errors and to ensure the accuracy of the collected signals, the plants are allowed to adapt for half an hour after the electrode is pierced and the data is recorded synchronously. The collected original aloe electrical signal is shown in figure 3. Use wavelet packet analysis to de-noise the collected aloe electrical signal. The de-noised plant electrical signal is shown in figure 4. Aloe electrical signal energy maps of different periods during a month are used as the original data set. 60% of the sum of the electrical signals in the two different growth states of A and B are used as the training set, 20% as the validation set, and 20% as the test set.

4.2. Data preprocessing
Since the CNN is more suitable for the recognition of two-dimensional pictures, this paper proposes to use short-time Fourier transform to convert the aloe electrical signal into the energy map of the signal, and use the energy map as the input of the CNN.

The essence of short-time Fourier transform is to multiply an electrical signal with a window function to obtain a series of Fourier change results [10]. Arranging these results according to a certain rule, a two-dimensional electrical signal graphic representation can be obtained, such as shown in figure 5. The STFT form is shown in the following formula (2).

$$STFTz(t, f) = \int_{-\infty}^{\infty} [z(u)g^*(u-t)]e^{-j2\pi fu}du$$

Among $z(t)$ is the source signal of aloe vera, $g(t)$ is the window function.

In order to facilitate the calculation, the aloe electrical signal can be discretized. The mathematical form is shown in the following formula (3).

$$STFTz(m,n) = \sum_{k=-\infty}^{\infty} z(k)g^*(kT-mT)e^{-j2\pi fu(kT)}$$

5. Model establishment

5.1. Classification and evaluation criteria

This paper intends to use confusion matrix to evaluate the research of plant growth status diagnosis method. The confusion matrix can deeply describe the accuracy of the classification model of the plant growth state. In this paper, Aloe A with good growth status is defined as positive, and Aloe with poor growth status is defined as B. For this model, aloe with better growth status is predicted as A becoming TP, and B with poor growth status is predicted as A becoming FN. Predicting a poor growth state as B becomes FP, and predicting a good growth state as B is called TN. The total number of all states is N. Use the classification Accuracy, True Positive Rate and False Positive Rate to evaluate the quality of the classification model.

Accuracy can express the prediction accuracy of the classification network model. The specific formula is as follows:

$$Accuracy = \frac{(TP + TN)}{N}$$

The true positive rate (TPR) indicates that the results of the plant growth state predicted by the network model are consistent with reality. This indicator is also called sensitivity or recall, which can reflect the sensitivity of the network model in this article. The specific formula is as follows:
The false positive rate (FPR) indicates the proportion of incorrect classification of plant electrical signals by the model. This indicator is also called fallout. The specific formula is as follows:
\[
FPR = \frac{FP}{FP + TN}
\]  
(6)

The total number of samples is \( N \), and the formula is as follows:
\[
N = TP + FP + FN + TN
\]
(7)

5.2. CNN-based plant state diagnosis model

The CNN model based on the electrical signals of aloe vera used in this paper is an autonomously built neural network model mainly including three convolution layers and two fully connection layers [5]. The model structure is shown in figure 6. In the CNN model, each module includes convolution, batch normalization, maximum pooling layer and RELU layer. Input the feature map into the network model, and improve the model training electrical signal feature map through Batch Normalization (BN). Use the ReLU function to perform nonlinear mapping on the output result of the convolutional layer. After the data set passes Conv3, the result is output, and the result is one-dimensional after Flatten. Finally, the fully connected layer is used to output the classification result: FC1 (16, 256), FC2 (16, 2).

\[
TPR = \frac{TP}{TP + FN}
\]
(5)

Figure 6. CNN model structure diagram.

The loss curve of the CNN classification model training process is shown in figure 7. There were obvious fluctuations from model training to the 7th epoch, but the fluctuations were within the normal range. At the 20th epoch, the verification curve showed an upward trend, and then returned to stability until the 30th epoch, when the model training ended. It is obtained that the accuracy of the network model to classify the electrical signals of aloe in different states is about 94%, and the misjudgment rate is close to 5%.
5.3. Plant state diagnosis model based on CNN-LSTM

CNN and LSTM are currently two widely used models in deep learning. CNN has great advantages in image processing, and LSTM neural network, as a special RNN, can effectively learn the long-term dependent information contained in the signal. Based on the hybrid deep neural network classification model of CNN and LSTM, the CNN is used to extract the electrical signal features, and then the extracted electrical signal feature data is connected to the LSTM, and the electrical signal characteristics after the multi-layer convolutional layer are analyzed sort. The CNN-LSTM model system process is shown in figure 8. Compared with only using the CNN network model, the LSTM model is used in the CNN-LSTM network hybrid model, which can better analyze the time series of the aloe electrical signal data and solve the problem of gradient disappearance.

After passing through the third convolutional layer, the hybrid model can map the extracted distributed data features into the sample space through the fully connected layer, pass the data after Flattern through the LSTM layer, and analyze the features extracted by the model through the LSTM layer The electrical signal data is dependent on the time dimension. Figure 9 shows the loss curve of the training process based on the CNN-LSTM hybrid neural network for plant growth state classification research. The CNN-LSTM model is used to train the electrical signals of aloe in different growth states, and the network model is obtained to classify the electrical signals of aloe in different states. The accuracy rate can reach 97% and the misjudgment rate is as low as 4%.

![Figure 7. CNN model training loss curve.](image)

![Figure 8. CNN-LSTM system process.](image)
5.4. Analysis and comparison of different diagnostic models
In this paper, the CNN and CNN-LSTM deep hybrid neural network are used to train and classify the electrical signals of aloe in different growth states. The training loss comparison of CNN and CNN-LSTM models is shown in figure 10. It can be seen from the figure that the training loss of the two models from the 1st epoch to the 9th epoch are both large and abnormal. However, the CNN-LSTM model shows better performance, and it has been a stable trend since the 3rd epoch.

By testing the CNN-LSTM and CNN models, the classification results of aloe electrical signals in different growth states are shown in table 1. The test accuracy of the improved CNN LSTM hybrid network model is as high as 0.9722, and the false positive rate is as low as 0.0382 and the true positive rate (TPR) is 0.9549. Both in accuracy and sensitivity are higher than CNN. On the whole, the training loss of the CNN-LSTM model is much better than that of the CNN model.

|        | ACC    | TPR    | FPR    |
|--------|--------|--------|--------|
| CNN    | 0.9446 | 0.9327 | 0.0476 |
| CNN-LSTM | 0.9722 | 0.9549 | 0.0382 |

6. Conclusion
In conclusion, Liliaceae plant Aloe as the research object with the modern detection technology to extract the electrical signal of Aloe by using wavelet packet analysis to remove the noise signal in the
electrical signal and the short time Fourier change to convert the de-noised electrical signal into an energy map. The energy map is used as the input value of the later model; and the electrical signals of different growing states of aloe are trained and classified by the CNN neutral and the CNN LSTM hybrid neutral network model. It is found that the improved construction of CNN-LSTM hybrid network model can adaptively discover the changes of electrical signals in different growth states, and the feature extraction of electrical signals of aloe is more obvious through comparative research, and compared with CNN neutral network, CNN-LSTM a hybrid network model classification test which has a higher accuracy rate and has a good effect in classifying the growth status of aloe. Therefore, the built-up CNN-LSTM neural network model can be used to realize the online diagnosis of plant growth status when the plant electrical signal is used as the input information.

7. References

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Acknowledgments
This work is supported by the National Natural Science Foundation of China (61971312). The authors wish to express their gratitude.