Plant electrical signal-based method for identifying copper stress in lettuce

Xiaohui Zhang[1*], Zhaolin Zhou[1], Hongbiao Ma[2], Qiao Wang[1], Jian Yang[1], Zeyu Zhai[1], Xintian He[1]

(1. *College of Electrical Engineering, Henan University of Technology, Zhengzhou 450001, China*;
2. *School of Information Engineering, Henan Institute of Science and Technology, Xinxiang 453003, Henan, China*)

Abstract: The healthy growth of crops is very important for itself, especially the heavy metal pollution in the growth environment is especially worth studying. The identification of heavy metal pollution in crops usually requires long-term morphological observation or physiological and biochemical experiments, which is time-consuming and labor-intensive. Addressing the limitations of traditional detection methods, which rely on a single signal feature and exhibit restricted classification capabilities, this study examined lettuce leaves subjected to copper ion stress alongside healthy lettuce leaves. The study systematically analyzed the evolutionary patterns of plant electrical signal characteristics across different stages of copper stress. Building upon this analysis, a novel lettuce copper stress identification method was proposed, integrating multi-wavelet entropy features with BP_Adaboost ensemble learning. Experiments revealed that lettuce exhibits a dynamic evolution of its electrophysiological response to copper stress, progressing through stages of "stress-transition-adaptation." During the 2 h stress period, signal characteristics exhibited significant differences, with model accuracy peaking at 94.0%. Subsequently, during the 4 h transition period, accuracy declined to 87.3%. In the 6 h adaptation period, accuracy further decreased to 63.3% due to the restoration of physiological homeostasis. The integrated model outperformed both BP and SVM algorithms across all stages, demonstrating its effectiveness in capturing early stress features in plants and offering a novel approach for the early monitoring of heavy metal contamination in crops.

Keywords: Adaboost, lettuce leaves, wavelet entropy, copper stress, electrical signal
DOI: 10.25165/j.ijabe.20261902.9566

Citation: Zhang X H, Zhou Z L, Ma H B, Wang Q, Yang J, Zhai Z Y, et al. Plant electrical signal-based method for identifying copper stress in lettuce. Int J Agric & Biol Eng, 2026; 19(2): 103–111.

1 Introduction

The information transmission system of plants is composed of plant electrical signals, chemical signals, mechanical signals, and water signals[1]. The plant electrical signal is an important physiological signal for plants to express relevant information in the body during the growth and change process, and it is the initial response of plants to environmental changes[2]. It can not only reflect the growth of plants themselves, but also reflect the growth environment of plants[3]. Once humans eat vegetables contaminated by heavy metals, their health will be harmed[4]. Therefore, it is of great significance to human health to detect heavy metal pollution through the study of vegetable electrical signals[5].

In recent years, there have been a lot of studies on the classification and recognition of plant electrical signals. Chatterjee et al. used linear and nonlinear methods to extract 11 features from plant electrical signals. Different machine learning algorithms (i.e., Fisher's linear discriminant analysis, quadratic discriminant analysis, Naive Bayes classifier, and Markov classifier) were used to classify plant electrical signals under three external stimuli (NaCl, H_2SO_4, and O_3), and the optimal accuracy was about 73.67%[6]. A key constraint of this approach, however, lies in the inherent limitations of the traditional machine learning algorithms utilized: these methods exhibit excessive reliance on manual feature engineering, lacking the capability to automatically learn hierarchical and abstract feature representations directly from raw plant electrical signals. This dependence not only introduces unavoidable subjective bias during the manual feature selection process but also often leads to the loss of latent, high-dimensional information inherent in the original signal data. Chen et al.[7] applied four classifiers—template matching, back-propagation artificial neural network, support vector machine, and deep belief network—to identify electrical stimulus-induced plant action potential. Using the template matching algorithm, the classification accuracy reached 96%, demonstrating its effectiveness in the specific task of action potential recognition. However, the application of template matching is associated with certain inherent constraints tied to its working mechanism. It relies on pre-established "standard templates" of action potentials, and when signal variations occur, such as those caused by differences in plant species, changes in growth stages, or environmental noise (e.g., slight shifts in signal peak timing or amplitude), its recognition performance may be affected. Additionally, the method is primarily designed for the classification of action potentials, and it is not well-suited for identifying non-action potential electrical signals (e.g., slow-wave potentials). This characteristic limits its scope of application in broader plant stress response studies, where the analysis of multiple types of electrical signals may be required. Wang et al. used 1D-CNN and CGAN to effectively identify the salt tolerance of seedling plants, with an accuracy rate of 92.31%[8]. This method leverages deep learning to realize automatic feature extraction, which is a notable advantage for plant signal analysis.

Received date: 2024-11-24 **Accepted date:** 2025-12-22

Biographies: Zhaolin Zhou, MS, research interest: intelligence detection, Email: 17737293542@163.com; **Hongbiao Ma**, MS, research interest: sensor technology, Email: 121209796@qq.com; **Qiao Wang**, PhD, research interest: sensor technology, Email: wqiao2010@haut.edu.cn; **Jian Yang**, MS, research interest: intelligence detection, Email: yjian@stu.edu.cn; **Zeyu Zhai**, MS, research interest: intelligence detection, Email: 2025930554@stu.haut.edu.cn; **Xintian He**, Undergrad, research interest: intelligence detection, Email: 976778389@qq.com.

***Corresponding author: Xiaohui Zhang**, PhD, Associate Professor, research interest: plant electrical signals. College of Electrical Engineering, Henan University of Technology, Zhengzhou 450001, China. Tel: +86-18623716795, Email: xiaohui.xh@163.com.

However, it also has certain limitations associated with its design and data requirements. Specifically, the method shows high dependence on specific task scenarios: it is designed exclusively for salt tolerance identification and cannot be directly extended to classify signals induced by other types of stresses, such as drought, acid rain, or ozone. Li et al.[9] classified and recognized wheat seedling signals of drought and salt stress by support vector machine with one-to-one classification strategy; the accuracy rate of binary classification reached 94.44% and that of triple classification reached 96.3%. These results demonstrate the effectiveness of SVM-based methods in specific plant stress signal recognition tasks. However, such methods still face inherent bottlenecks when applied to large-scale, high-frequency plant electrical signal datasets. Specifically, as the number of signal samples or the dimensionality of raw data increases, the computational complexity of SVMs rises sharply, which in turn leads to prolonged training times and degraded real-time performance.

For the recognition of plant electrical signals, most previous studies used a single classifier. However, due to the nonlinearity and non-stationarity of plant electrical signals and their sensitivity to external interference, the signal information is rich[10], so the single classifier has certain limitations[11]. In this study, an Adaboost integrated algorithm based on multi-wavelet entropy feature and BP network as a base classifier was proposed to identify copper stress in lettuce leaves. First, the control group signal and intimidation group signal are decomposed and reconstructed by wavelet transform. Then, the wavelet singular entropy, wavelet energy entropy, and wavelet square difference entropy of both approximation coefficients and detail coefficients are calculated, using the entropy as classification characteristics. Finally, the training model is obtained by BP_Adaboost integration classifier, then forecast by the model. By comparing the recognition rate of BP_Adaboost classifier with BP neural network classifier and SVM classifier, it is finally proved that the performance of BP_Adaboost classifier is better than BP neural network classifier and SVM classifier in the study of copper stress recognition of lettuce leaves electrical signal, and has a good recognition rate.

For the traditional manual observation and detection method, its subjectivity is strong, the task is heavy, and it cannot achieve real-time detection. For image and vision detection methods[12,13], computer vision technology is used to analyze and process plant images and extract plant characteristics and growth states[14]. The recognition accuracy will be interfered with by complex plant structures and backgrounds, and image acquisition and processing require a lot of time and computing resources. For the detection method of wireless communication[13], the use of wireless sensor network to monitor the growth environment and state of plants in real time will be affected by the stability and coverage of network signals, and the real-time data will be limited. As for the detection method of sensors, using sensors to measure the environmental parameters and physiological indicators of plants, its installation and maintenance costs are high, and the environment and errors will interfere with it. Machine learning detection methods[15], such as Adaboost algorithm, can make predictions through model training, so as to achieve the effect of real-time monitoring, which is helpful to timely discover and deal with abnormal situations in the process of plant growth.

In this study, the multi-wavelet entropy feature extraction method is introduced, which provides a new feature extraction idea for the study of copper stress in lettuce leaves. The multi-wavelet entropy can reflect the distribution characteristics of the signal, and can better describe the effect of copper stress on the signal of plant leaves[16]. Secondly, BP_Adaboost model is used for classification recognition, which combines the advantages of BP neural network and Adaboost algorithm, and can improve classification efficiency on the premise of ensuring accuracy. The model can not only effectively identify copper stress in lettuce leaves, but also has certain universality, and can be applied to classification problems in other fields. Finally, through the effective identification of copper stress in lettuce leaves, this study provides a new method for plant health monitoring and early warning. Copper stress in lettuce leaves is a common problem in the process of plant growth[17]. The results of this study are helpful for timely detection and early warning of copper stress, providing scientific basis for agricultural production and reducing crop losses.

In conclusion, the results of this study are innovative and practical in terms of feature extraction methods and classification models[18], providing a new solution for the effective identification of copper stress in lettuce leaves, and contributing to the development of plant health monitoring and early warning.

2 Materials and methods

This study investigates methods for identifying plant electrical signals under copper stress in lettuce, using samples provided by Henan Agricultural University. After field cultivation, lettuce plants were transplanted into plastic pots filled with homogenized field soil collected from the same plot. Subsequently, all pots were placed in Faraday cages in a constant-environment laboratory maintained at 20°C and 60% relative humidity. The plants were then allowed to grow while their development was monitored to ensure normal growth. No additional fertilizer was applied during the experiment. All plants received identical irrigation schedules and light conditions, ensuring that copper stress was the only factor distinguishing the stress and control groups. When the experimental plants attained the 10-leaf growth stage, the root zone of plants in the stress group was irrigated with 50 mL of a 400 μmol/L copper nitrate ($Cu(NO_3)_2$) solution. For the control group, an equal volume (50 mL) of distilled water was applied to the root zone using the same irrigation method to ensure consistency in experimental conditions.

Based on the above experimental design, plant electrical signals from lettuce were collected in batches. Data were acquired under four conditions: without copper stress and at 2, 4, and 6 h after the onset of copper stress. The plant electrical signal acquisition system and procedure are shown in Figure 1. This acquisition system was developed by the Circuit Laboratory of Henan Polytechnic University[11,19].

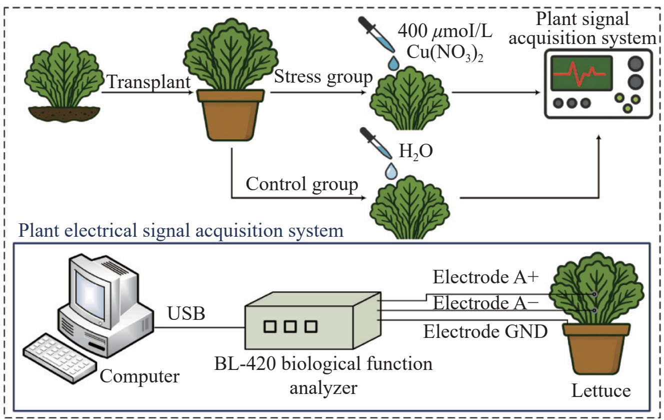

Figure 1 Experimental procedure and plant electrical signal acquisition system for lettuce under copper stress

The plant electrical signal acquisition system utilizes medical-grade high-sensitivity ECG patch electrodes to minimize damage to plants. During measurement, the two electrodes are placed at different positions on the same robust, broad leaf, with a 10 cm distance between them. The entire collection process was conducted within a Faraday cage. The reference electrode is inserted into the potting soil. The acquisition system operates at a sampling frequency of 2 kHz, incorporating a 500 Hz low-pass filter and a 0.053 Hz high-pass filter to suppress high-frequency noise and baseline drift. Electrophysiological signals were recorded from the stressed lettuce plants at 2, 4, and 6 h post-stress, with each recording session lasting 10 min. The control group underwent 10 min of plant electrical signal collection simultaneously. Following the aforementioned data collection protocol, each stage can record 1 152 256 data points. Across the three stress stages and the control group, the entire experiment yields approximately 4.61×10^6 data points. Each data point represents the instantaneous potential difference between the two measurement electrodes positioned on the lettuce leaf at the corresponding moment. This potential difference reflects the combined effect of variations in cell membrane potential and ion flux across different regions of the leaf, thereby providing a direct reflection of the lettuce's physiological response to copper stress.

3 Feature extraction of plant electrical signals based on multi-wavelet entropy

Different wavelet entropies reflect the distribution characteristics of signals from different perspectives, which provides the basic premise for feature extraction of the electric signal of lettuce leaves. If the advantages of multiple entropies are combined to analyze the electric signal of lettuce leaves, features with high reliability can be extracted[20].

Due to the fact that the raw plant electrical signals are time-varying and non-stationary time series, directly extracting features may cause short-term stress responses and local fluctuations to be obscured. Therefore, in this study a sliding window of 512 data points was used, with a step size of 256 data points, to segment the denoised plant electrical signals into partially overlapping windows, so that the signal within each window can be regarded as approximately stationary. The plant electrical signals at each of the four stages were thus divided into 4500 feature samples, on the basis of which different wavelet entropy features were analyzed.

3.1 Wavelet singular entropy

Suppose that the wavelet decomposition of the electric signal from the lettuce leaves under the j ($j = 1, 2, \dots, m$) scale is $D_j(n)$, and D is the $m\times n$ matrix. According to the singular value decomposition theory, for matrix $D_{m\times n}$, there must be matrix $U_{m\times l}$, matrix $\Lambda_{l\times l}$, and matrix $V_{l\times n}$, so that the matrix $D_{m\times n}$ decomposition is as follows:

$$D_{m\times n} = U_{m\times l}\Lambda_{l\times l}V_{l\times n} \tag{1}$$

The main diagonal element $\lambda_i (i = 1,2,\dots,l)$ of matrix $\Lambda_{l\times l}$ is the singular value of the wavelet transform result, and it is the non-negative value arranged in the order from large to small, namely $\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_l \geq 0$[21]. In order to quantitatively describe the frequency components and distribution characteristics of the electric signal of lettuce leaves, the wavelet singular entropy is defined as:

$$W_s = \sum_{i=1}^{k} \Delta p_j \tag{2}$$

where, Δp_j is the j order incremental wavelet singular entropy.

$$\Delta p_j = -\left[\frac{\lambda_i}{\sum_{j=1}^{l}\lambda_j}\right]\log\left[\frac{\lambda_i}{\sum_{j=1}^{l}\lambda_j}\right] \tag{3}$$

3.2 Wavelet variance entropy

For a given signal, the variance spectrum $\left\{p_w(j) = \frac{1}{N}\|W_j\|^2\right\}$, $j = 1, 2, \dots, m$ is obtained after wavelet decomposition, where, W_j is the variance spectrum of wavelet coefficients at scale j. The wavelet variance entropy is defined as[22]:

$$W_v = -\sum_{j=1}^{m} p_j \ln(p_j) \tag{4}$$

where, $p_j = p_w(j)/\sum_j p_w(j)$ represents the probability of variance at j scale.

3.3 Wavelet energy entropy

Let $E = E_1, E_1, \dots, E_m$ be the wavelet energy spectrum of lettuce leaves signal $x(t)$ on m scales, then E can form a division of signal energy in the scale domain. According to the characteristics of orthogonal wavelet, the total signal power E within a certain time window is equal to the sum of the power E_j of each component, and let $p = E_j/E (j = 1, 2, \dots, m)$, then $\sum p_j$[23]. Therefore, the defined wavelet energy entropy is:

$$W_e = -\sum_{j=1}^{m} p_j \ln(p_j) \tag{5}$$

When $p_j = 0$, $p_j \ln(p_j) = 0$.

The multi-wavelet entropy feature was constructed based on the electrical signals of lettuce leaves in stress group. The specific steps are as follows:

Step 1: Conduct four-layer wavelet decomposition on the stress group's electrical signal $x(n)$, and extract four high-frequency coefficients CD1, CD2, CD3, CD4, and low-frequency coefficient CA5 respectively.

Step 2: Reconstruct the wavelet decomposition coefficient and extract the signal in each frequency range. The reconstructed electric signals of each frequency band in normal group and stress group are shown in Figure 2 and Figure 3, denoted by CD1, CD2, CD3, CD4, and CA5 respectively.

Step 3: The wavelet energy entropy, wavelet singular entropy, and wavelet square difference entropy of reconstructed signals with high frequency coefficients are calculated respectively. $W_e(i)$ denotes the wavelet energy entropy of X_i, $W_s(i)$ denotes the wavelet singular entropy of X_i, and $W_v(i)$ denotes the wavelet square difference entropy of X_i, $i = 1, 2, 3, 4, 5$.

Step 4: Construct multi-wavelet entropy feature vectors.

$$P = [W_{si}, W_{ei}, W_{vi}] \quad i = 1,2,3,4,5 \tag{6}$$

A comparative analysis of the raw signal waveforms in Figures 2 and 3 reveals that the electrical signals of lettuce in the control group exhibited distinct physiological fluctuations, indicating the plants were in a normal growth phase. However, for the stress group at 6 h post-copper stress, the frequency of physiological fluctuations in lettuce electrical signals decreased markedly, accompanied by diminished amplitude variability. This observation suggests that both the rate of cell membrane potential changes and ion mobility across different leaf regions were reduced in stressed lettuce, thereby indicating inhibition of its growth activity.

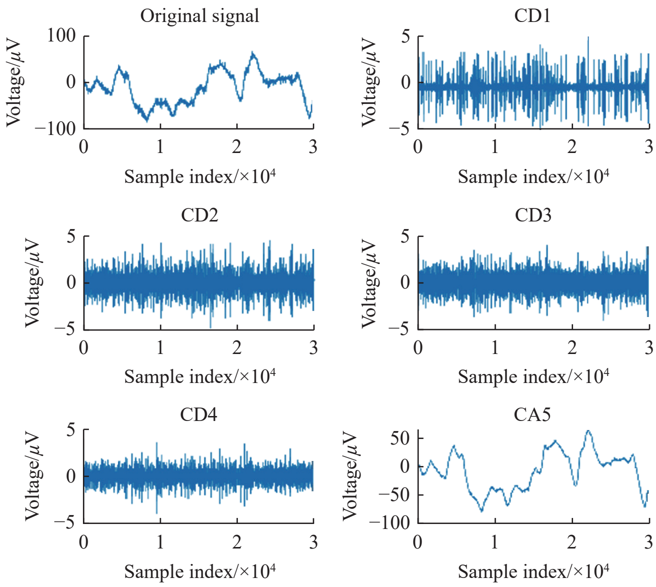

Figure 2 The electrical signal after reconstruction of the electrical signal of lettuce in each frequency band (normal group)

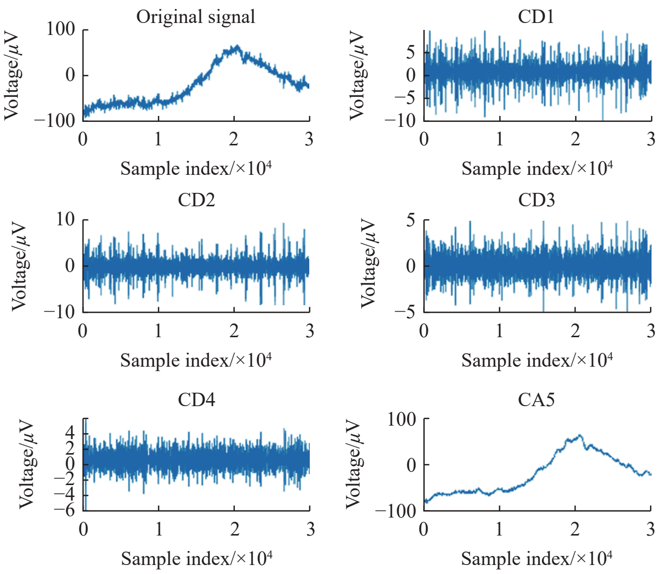

Figure 3 The electrical signal after reconstruction of each frequency band of the lettuce electrical signal (stress group, at 6 h post-stress)

3.4 BP_Adaboost ensemble classifier

Ensemble Learning is a model which achieves higher accuracy by combining multiple weak learners[24]. The training sample set is used to train these weak learners in turn, and these weak learner models are used for joint prediction[25]. BP neural network is a multi-layer feedforward neural network that transmits signals forward and errors backward[26]. BP_Adaboost model takes BP neural network as a weak learner, trains BP neural network repeatedly to predict sample output, and obtains a strong classifier composed of multiple BP neural network weak classifiers through Adaboost algorithm[27-29]. The electric signal recognition algorithm flow of lettuce leaves based on BP_Adaboost model is shown in Figure 4. The algorithm flow is as follows:

Data selection and network initialization. Randomly select m groups from the multi-wavelet entropy feature vectors as training data, initialize the distributed weights $D_t(i) = 1/m$ of the test data, and initialize the weights and thresholds of BP neural network.

BP neural network classifier prediction. When training the t th BP neural network classifier, the BP neural network is trained with the training data and the output of the training data is predicted; the prediction error e_t of the prediction sequence $g(t)$ is obtained.

$$e_t = \sum_i D_t(i) \quad i = 1,2,\ldots,m(g(t) \neq y) \tag{7}$$

$g(t)$ is the prediction classification result; y is the expected classification result.

Calculate the weight of the predicted sequence. According to the prediction error e_t of the prediction series $g(t)$, a_t is calculated, which is the weight of the series. The weight calculation formula is:

$$a_t = \frac{1}{2}\ln\left(\frac{1-e_t}{e_t}\right) \tag{8}$$

Adjust the weight of the test data. According to the predicted sequence weight a_t, the weight of the next round of training samples is adjusted, and the adjustment formula is:

$$D_{t+1}(i) = \frac{D_t(i)}{B_t}\cdot\exp(-a_t y_t g_t(x_i)) \quad i = 1,2,\ldots,m \tag{9}$$

B_t is the normalization factor, which aims to make the sum of distribution weights equal to 1 under the condition that the weight proportion is unchanged.

BP_Adaboost classification function. After T rounds of BP neural network training, the classification function $f(g_t,a_t)$ of BP neural network in group T is obtained, and the BP_Adaboost ensemble classifier function $f(g_t,a_t)$ is obtained by combining the classification function $h(x)$ of BP neural network in group T.

$$h(x) = \text{sign}\left(\sum_{t=1}^{T} a_t f(g_t,a_t)\right) \tag{10}$$

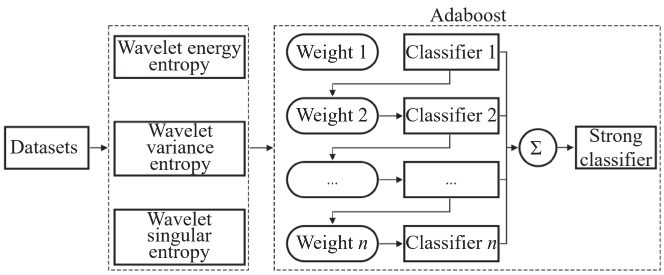

Figure 4 Algorithm flow of electrical signal identification of lettuce leaves based on BP_Adaboost model

4 Classifier simulation results

This paper will evaluate and validate the performance of the electrical signal classification model for lettuce plants under copper stress conditions using the following performance metrics.

Accuracy (ACC) refers to the proportion of the number of correctly classified samples in the multi-wavelet entropy test samples.

$$\text{ACC} = \frac{\text{TP}+\text{TN}}{\text{TP}+\text{TN}+\text{FP}+\text{FN}} \tag{11}$$

In this study, copper-stressed samples are treated as the positive class and control samples as the negative class. Sensitivity (SEN), also referred to as the true positive rate (TPR), measures the ability to correctly identify stressed samples:

$$\text{SEN} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{12}$$

The false positive rate (FPR) is defined as:

$$\text{FPR} = \frac{\text{FP}}{\text{FP}+\text{TN}} \tag{13}$$

Specificity (SPE), also known as the true negative rate (TNR), measures the ability to correctly identify control samples:

$$\text{SPE} = \frac{\text{TN}}{\text{TN}+\text{FP}} \tag{14}$$

F1 score (F1), Harmonic mean of Precision (P), and Recall (R):

$$\text{P} = \frac{\text{TP}}{\text{TP}+\text{FP}} \tag{15}$$

$$\text{R} = \frac{\text{TP}}{\text{TP}+\text{FN}} \tag{16}$$

$$\text{F1} = \frac{2\text{PR}}{\text{P}+\text{R}} \tag{17}$$

Assume that the ROC curve is formed by the sequential connection of points with coordinate $\{(x_1,y_1),(x_2,y_2),\ldots,(x_m,y_m)\}$ $(x_1=0, x_m=1)$, then the AUC can be estimated:

$$\text{AUC} = \frac{1}{2}\sum_{i=1}^{m-1}(x_{i+1}-x_i)(y_i+y_{i+1}) \tag{18}$$

Among the test samples, copper-stressed lettuce signals were treated as the positive class and control signals as the negative class. The number of the control group judged as the control by the classifier was denoted as TN (True Negative), and the number of the stress group judged as FP (False Positive). The quantity of stress group judged by the classifier as stress group was denoted as TP (True Positive), and the quantity judged as control group was denoted as FN (False Negative).

Based on the wavelet energy entropy, wavelet squared difference entropy, and wavelet singular entropy extracted from the features, a multi-wavelet entropy feature vector $P=[W_{si}, W_{ei}, W_{vi}](i=1,2,3,4,5)$ is constructed for the electrical signals of lettuce plants under copper stress. These feature vectors share the same dimensionality across all feature datasets, meaning that 4500 sets of feature vectors exist for all four stages, including the normal group. Each feature vector comprises five energy entropy features, five variance entropy features, and five singular entropy features. Based on this, the constructed BP_Adaboost algorithm was trained and validated. The specific experimental setup is listed in Table 1.

Table 1 Simulation results of BP neural network classifier

Stage	Total sample	Base learner hidden layers	Number of base learners	Cross validation
2 h	4500	(100, 50)	10	5-fold
4 h	4500	(100, 50)	10	5-fold
6 h	4500	(100, 50)	10	5-fold

Figures 5 and 6 demonstrate the performance of the BP-Adaboost model in recognizing plant electrical signals under different stages of copper stress. Overall, the model demonstrates strong classification capabilities for plant electrical signals under copper stress conditions. Further analysis reveals that as the duration of stress increases, the detection accuracy at each stage shows a gradual decline. Correspondingly, the ROC curve also indicates that in a binary classification task, the model's ability to distinguish between coercive signals and control signals diminishes as coercion time increases. It should be noted that the data preprocessing workflow and model hyperparameter configuration employed across all stages were identical, and the results were validated through multiple repeated experiments. Therefore, differences in model settings or training strategies can be ruled out as causes of this phenomenon. This performance variation likely reflects the inherent differences in the electrical signal response characteristics of plants across distinct stress stages.

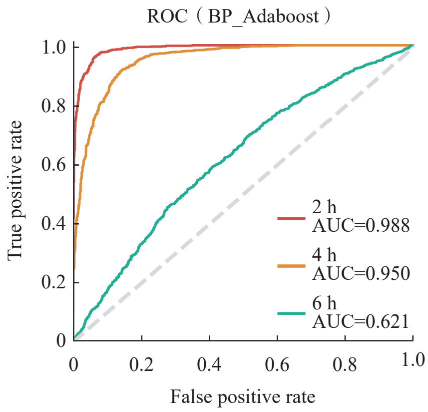

Figure 5 BP_Adaboost model ROC curve

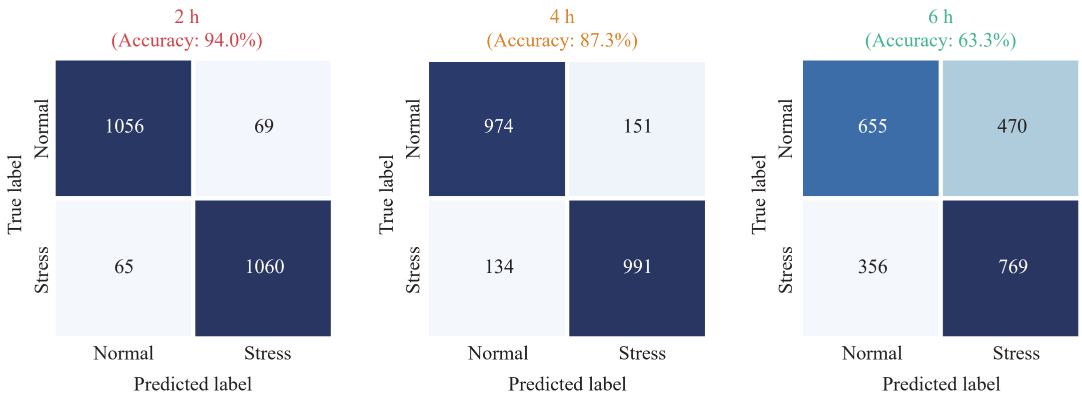

Figure 6 BP_Adaboost model confusion matrix

To further explore the aforementioned phenomenon and its underlying significance, this paper conducted a systematic analysis of the characteristic data. First, the raw multidimensional features for each coercion stage are standardized to ensure comparability across different measurement scales. Subsequently, principal component analysis (PCA) was employed to screen high-contribution features at each stage and perform linear dimensionality reduction. The information most relevant to stress identification was projected onto a discriminant axis that maximally distinguished the normal group from the stressed group, thereby yielding the corresponding one-dimensional scalar feature. Finally, kernel density estimation (KDE) was performed on the scalar features of the normal and stressed groups, respectively. The density curves were then overlaid to obtain the probability distributions of the two sample categories for this discriminative feature.

As shown in the results of Figure 7, by the 6 h stage, the distribution of electrical signal characteristics in the stressed group had become highly overlapping with that of the control group, indicating that relying solely on current features is no longer sufficient to effectively distinguish between the two groups. Further comparison across different stages reveals: During the first 2 h after copper stress onset, the stress group and control group exhibited minimal overlap in feature distribution and maximum separability. By the 4 h stage, the overlap in their distributions had significantly increased, resulting in a corresponding reduction in their distinctiveness. By the 6 h stage, the two feature types had nearly completely overlapped, with the classification boundary becoming significantly blurred. This trend aligns with the model's recognition performance gradually declining as stress duration increased. In summary, the performance differences observed across different stages are not attributable to insufficient model generalization capabilities, but rather stem from inherent variations in the distribution of plant electrical signals at each developmental phase. This data-level indivisibility directly reflects the fundamental transformation of electrophysiological activity during different stages of plant stress responses. It also reveals a close intrinsic coupling between the distinctiveness of electrical signal characteristics and the homeostatic regulatory mechanisms within plants.

From a plant physiology perspective, the dynamic evolution of this signal characteristic aligns with the theory of the plant general adaptation syndrome (GAS). Specifically, when copper stress is continuously applied to lettuce, its stress effects exhibit a dynamic and continuous evolution pattern: The toxic effects of heavy metals disrupt the normal physiological rhythms of lettuce and cause significant alterations in plant electrical signals. On the other hand, heavy metal stress can induce lettuce to synthesize metal-binding peptides such as phytochelatins, which expel toxic metal ions from the plant via ion pump mechanisms on the cell membrane. At the level of plant electrical signals, this manifests specifically as: The core characteristic parameters of its oscillation frequency and amplitude gradually converged toward the normal electrical signal characteristics of the control group. The differences between the two groups progressively diminished and eventually disappeared, ultimately restoring the plant's electrical signals to normal physiological levels.

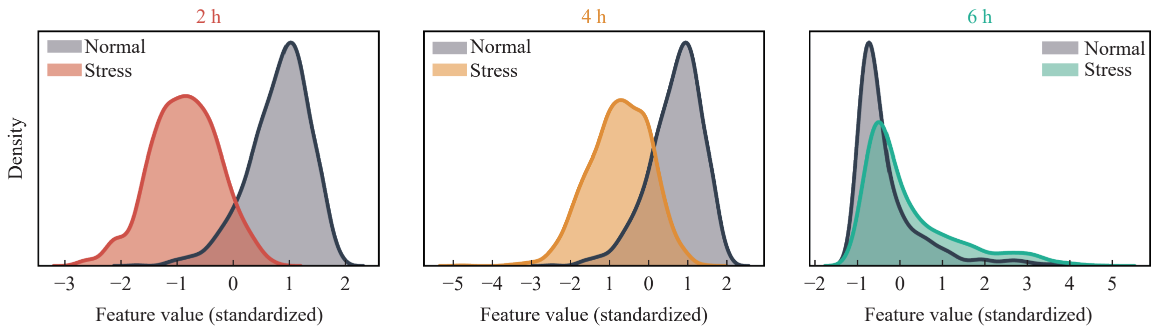

Figure 7 Probability density distribution of key discrimination features in electrical signals of lettuce plants under copper stress

To further validate the classification performance of the BP_Adaboost model and provide supporting evidence for the existence of the general adaptation syndrome in plants, this study selected the BP neural network and SVM model as baseline methods for comparative experiments. Support Vector Machines and BP neural networks, as classical algorithms in this field[30], have been widely applied in feature recognition research and have demonstrated outstanding performance.

ROC curves for the BP neural network, SVM, and BP_Adaboost were plotted separately for each stress duration (2 h, 4 h, and 6 h) in Figure 8 to compare the discrimination capabilities of the three models between the copper-stressed lettuce group and the control group. The area under the ROC curve (AUC) serves as a threshold-independent comprehensive evaluation metric. A curve closer to the upper-left corner and a higher AUC value indicate superior classification performance. To ensure fairness in comparison, all models underwent identical preprocessing procedures and consistent validation settings across all stages, with results derived from multiple replicate experiments. The results indicate that BP_Adaboost demonstrates superior classification performance across all stress stages. Meanwhile, as the duration of stress increased, the overall ability of all three models to distinguish between stress signals and control signals showed a declining trend. This phased change aligns with the pattern observed in plants during the late stages of stress exposure, where physiological regulation may be initiated through the General Adaptation Syndrome (GAS), leading to a gradual attenuation of electrical signal differences. This provides further support for the existence of the GAS phenomenon. This phased change aligns with the pattern observed in plants during the late stages of stress exposure, where physiological regulation may be initiated through the General Adaptation Syndrome (GAS), leading to a gradual attenuation of electrical signal differences. This provides further support for the existence of the GAS phenomenon.

To further investigate the error characteristics of these three classifiers, this study constructed confusion matrices for each stress duration using the same decision rules, as shown in Figure 9. Elements on the main diagonal represent correctly classified samples, while elements off the diagonal indicate misclassification.

Results indicate that in the later stages of stress, the primary error pattern stems from increased confusion regarding the boundary between stress and control samples. Specifically, the proportion of stress samples misclassified as control samples was higher, indicating that electrophysiological signals induced by prolonged copper stress gradually became more similar to those of the control group. This observation is highly consistent with the analysis of the probability density distribution of discriminant features.

The current results further indicate that the decline in phase recognition accuracy after 6 h is not attributable to insufficient model performance, but rather stems from the gradual normalization of plant electrical signals during the lettuce's autonomous physiological regulation process, leading to a significant reduction in feature distinguishability. Although all three classifiers exhibit this trend, BP_Adaboost consistently maintains higher values along the main diagonal than BP and SVM, indicating its greater adaptability to reduced feature separability.

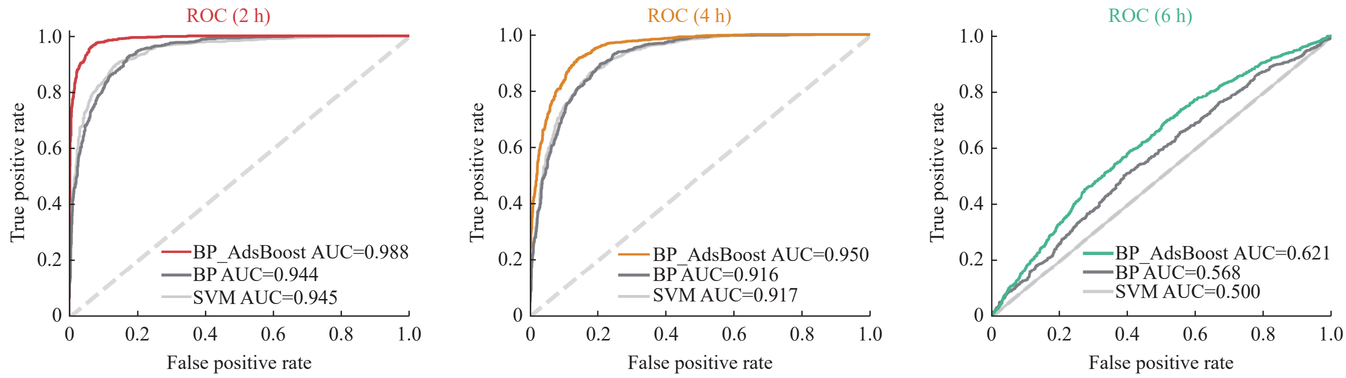

Figure 8 Comparative ROC curves of BP, SVM and BP_Adaboost classifiers under different copper stress durations

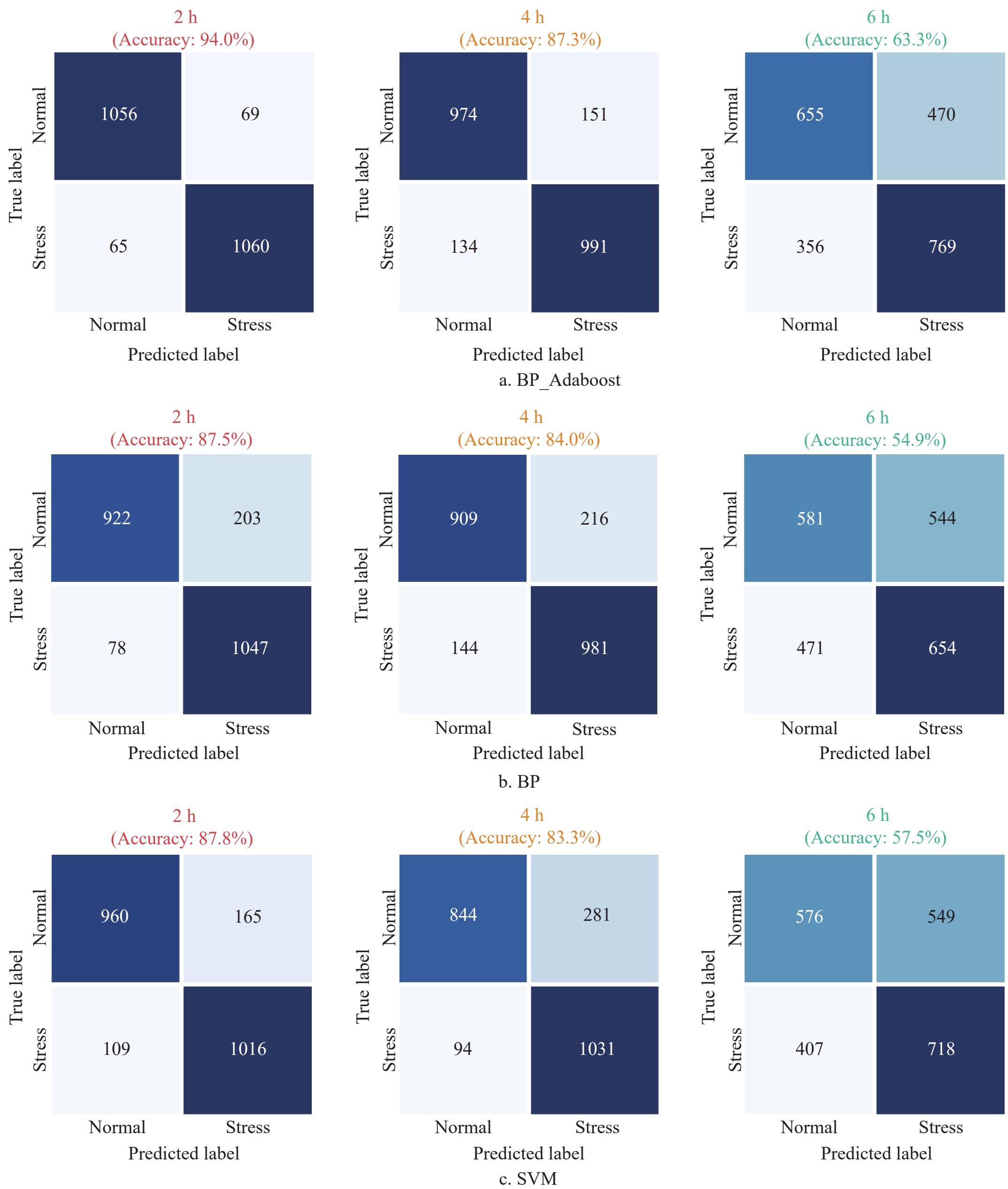

Figure 9 Confusion matrices of BP_Adaboost, BP and SVM classifiers under different copper stress durations

5 Conclusions

This study proposes a lettuce copper stress recognition method integrating multi-wavelet entropy features with BP_Adaboost ensemble learning. Building upon this approach, it delves into the dynamic evolution patterns of plant electrophysiological responses, systematically revealing the underlying mechanisms behind model recognition performance differences across distinct stress stages. The main conclusions are as follows:

1) Experimental results indicate that as the duration of copper stress on lettuce increases, its plant electrical signals undergo dynamic changes across three distinct phases: stress period, transition period, and adaptation period. Specifically, during the initial stage of the stress (2 h), the intense fluctuations in ion flow resulted in significant differences in the electrical signal characteristics compared to the normal group. The model recognition accuracy reached its peak at 94.0%. As plants activate their physiological defense mechanisms (4 h), signal characteristics begin to converge, causing recognition accuracy to drop to 87.3%. By the adaptation phase (6 h), as plants established a new steady state, the electrical signal characteristics highly overlapped with those of the normal group, significantly increasing recognition difficulty and further reducing accuracy to 63.3%.

2) Comparative experiments demonstrate that the BP_Adaboost model outperforms traditional BP neural networks and SVM algorithms in classification performance across all stress stages. Especially during the adaptation phase (6 h) when feature confusion is severe, this model effectively captures subtle deep features through its adaptive weighting mechanism, demonstrating superior robustness and generalization capabilities.

3) This study incorporates the theory of the general adaptation syndrome (GAS) into the analysis of plant electrical signals, elucidating from a biological perspective the fundamental cause of the reduced recognition rate of plant electrical signals during the late stages of stress. This finding further confirms the dynamic coupling relationship between plant electrical signals and physiological activities, and also provides new insights into understanding the dynamic adaptation process of lettuce under copper stress.

In summary, as listed in Table 2, this study successfully developed a high-performance classification model for early detection of copper stress in lettuce. By thoroughly analyzing the intrinsic relationship between electrical signal feature changes and biological physiological activities, it provides crucial theoretical foundations and technical support for the early warning and precise detection of heavy metal pollution in plants.

Table 2 Performance comparison of different classifiers across various copper stress stages

Stage	Model	Accuracy/%	Sensitivity/%	Specificity/%	F1-score/%	AUC
2 h	BP	87.7±1.6	93.1	82.0	88.2	0.944
	SVM	87.8±1.0	90.3	85.3	88.1	0.945
	BP_Adaboost	**94.3±0.6**	**94.2**	**94.0**	**94.1**	**0.988**
4 h	BP	83.5 ± 0.8	87.2	80.8	84.5	0.916
	SVM	82.8 ± 0.6	91.6	75.0	84.6	0.917
	BP_Adaboost	**87.2 ± 0.5**	**88.4**	**87.4**	**87.9**	**0.950**
6 h	BP	56.0 ± 0.8	58.1	51.6	56.3	0.568
	SVM	57.3 ± 1.1	63.8	51.2	60.0	0.500
	BP_Adaboost	**58.6 ± 1.2**	**59.8**	**57.2**	**59.0**	**0.621**

Acknowledgements

This work was supported by the High Performance Computing Platform of Henan University of Technology.

[References]

[1] de Toledo G R A, Parise A G, Simmi F Z, Costa A V L, Senko L G S, Debono M W, et al. Plant electrome: the electrical dimension of plant life. Theoretical and Experimental Plant Physiology, 2019; 31: 21–46.

[2] Gao X, Xi G, Liu K, Liu Q. The study of de-noising method about plant electrical signal based on wavelet. Journal of Xi'an University of Technology, 2013; 29(1): 92–97. (in Chinese)

[3] Zhang X H, Li Y Z, Ma H B. Design of online measuring system of plant electrical signal. Computer Measurement & Control, 2014; 22(11): 3728–3731. (in Chinese)

[4] Ye C Y. Research status of phytoremediation of heavy metal pollution in soil. Modern Agricultural Science and Technology, 2021(17): 169–170. (in Chinese)

[5] Yang L, Ma Y H. Review of heavy metal pollution and heavy metal enrichment plants. Anhui Agricultural Science Bulletin, 2020; 26(23): 102–105. (in Chinese)

[6] Chatterjee S K, Das S, Maharatna K, Masi E, Santopolo L, Mancuso S, et al. Exploring strategies for classification of external stimuli using statistical features of the plant electrical response. Journal of Royal Society Interface, 2015; 12(104): 20141225.

[7] Chen Y, Zhao D J, Wang Z Y, Wang Z Y, Tang G, Huang L. Plant electrical signal classification based on waveform similarity. Algorithms, 2016; 9(4): 70.

[8] Qin X H, Wang Z Y, Yao J P, Zhou Q, Zhao P F, Wang Z Y, et al. Using a one-dimensional convolutional neural network with a conditional generative adversarial network to classify plant electrical signals. Computers and Electronics in Agriculture, 2020; 174: 105464.

[9] Li J H, Li Y, de Oliveira R F, Yao J P, Huang L, Wang Z Y. Identification of isotonic drought stress and salt stress in wheat seedling based on plant electric signal. Transactions of the Chinese Society for Agricultural Machinery, 2021; 52(7): 231–236. (in Chinese)

[10] Meng X L, Xi G, Zhang X H, Liu K. Analysis of characteristics of electrical signals in the leaves of three species of plants. Journal of Xi'an University of Technology, 2011; 27(2): 209–213. (in Chinese)

[11] Zhang X H, Yu N M, Xi G, Meng X L. Changes in the power spectrum of electrical signals in maize leaf induced by osmotic stress. Chinese Science Bulletin, 2012; 57(4): 413–420.

[12] Üncü I S, Kayaku M. Determination of efficient light source for wheat plant by using decision trees method. Fresenius Environmental Bulletin, 2021; 30(2): 2807–2812.

[13] Costa L, Ampatzidis Y, Rohla C, Maness N, Cheary B, Zhang L. Measuring pecan nut growth utilizing machine vision and deep learning for the better understanding of the fruit growth curve. Computers and Electronics in Agriculture, 2021; 181: 105964.

[14] Chang C L, Chung S C, Fu W L, Huang C C. Artificial intelligence approaches to predict growth, harvest day, and quality of lettuce (*Lactuca sativa* L.) in a IoT-enabled greenhouse system. Biosystems Engineering, 2021; 212: 77–105.

[15] Wang P P, Meng F R, Donaldson P, Horan S, Panchy N L, Vischulis E, et al. High throughput measurement of plant fitness traits with an object detection method using Faster R-CNN. New Phytologist, 2022; 234: 1521–1533.

[16] Suk J W, Ryoo I T. Implementation of non-contact plant growth measurement system based on USN technologies. Journal of the Korea Society of Computer and Information, 2010; 15(10): 137–145.

[17] Zhao B, Zhang Y H, Duan A W, Liu Z D, Xiao J F, Liu Z G, et al. Estimating the growth indices and nitrogen status based on color digital image analysis during early growth period of winter wheat. Frontiers in Plant Science, 2021; 12: 619522.

[18] Tessmer O L, Jiao Y H, Cruz J A, Kramer D M, Chen J. Functional approach to high-throughput plant growth analysis. BMC Systems Biology, 2013; Supp.6: S17. doi: 10.1186/1752-0509-7-S6-S17.

[19] Sun H Q, Zhang X H, Yu Z, Xi G. Feature recognition of crop growth information in precision farming. Complexity, 2018; 1: 9250832.

[20] Shu B. Feature extraction of plant electrical signals based on multi-wavelet entropy and signal entropy. Computer Knowledge and Technology, 2016;

12(7): 178–180. (in Chinese)

[21] Fu H K. Feature extraction of plant electrical signals based on multi-wavelet entropy and signal entropy. Journal of Agricultural Mechanization Research, 2013; 35(9): 38–40,47. (in Chinese)

[22] Mao Q, Diao H H, Zhang X B. A speech endpoint detection method based on variance and spectral entropy. Journal of Changzhou Institute of Technology, 2021; 34(2): 36–40, 52. (in Chinese)

[23] Xu T Y, Zhang Y. Response algorithm of driver fatigue driving behavior based on wavelet energy entropy. Computer Simulation, 2021; 38(11): 133–137. (in Chinese)

[24] Cui L L, Wang S X. Mapping the daily nitrous acid (HONO) concentrations across China during 2006–2017 through ensemble machine-learning algorithm. Science of the Total Environment, 2021; 785: 147325.

[25] Hoffmann L, Fortmeier I, Elster C. Uncertainty quantification by ensemble learning for computational optical form measurements. Machine Learning: Science and Technology, 2021; 2(3): 035030.

[26] Lai M T. Research on enterprise financial risk forecast method based on BP neural network algorithm. Microcomputer Applications, 2021; 37(12): 155–157. (in Chinese)

[27] Qu Z J, Liu H X, Wang Z X, Xu J, Zhang P, Zeng H. A combined genetic optimization with AdaBoost ensemble model for anomaly detection in buildings electricity consumption. Energy & Buildings, 2021; 248: 111193.

[28] Suk J, Kim S, Ryoo I. Non-contact plant growth measurement method and system based on ubiquitous sensor network technologies. Sensors-Basel, 2011; 11(4): 4312–4334.

[29] Olas J J, Fichtner F, Apelt F. All roads lead to growth: imaging-based and biochemical methods to measure plant growth. Journal of Experimental Botany, 2019; 71(1): 11–21.

[30] Aksoy E E, Abramov A, Woergortter F, Scharr H, Fischbach A, Dellen B. Modeling leaf growth of rosette plants using infrared stereo image sequences. Computers and Electronics in Agriculture, 2015; 110: 78–90.