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A Cloud Model-based Prediction Method for Scientific Cultivation with Smaller Flower Seed Bulbs

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Abstract. Aiming at insensitivity to growth regulators during the cultivation of smaller flower seed bulbs, the cloud model-based prediction method is proposed. Define the growth feature cloud model, replace the intra-class distance calculation with the degree of certainty of the growth parameters on its cloud model, set the feature weight according to the sensitivity of the growth feature to the growth regulator in smaller seed bulbs cultivation, and finally complete the classification prediction by calculating the degree of certainty of all the feature values by weighting. According to the goal of growth, growth regulators are scientifically selected through effectively prediction to control cultivation of smaller seed bulbs. Finally, the experiment of smaller lily bulbs cultivation proves that this method is obviously superior to the traditional conventional classification method and can better control the scientific cultivation of smaller seed bulbs. Next, we will expand the number and variety of experimental data and further adjust the model parameters to make it more universal and accurate.

Keywords: scientific cultivation, prediction, cloud model, smaller flower seed bulbs

1 Introduction

In the past five years, the informatization of the planting industry has achieved rapid development. The construction of informatization platform has been mature and widely used in the production and sales of crops, vegetables, flowers and trees, which plays an important role. At present, the focus of planting information development has shifted from information platform construction to planting controllable analysis on scientific cultivation, disease control and other aspects of planting [1-3].

At the International Plant Phenotypic Conference, the world's top scholars have paid more and more attention to the analysis and application of big data in plant phenotypic research. Most plant scholars generally believe that big data analysis method can transform plant phenotypic data and physiological parameters into easily understood botanical knowledge, which can solve key problems in plant phenotypic research [4-5]. Obviously, big data method can play an important role in phenotypic control research of flower cultivation.

The growth of flowers is closely related to the environment [6-7], such as intensity of light, humidity, phosphorus and potassium in soil, and so on. Their growth is highly random and difficult to control. Now, most flower phenotypic control technologies are based on the differentiation and growth habits of flower seed bulbs under natural conditions, and mainly rely on artificial experience to adjust environmental conditions for controlling flower growth. This lacks rigorous data analysis. Advanced information technology is needed to control the growth of flowers.

In fact, when various scientific cultivation measures are applied, the growth characteristics of larger seed bulbs are always more obvious than smaller. Therefore, we cannot only rely on artificial experience to control the cultivation of smaller seed bulbs, but need more accurate data analysis and support. The statistical analysis method based on the limited samples cannot meet the research needs of modern flower phenotype control technology. With the development of big data technology, many excellent research results have emerged in the study of plant phenotype, which has obvious advantages over these traditional statistical tools such as SPSS, COVAIN and so on. They mainly focus on the research of plant image and gene, but few in the field of flower phenotypic control.

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In view of the problem that the response to growth regulators is not significant and it is difficult for the growth characteristics to control in the cultivation of flower smaller seed bulbs, conventional classification method is furtherly improved with cloud model. The KNN method is improved with the inner distance calculation idea in Kmeans clustering method instead of calculate the distance between a sample point and its adjacent points in KNN method. And category of one sample point is determined by the distance from it to a core point of every class. However, this distance is not calculated as the distance between any two points. Instead, each class is represented by a specific cloud model, and then the degree of certainty of the sample point on every class's cloud model is calculated. This degree of certainty represents the distance from the sample point to the class core point. The main works are as follows.

(1) Train and define the cloud models of the main growth characteristics of the smaller seed bulbs when different growth regulators are used.

(2) Use the certainty of cloud model to replace the distance calculation between two points in the conventional method, and then define the cloud model-based prediction method.

(3) The required growth regulator can be predicted with the goal of cultivating phenotypes of smaller seed bulbs, and the experimental analysis was carried out.

2 Theoretical Basis

2.1 Cloud Model

The cloud model is an uncertain intelligent model reflecting the correlation between randomness and fuzziness [8]. In the study of practical problems, fuzziness mainly comes from the uncertainty of people's subjective cognition about objective reality, and randomness mainly comes from the environmental uncertainty of objective reality, such as time, space, temperature, humidity and so on. The cloud model uses the expected value to express the exact realization of the qualitative concept in the quantitative domain, and uses the entropy to express the uncertainty measure of the qualitative concept [9]. Because of the uncertainty of the entropy own, it also uses the hyper entropy to describe the uncertainty of the entropy. So, the cloud model can express a concept through three digital attributes, which are expected value, entropy and hyper entropy. The expected value is expressed in Ex , entropy in En , and hyper entropy in He [10]. In a word, the cloud model can well express the fuzziness of subjective cognition and the randomness of objective reality together.

Cloud model can be used for fuzzy control, fuzzy decision, fuzzy classification, and so on. In recent years, it has been used by many scholars for risk analysis, status assessment and prediction. The cloud model is used for an integrated risk analysis for tank cargo handling operation in the reference [11] and operational safety assessment of straddle-type monorail vehicle system in the reference [12]; and it is used to evaluate risk status of excavation in urban dense areas in the reference [13]. In the reference [14], it is used for condition assessment of distribution automation remote terminal units. Furthermore, it is used to predict stock price for new energy vehicle enterprises [15]. And in the reference [16], it is demonstrated that it can handle the uncertainty of datasets in the clustering process well, in addition to exhibiting robustness with unclear clusters. It can be seen from existing research that cloud models are good at solving the problem of ambiguity and randomness, especially in natural language decision-making and fuzzy classification.

2.2 The Kmeans Method

Kmeans method is one of the classic clustering methods, which is an unsupervised method and is often used for prediction or clustering analysis in various fields. Many scholars have improved the Kmeans algorithm to satisfy some requirements in practice. Fixed-centered Kmeans algorithm is proposed in the reference [17], which can achieve classification by fixing the center point of the class. Although it has more limitations than Kmeans, it is more superior for some performance indicators [17]. In reference [18], Kmeans was used to predict hydraulics performance in drain envelopes, which makes results satisfying. In the reference [19], Kmeans method is improved based on nearest neighbor, which solves classification of imbalanced data.

The main idea of Kmeans method is as follows. Firstly, set the value of k according to the actual research needs, and divide the dataset into k categories. The setting principle of k is to minimize the distance between data points in the same class and maximize the distance between data points in different classes. Secondly, each category has a center point, and then calculate the distance between a sample point and its category center point and the distance between centers of different categories. Thirdly, give the distances different proportional weights. Finally, obtain the optimal classification results through the sequence [20]. There are three common methods for distance calculation, including Manhattan distance, Euclidean distance and Chebyshev distance. When the sample data are not significantly different, these methods will reduce the accuracy of classification algorithms. This is also the main disadvantage of the conventional Kmeans method.

2.3 The KNN Method

KNN (K-Nearest Neighbors) is a popular classification method, which is supervised classification. The number of categories and samples with category characteristics are known. Its main ideas are as follows. First of all, set the number of adjacent sample points, generally recorded as *k*. Then, find *k* adjacent points closest to the sample points of the unknown class. And every of the *k* adjacent points has its own category. Finally, the category with the most adjacent points is taken as the category of the sample point.

KNN method is a classical classification method, which is widely used in many research fields and has been improved. In reference [21], KNN was improved as a semi-supervised feature selection method to uncertainty measure, which performs excellent performance. In reference [22], KNN was used as supervised machine learning method. In reference [23], KNN was used to similarity search over the encrypted datasets, and achieved good experimental results. KNN is a superior classification method, but it is very difficult to work with larger datasets. Because the time complexity of KNN method will increase as the dataset becomes larger. At the same time, the accuracy of KNN method is very poor for densely distributed data.

3 Cloud Model-based Prediction Method

In reality, the characteristics of many sample data are not obvious, which can make their classification fuzzy and difficult to be accurate. The classification and prediction of the growth of smaller seed bulbs in flower cultivation are also facing the same trouble. Many growth regulators can affect the development of smaller flower seed bulbs and make their growth characteristics different, but these differences are not significant. In the cultivation of smaller flower seed bulbs, more accurate data analysis and prediction techniques are needed to achieve more satisfactory and more controllable cultivation results.

Therefore, this paper combines the advantages of KNN and Kmeans methods, and replaces the distance with cloud model and degree of certainty of cloud drop, and then proposes a cloud model-based prediction method for scientific cultivation with small flower seed bulbs. The main idea of this method is as follows.

First of all, set the value of k according to the different types of growth regulators, that is, set the number of categories as much as the types of growth regulators commonly used in the cultivation of a certain variety flower. Then, the sample data on main growth characteristics under the influence of different growth regulators are trained to obtain their best cloud model to classify. The degree of certainty of phenotypic samples on the its cloud model takes the place of the in-class distance in the conventional methods to achieve sample classification. Finally, the required growth regulators are predicted according to the classification results of samples. Because the response of the smaller seed bulbs to different growth regulators is not significant, there is more than one choice of growth regulators for the same culture target. Therefore, we finally choose two best classification results instead of the one.

The cloud model of nth growth characteristic on kth class is defined as $C_k^n\,(Ex_k^n, En_k^n, He_k^n)$. The characteristic sample sequence is represented by X, and the sample value of nth characteristic is represented by x_n, as shown in Formula 1. At the same time, there are the two conditions, including $x_n \sim N\,(Ex_k^n, {\sigma_k^n}^2)$ and $\sigma_k^n \sim N\,(En_k^n, {He_k^n}^2)$. Here, N represents normal distribution, and its two parameters represent expectation and variance respectively. And the relationship between the sample and its degree of certainty on the characteristic cloud model is shown in Formula 2, where NORMAL is a normal function, and $u_{x_n}^k$ is the degree of certainty of the sample x_n on the nth characteristic cloud model under the influence of the kth growth regulator, and so *f* represents the corresponding relationship between x_n and $u_{x_n}^k$.

$$X = \{x_1, x_2, ..., x_n\}. \tag{1}$$

$$f(x_n, u_{x_n}^k) = NORMAL(Ex_k^n, NORMAL(En_k^n, He_k^{n^2})). \quad \textbf{(2)}$$

If the sample value belongs to kth category, its degree of certainty is calculated as Formula 3.

$$u_{x_n}^k = \exp(-(x_n - Ex_k^n)^2 / (2 \times \sigma_k^n)^2). \quad \textbf{(3)}$$

If the number of growth characteristics is expressed in s and the weight of each characteristic is expressed with Δ, the weight of the nth characteristic is Δ_n. And the sum of all weights is one, see Formula (4).

$$\sum_{n=1}^{s} \Delta_n = 1. \quad \textbf{(4)}$$

The final degree of certainty of sample X can be got with Formula (5).

$$\mu(X)^k = \sum_{n=1}^{s} (u_{x_n}^k \times \Delta_n). \quad \textbf{(5)}$$

Finally, the two classes corresponding to the maximum degrees of certainty are recommended. And in the two categories, the degree of certainty of the sample is more than 50%, and the degree of certainty of all features is not 0. Therefore, we can finally obtain two growth regulators that are the cultivation methods with great promise to achieve the flower growth goals.

4 Experiment and Analysis

4.1 The Experimental Process

In the experiment, the cultivation data of 440 lily bulbs with 5-8 cm under the influence of SA or ACC at different concentrations were taken. And the growth characteristics included plant height, leaf length, internode length, stem diameter, and leaf number. Take 440 data to train the characteristic cloud models, and take 40 data for prediction. Four growth regulators were used in the cultivation experiment, including SA of 0.2mg/L, SA of 0.5mg/L, ACC of 20μmol/L and ACC of 50μmol/L. So, set the value of k to 4. Train the growth characteristic samples under the influence of each type of growth regulator to obtain the corresponding growth characteristic cloud models. The three parameters of each characteristic cloud model under different growth regulators are shown in Table 1.

Table 1. The three parameters of each characteristic cloud model

Growth regulator	Growth characteristics and its cloud model parameters				
	Plant height	Leaf length	Internode length	Stem diameter	Leaf number
SA 0.2mg/L	(21.21,0.6,0.02)	(10.6,0.47,0.02)	(2.01,0.13,0.02)	(0.5,0.05,0.01)	(28.59,0.51,0.02)
SA 0.5mg/L	(22.35,1.21,0.02)	(10.35,0.6,0.02)	(2.27,0.1,0.02)	(0.45,0.05,0.01)	(26.73,1.97,0.02)
ACC 20μmol/L	(21.33,1.55,0.02)	(11.44,0.83,0.02)	(1.74,0.1,0.02)	(0.48,0.03,0.01)	(28,1.62,0.02)
ACC 50μmol/L	(22.45,1.23,0.02)	(11.27,0.91,0.02)	(2.15,0.12,0.02)	(0.45,0.05,0.01)	(27.94,3.71,0.02)

Under the influence of different growth regulators, the experimental diagrams of cloud models of growth characteristics are shown below. Four kinds of growth regulators are used in the experiment, so there are four groups of figures on growth characteristic cloud models. See Fig. 1 to Fig. 4.

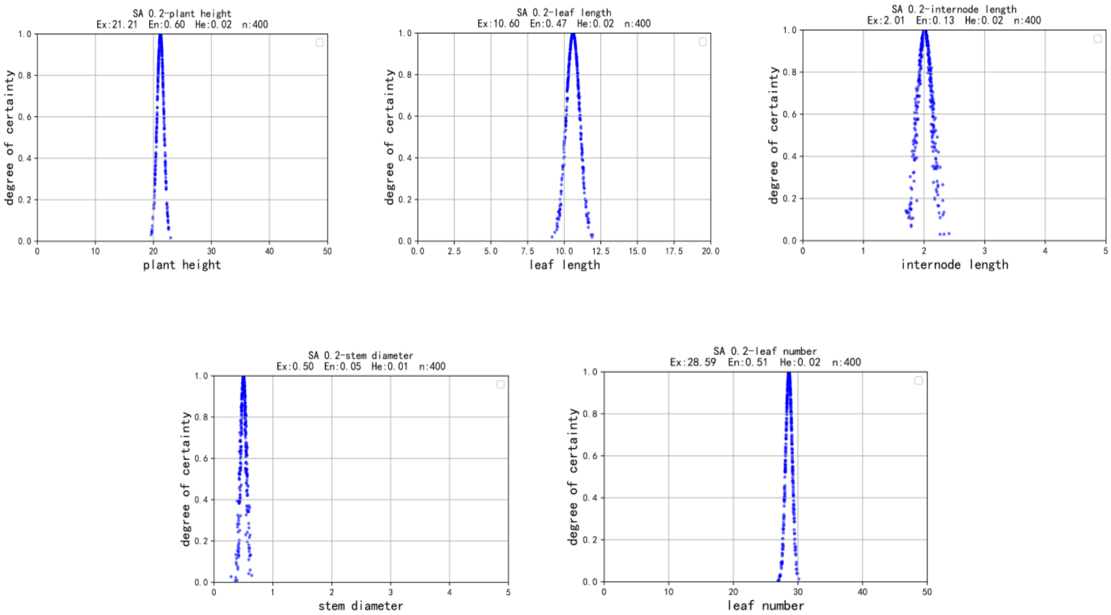

Fig. 1. Each characteristic cloud model figure under SA of 0.2mg/L

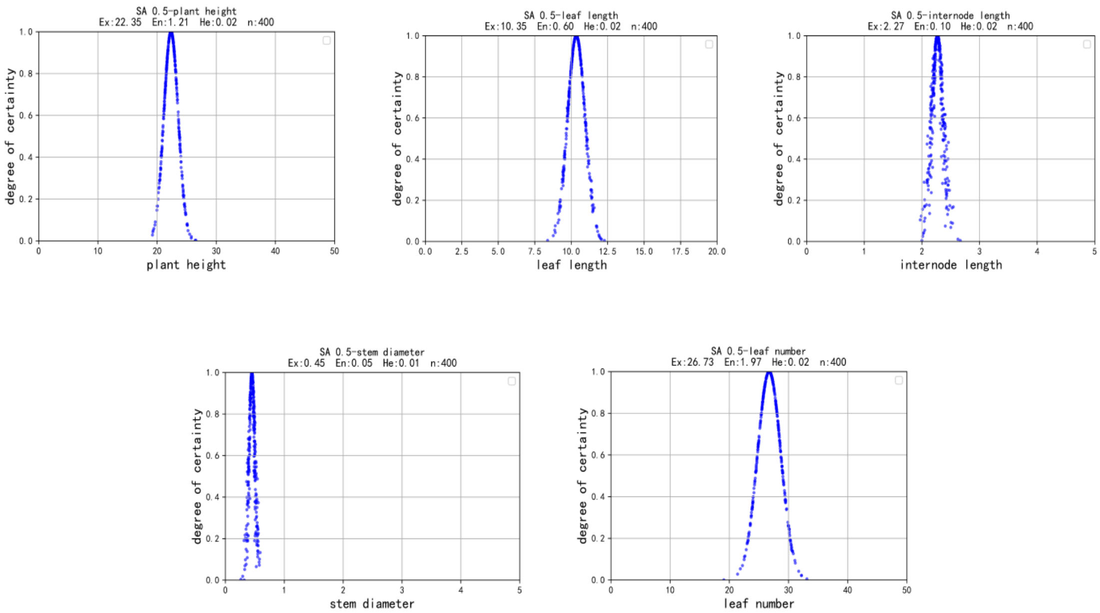

Fig. 2. Each characteristic cloud model figure under SA of 0.5mg/L

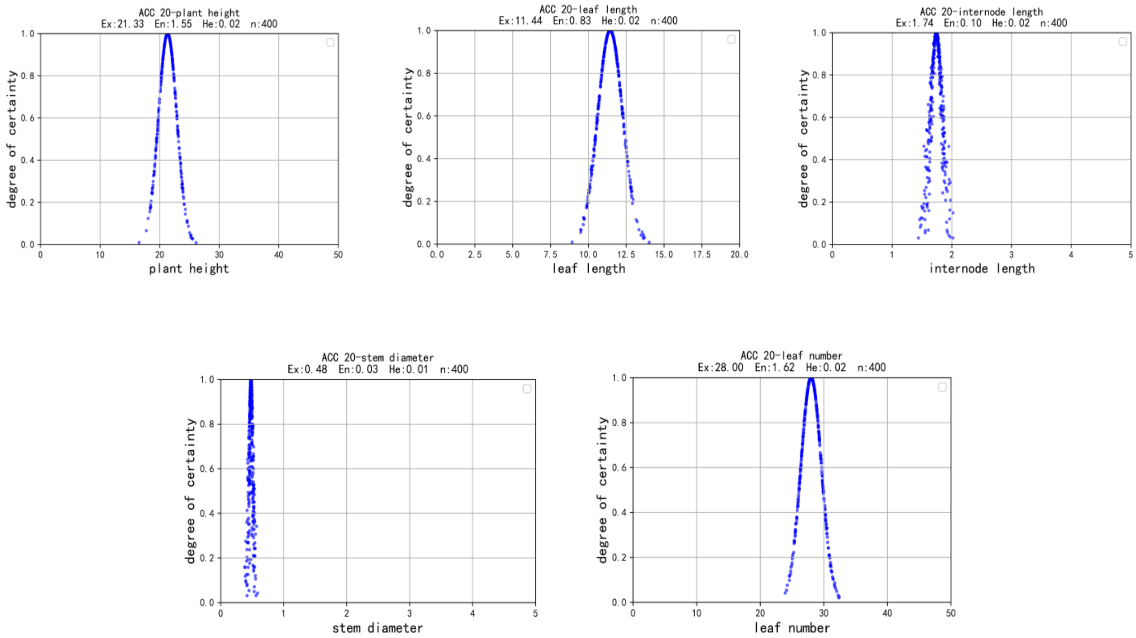

Fig. 3. Each characteristic cloud model figure under ACC of 20μmol/L

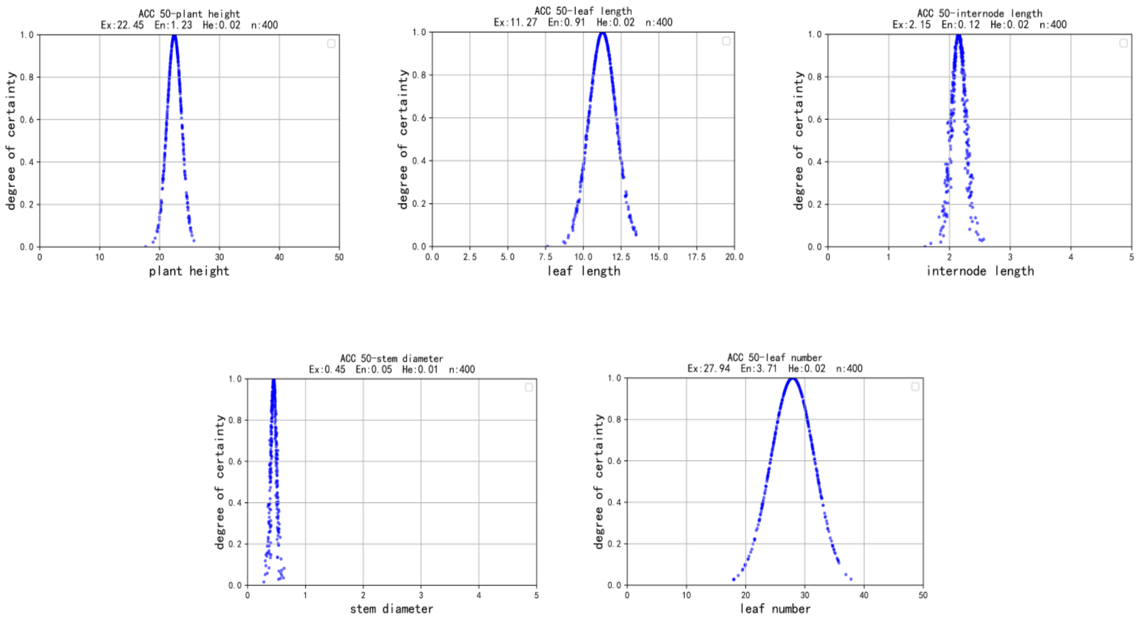

Fig. 4. Each characteristic cloud model figure under ACC of 50μmol/L

From the above four groups of figures, it can be seen that the growth characteristics of smaller flower seed bulbs cannot be changed very significantly by growth regulators.

In the experiment, weights were set according to the sensitivity of growth characteristics to four growth regulators. And the weights of five growth characteristics are shown in Table 2.

Table 2. The weights of five growth characteristics

Growth characteristics	Plant height	Leaf length	Internode length	Stem diameter	Leaf number
Weights	0.3	0.3	0.25	0.05	0.1

Next, take ten smaller lily seed bulbs as an example, and the calculation process and prediction results of the method are as follows. The data of ten samples are shown in Table 3.

Table 3. The growth parameters of ten smaller lily seed bulbs

Sample No	Plant height	Leaf length	Internode length	Stem diameter	Leaf number	Growth regulator used
1	21.2	10.8	2.1	0.45	28	SA of 0.2mg/L
2	20.63	9.8	1.9	0.5	28	SA of 0.2mg/L
3	21.71	11.1	2.1	0.5	29	SA of 0.2mg/L
4	23	10.8	2.2	0.5	28	SA of 0.5mg/L
5	20.3	10.4	2.1	0.45	26	SA of 0.5mg/L
6	20.8	12.4	1.9	0.4	27	ACC of 20μmol/L
7	22.3	11.2	1.8	0.5	29	ACC of 20μmol/L
8	23.6	12.3	2.3	0.5	26	ACC of 50μmol/L
9	21.1	11.5	2.2	0.45	32	ACC of 50μmol/L
10	20.2	10.6	2	0.45	30	ACC of 50μmol/L

First, respectively calculate the degree of certainty of every feature sample on the corresponding feature cloud models. Under the four characteristic cloud models on plant height, the degree of certainties of plant height in the above samples are shown in Table 4.

Table 4. The degree of certainties of plant height in the above samples

Cloud model	Plant height and its degree of certainty on characteristic cloud models									
	21.2	20.63	21.71	23	20.3	20.8	22.3	23.6	21.1	20.2
(21.21,0.6,0.02)	0.9999	0.6311	0.7103	0.0125	0.3220	0.7945	0.1968	0.0004	0.9836	0.2476
(22.35,1.21,0.02)	0.6387	0.3668	0.8704	0.8666	0.2406	0.4429	0.9992	0.5888	0.5888	0.2087
(21.33,1.55,0.02)	0.9965	0.9036	0.9706	0.5615	0.8029	0.9435	0.8231	0.3443	0.9891	0.7678
(22.45,1.23,0.02)	0.5989	0.3373	0.8356	0.9055	0.2195	0.4093	0.9926	0.6480	0.5499	0.1900

Under the four characteristic cloud models on leaf length, the degree of certainties of leaf length in Table 3 are shown in Table 5.

Table 5. The degree of certainties of leaf length in ten samples

Cloud model	Leaf length and its degree of certainty on characteristic cloud models									
	10.8	9.8	11.1	10.8	10.4	12.4	11.2	12.3	11.5	10.6
(10.6,0.47,0.02)	0.9150	0.2414	0.5740	0.9150	0.9150	0.0007	0.4496	0.0016	0.1655	1.0000
(10.35,0.6,0.02)	0.7580	0.6611	0.4632	0.7580	0.9966	0.0032	0.3721	0.0055	0.1637	0.9180
(11.44,0.83,0.02)	0.7452	0.1450	0.9203	0.7452	0.4600	0.5160	0.9595	0.5880	0.9974	0.6025
(11.27,0.91,0.02)	0.8763	0.2747	0.9829	0.8763	0.6360	0.4661	0.9971	0.5303	0.9689	0.7646

Under the four characteristic cloud models on internode length, the degree of certainties of internode length in Table 3 are shown in Table 6.

Table 6. The degree of certainties of internode length in ten samples

Cloud model	Internode length and its degree of certainty on characteristic cloud models									
	2.1	1.9	2.1	2.2	2.1	1.9	1.8	2.3	2.2	2
(2.01,0.13,0.02)	0.7994	0.7157	0.7994	0.3686	0.7994	0.7157	0.2955	0.0978	0.3686	0.9972
(2.27,0.1,0.02)	0.2662	0.0019	0.2662	0.7990	0.2662	0.0019	0.0000	0.9596	0.7990	0.0355
(1.74,0.1,0.02)	0.0026	0.3096	0.0026	0.0000	0.0026	0.3096	0.8480	0.0000	0.0000	0.0452
(2.15,0.12,0.02)	0.9225	0.1331	0.9225	0.9225	0.9225	0.1331	0.0192	0.4839	0.9225	0.4839

Under the four characteristic cloud models on stem diameter, the degree of certainties of stem diameter in Table 3 are shown in Table 7.

Table 7. The degree of certainties of stem diameter in ten samples

Cloud model	Stem diameter and its degree of certainty on characteristic cloud models									
	0.45	0.5	0.5	0.5	0.45	0.4	0.5	0.5	0.45	0.45
(0.5,0.05,0.01)	0.6326	1.0	1.0	1.0	0.6326	0.1601	1.0	1.0	0.6326	0.6326
(0.45,0.05,0.01)	1.0	0.6326	0.6326	0.6326	1.0	0.6326	0.6326	0.6326	1.0	1.0
(0.48,0.03,0.01)	0.6487	0.8250	0.8250	0.8250	0.6487	0.0461	0.8250	0.8250	0.6487	0.6487
(0.45,0.05,0.01)	1.0	0.6326	0.6326	0.6326	1.0	0.6326	0.6326	0.6326	1.0	1.0

Under the four characteristic cloud models on leaf number, the degree of certainties of leaf number in Table 3 are shown in Table 8.

Table 8. The degree of certainties of leaf number in ten samples

Cloud model	Leaf number and its degree of certainty on characteristic cloud models									
	28	28	29	28	26	27	29	26	32	30
(28.59,0.51,0.02)	0.5181	0.5181	0.7279	0.5181	0.0000	0.0084	0.7279	0.0000	0.0000	0.0234
(26.73,1.97,0.02)	0.8131	0.8131	0.5164	0.8131	0.9340	0.9907	0.5164	0.9339	0.0284	0.2538
(28,1.62,0.02)	1.0	1.0	0.8274	1.0	0.4687	0.8274	0.8274	0.4687	0.0482	0.4687
(27.94,3.71,0.02)	0.9999	0.9999	0.9601	0.9999	0.8725	0.9685	0.9601	0.8725	0.5503	0.8575

Furthermore, the degree of certainty of the sample data on different growth regulator was calculated by weighting. This degree of certainty can represent the possibility of using a certain type of growth regulator in the sample. Take No. 1 sample as an example. After weighted calculation, the possibility of using growth regulator in No. 1 sample is shown in Table 9.

Table 9. The final determination of sample No. 1

Growth regulator	Sample No. 1					Possibility
	21.2	10.8	2.1	0.45	28	
SA 0.2mg/L	0.9999	0.915	0.7994	0.6326	0.5181	0.85776
SA 0.5mg/L	0.6387	0.758	0.2662	1	0.8131	0.61687
ACC 20μmol/L	0.9965	0.7452	0.0026	0.6487	1	0.65560
ACC 50μmol/L	0.5989	0.8763	0.9225	1	0.9999	0.82318

Finally, the two corresponding cloud models with the highest degree are taken as the final prediction results. The prediction results are shown in Table 10.

Table 10. The prediction results of ten samples

Sample No	Used actually	1st prediction	2nd prediction
1	SA of 0.2mg/L	SA of 0.2mg/L	ACC of 50μmol/L
2	SA of 0.2mg/L	SA of 0.2mg/L	ACC of 20μmol/L
3	SA of 0.2mg/L	ACC of 50μmol/L	SA of 0.2mg/L
4	SA of 0.5mg/L	SA of 0.5mg/L	ACC of 50μmol/L
5	SA of 0.5mg/L	ACC of 50μmol/L	SA of 0.5mg/L
6	ACC of 20μmol/L	ACC of 20μmol/L	NULL
7	ACC of 20μmol/L	ACC of 20μmol/L	ACC of 50μmol/L
8	ACC of 50μmol/L	ACC of 50μmol/L	SA of 0.2mg/L
9	ACC of 50μmol/L	ACC of 50μmol/L	ACC of 20μmol/L
10	ACC of 50μmol/L	SA of 0.2mg/L	ACC of 50μmol/L

4.2 Comparative Analysis

The smaller flower bulbs are insensitive to four growth regulators. After using four growth regulators, their growth characteristics are changed in a similar range. However, the algorithm can accurately predict the growth regulator used according to the small changes in the growth characteristics. In the experiment, the growth regulators used in 40 groups of samples were all correctly predicted.

Relatively, if the category characteristics of 400 samples are ignored, the Kmeans method is used to cluster these samples. In the experiment, the value of k is still set to 4, its prediction rate for these samples is less than 50% because of the small diversity of samples and the dense data distribution.

Finally, the KNN method was used to predict on these datasets. In the experiment, repeatedly setting the value of k, it is found that when the value of k is bigger than 3, the value is bigger, the prediction rate is lower. Therefore, the experimental value of k is 3. On these densely distributed datasets, the prediction rate of the KNN method is 58%.

As a result, the method proposed in this paper can classify data with small differences more accurately. And it can meet the needs of scientific cultivation of smaller flower seed bulbs.

5 Conclusion

The growth of flowers is affected by the objective environment, which makes them strong randomness, and constrained by the nature of the seed bulbs. Their growth has unique regularity that also has a certain ambiguity. Even it is impossible for the same variety of seed bulbs to have the complete same growth characteristics. In the same environment, the growth parameters of the same kind of seed bulbs are basically normal distribution. And the normal cloud model can well describe the coexistence of fuzzy and random phenomena in nature. So, the normal cloud model is used to describe the distribution law of growth parameters of flower bulbs.

In the cultivation of flower bulbs, the response of different size seed bulbs to growth regulators is different, and the response of bigger is often significant, while the response of smaller is not significant. In order to better guide the scientific cultivation experience, this paper improved the method of inner-class distance calculation with cloud model, and proposes a cloud model-based prediction method combined with the advantages of KNN and Kmeans methods, which can predict the kind of growth regulator that meet the needs of smaller seed bulbs cultivation. The main idea of this method is as follows.

Define the growth feature cloud model, replace the intra-class distance calculation with the degree of certainty of the growth parameters on its cloud model, set the feature weight according to the sensitivity of the growth feature to the growth regulator in smaller seed bulbs cultivation, and finally complete the classification prediction by calculating the degree of certainty of all the feature values by weighting.

Finally, the experiment of smaller lily bulbs cultivation proves that this method can solve the problem of inaccurate classification of samples with insignificant differences by the conventional methods and can better control the scientific cultivation of smaller seed bulbs. In the future, we will expand the number and variety of experimental samples and further adjust the model parameters to make it more universal and more accurate.

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