Retraction Notice

The Editor-in-Chief and the publisher have retracted this article, which was submitted as part of a guest-edited special section. An investigation uncovered evidence of systematic manipulation of the publication process, including compromised peer review. The Editor and publisher no longer have confidence in the results and conclusions of the article.

YL either did not respond directly or could not be reached.

Field weed recognition algorithm based on machine learning

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Abstract. Currently, large-scale spraying of herbicides pollutes the environment, destroys the quality of cultivated land, and increases the cost of agricultural production. For this reason, "precision farming," in which machine learning technology is used to detect weeds in crops and soil and then herbicides are sprayed at specific locations according to the distribution of weeds, is proposed. Machine learning is a multidisciplinary interdisciplinary major, covering knowledge of probability theory, statistics, approximate theory and complex algorithms. Machine learning uses computers as tools and is committed to simulating human learning methods in real time, and divides existing content into knowledge structures to effectively improve learning efficiency. We aim to use machine learning technology to study weed detection algorithms and provide feasible solutions for accurate weed classification and variable spraying of herbicides. Based on the research of four kinds of germinated corn and wheat weeds by Chinese and foreign experts, we use machine learning technology as the method of extracting and recognizing the combination of color features, shape features, and texture features. Plant development and software are used to process weeds to classify and identify wheat and corn. To better describe the gray distribution of each pixel and neighboring pixels, a more effective weed image classification function is required. The experimental results of this paper show that the machine learning-based weed image recognition classifier can describe the grayscale distribution of each pixel and adjacent pixels well, and it is beneficial to identify the characteristics of weeds, in which the correct rate of weed recognition exceeds 97.5%. *© 2022 SPIE and IS&T* [DOI: 10.1117/1.JEI.31.5.051413]

Keywords: machine learning; weed recognition; algorithm optimization; location feature.

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1 Introduction

The problem of farmland weeds is one of the most common biological disasters in agricultural production. If they cannot be effectively controlled, they will negatively impact agricultural production. Compared with most crops, weeds have the characteristics of developed root systems, fast reproduction speed, and strong absorption capacity. Under the same environmental conditions, farmland weeds tend to have certain advantages when competing with crops for water, light, soil nutrients, and growth space.

Currently, China still adopts the traditional method of spraying herbicides on a large area in a rough way to control weeds. Because chemical weeding has advantages in crop protection, economic cost, weeding efficiency, effective time, etc., replacing chemical weeding with other weed control methods is difficult in the short term. Chemical weeding is achieved according to different "differences" of herbicides, plant height and root depth formed due to "time differences" when seeds germinate, as well as plant tissue structure, growth morphology, and resistance characteristics between different species of plants. Therefore, how to quickly and accurately identify the weeds hidden in the "rows" of crops and how to accurately obtain the distribution information of weeds are the key links of variable spraying technology. The most efficient use of

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spraying technology can only be achieved by locating weeds quickly and accurately. Different herbicides can be sprayed for different weed systems to remove weeds in different areas and maximize the effect of variable spraying technology. This topic combines the actual farmland work scene and the farmland weed recognition method based on image processing technology to accurately, quickly, and intelligently detect and identify the field weed distribution information.

Shen et al. believed that weeding has always been a problem and used computer image processing technology to identify field weeds in a complex soil background. At the same time, the actual position of the weed was determined by the pixel position in the middle of the projection of the weed, but the actual efficiency was not high, and it is inconvenient to operate.[1] Zhao and Liu believed that traditional weed detection methods require manual design and feature extraction, that the process is complicated, and that the detection rate is low. For these reasons, they proposed a weed detection method based on convergent neural network. But the distinction between weeds and crops, which needs to be improved, was not considered.[2] Zhu et al. obtained remote sensing images of low-altitude rice fields and analyzing weed distribution maps to obtain reports on the exact application of weeds in the field. However, this experiment has no concrete practical experience and is not convincing.[3]

The innovation of this article lies in (1) using machine learning to identify weeds in the field, in which a method for locating the harvest nuclei based on harvest location features, that is, supersegmented block projection, is proposed. The spray blocks between the holes are identified, and pixel statistics and differentiation are conducted on each block to perform weed detection between the holes. (2) The detection algorithm estimates that the real-time detection accuracy of weeds is above 87.7%, and the fast and efficient identification algorithm is implemented on the DSP hardware platform to collect the distribution information of the field weeds to control the spraying device. The application of pesticides was guided, and a new development in field weed recognition technology in the embedded field was explored. (3) By comparing traditional weed identification and machine learning weed identification, this paper found that machine learning weed identification can more quickly and accurately locate and identify the location of field weeds, and the recognition rate reaches 97.5%, which greatly improves the efficiency of weed identification and removal.

2 Research Method of Field Weed Recognition Algorithm Based on Machine Learning

2.1 *Machine Learning*

Machine learning, known as ML, is an important topic in the field of modern advanced technology research, which includes a variety of subjects such as probability theory, statistics, similarity theory, algorithm analysis, and program framework theory.[4,5] Machine learning is the study of how machines imitate human actions by learning autonomously, learning new skills, and continuously improving the functions. It is the main component of artificial intelligence and the most important method for realizing machine autonomy. Machine learning has applications in many fields. According to its learning strategy, it is mainly used in big data analysis, big data mining, search engine, computer vision (CV), information system recommendation, financial risk analysis, medical diagnosis and so on. According to the learning method, it can be mainly divided into the induction method and the analogy method.[6,7]

2.2 *Necessity of Field Weed Identification*

2.2.1 *Harm of agricultural weeds*

Farmland weeds are grass plants that grow in the field, threaten crops, and are not planted deliberately.[8,9] They have survived long-term adaptation to local crops, agriculture, climate, soil, and other ecological conditions and factors. They are the most common plant in the natural environment.[10,11] Agricultural weeds have caused huge losses to agricultural production. Because of their special and tenacious biological properties, weeds have a particularly strong adaptability to the environment. Therefore, if weeds grow together with crops in the field, they will surely rob the crops of light and water for growth, so that crops often die due to lack of nutrients. The main risks of weeds are as follows:

(1) They compete with plants for water, nutrients, light, and space. Many weeds have strong root absorption capacity, rapid growth in the seedling stage, and high photosynthetic yield, and they can quickly reproduce, enabling significant plant growth. They have special characteristics that affect plants, and they absorb nutrients and light better than cultivated plants, thereby affecting the growth and development of cultivated plants.[12,13] Because weeds spread in many ways, having strong reproduction and regeneration, their life cycle is generally shorter than crops, with mature seeds ripening quickly; they have strong resistance and photosynthesis efficiency, so they can absorb nutrients and light.

(2) Weeds spread parasites and diseases. Many weeds are intermediate hosts for pathogen cultures, viruses, or parasites. They can spread diseases and insect pests and endanger the growth of plants.[14,15] For instance, thistle and badger are both carriers of dwarf shrub disease. Mosaic disease of many crops, vegetables, and fruit trees can be spread through weed propagation.[16,17]

(3) Weeds reduce crop yield and quality. Because weeds directly or indirectly damage plants in terms of water, nutrients, space, and the spread of pests and diseases, they ultimately affect crop yield and quality.[17,18]

2.2.2 *Ways of weeding in agriculture*

In view of the large number of weeds, it can be assumed that weed removal requires a lot of human and material investment.[19,20] Current weed control methods mainly include artificial weeds, mechanical weeds, chemical weeds, organic weeds, and physical weeds. Chemical weeds have the characteristics of being high yield, timely, labor saving, economical, etc.; they adapt to modern agricultural production activities, and promote the use of agricultural methods.[21,22] In recent years, the use of herbicides in China has increased rapidly. Chemical weeds will be an irreplaceable important weed control measure for a long time. Therefore, chemical weeding has become a very realistic problem in reducing weed hazards, reducing pollution, freeing up labor for weeds, improving weed identification, and realizing weed control automation and research.[23,24]

2.3 *Recognition Image Texture Feature Extraction*

The texture function is a visual function that does not depend on color or brightness and can reflect the uniformity of an image. It is an inherent feature of the surface of all objects and can be used as the basis for identifying these objects.[25] Different weeds and plants have different texture characteristics. For example, n species of grass have parallel veins, and the branches of weeds are similar to these texture. Parallel veins are veins unique to monocotyledons. The veins are generally arranged in parallel in the leaves, while the lateral veins are almost perpendicular to the midrib. Texture features can better describe the gray distribution of each pixel and neighboring pixels and should be an effective classification feature for weed images.[26,27]

The gray coexistence table is the statistical result of two pixels. Two pixels keep a certain distance in the image, and each pixel has a certain gray scale. In other words, the gray scale coexistence table $(\Delta m, \Delta n)$ represents the frequency distribution of the joint appearance of pairs of pixels with positions that are separated and gray values that are denoted as m and n, respectively. This is expressed by Q_r as

$$Q_r(m, n), (m = 0,1, \cdots, H-1; n = 0,1, \cdots, H-1), \tag{1}$$

where m and n are the gray levels of two pixels. The gray level of an image is the positional relationship between the two pixels, and the difference determines the distance and direction between the two pixels. When selecting the positional relationship between two pixels, a specific symbiosis shape ruler gray level is created:

$$Q_\gamma = \begin{bmatrix} Q_\gamma(0,0) & \cdots & Q_\gamma(0,n) & \cdots & Q_\gamma(0,H-1) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ Q_\gamma(m,0) & & Q_\gamma(m,n) & \cdots & Q_\gamma(m,H-1) \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ Q_\gamma(H-1,0) & \cdots & Q_\gamma(H-1,n) & \cdots & Q_\gamma(H-1,H-1) \end{bmatrix}. \tag{2}$$

In the field of image processing, image segmentation is basic and essential content for low vision, which is the basic requirement of visual image analysis and pattern recognition. At the same time, this is also a classic problem. So far there is no effective solution. For general image segmentation methods, there is no objective standard to evaluate whether the segmentation is successful.[28] Image segmentation algorithms are usually based on the discontinuity and similarity of one of the two features of the brightness value. Image segmentation is a technique and process of dividing an image into several specific areas with unique properties and proposing a target of interest. It is a key step between image processing and image analysis. From a mathematical perspective, image segmentation is the process of dividing digital images into disjoint regions. The process of image segmentation is also a labeling process, in which pixels belonging to the same region are assigned the same number.

Equations 3 to 7 explain several specific regions and objects of interest with unique properties in image processing. Angle second moment:

$$\mathrm{ASM} = \sum_m \sum_n q(m,n)^2. \tag{3}$$

Contrast:

$$\mathrm{CON} = \sum_m \sum_n (m-n)^2 q(m,n)^2. \tag{4}$$

Entropy:

$$\mathrm{ENT} = -\sum_m \sum_n q(m,n) \log_{10} q(m,n). \tag{5}$$

Correlation:

$$\mathrm{COR} = \frac{\sum_m \sum_n mn \cdot q(m,n) - I_m I_n}{\chi_m \chi_n}. \tag{6}$$

Moment of deficit:

$$ID = \sum_m \sum_n [1/(1+(m-n)^2)] \cdot q(m,n). \tag{7}$$

The table of gray-scale images appearing at the same time indicates that when the grayscale image table gives comprehensive information such as the grayscale image change direction, adjacent spacing, width, etc. It is the basis for analyzing local model structure and accounting rules.[29] In this paper, four second-order digitalangular distance parameters, contrast, entropy, correlation, and antigap are extracted from the gray matrix as the number of features for weed texture analysis.

2.4 *Support Vector Machine Algorithm*

The basic idea of support vector machine (SVM) can be summarized as follows: first the input space is transformed into high-dimensional space through nonlinear transformation and then the best linear classification surface in the new linear space transformation is found. Support vector machines are a class of generalized linear classifiers that perform binary classification of data in a supervised learning manner. The input space can be either a finite set space or the entire Eucoid space. This is achieved by defining appropriate kernel functions.

Through linear separation, SVM is developed from the best sorting area. The principle is as follows: assuming that the linearly separable sample set is a category label, it is separated by the following classification layer:

$$e \cdot c - a = 0. \tag{8}$$

The optimal classification surface can be regarded as the following constrained optimization problem, that is calculated as

$$\phi(e) = 1/2 \cdot \|e\|^2 = \frac{1}{2}(e \bullet e). \tag{9}$$

To this end, the Lagrange function is defined as

$$L(e, a, p) = \frac{1}{2}(e \bullet e) - \sum_{i=1}^{n} \beta_j \{u_j[(e \bullet c_j) + a] - 1\}. \tag{10}$$

Among them, $p_j > 0$ is the Lagrange coefficient. Our problem is finding the minimum value of the Lagrange function for e and a. The optimal classification function obtained after the solution is

$$g(x) = \mathrm{sgn}\{(e \bullet x_j) + a\} = \mathrm{sgn}\left\{\sum_{i=1}^{n} \beta_j u_j (x_j \bullet x) + a^*\right\}. \tag{11}$$

In the equation, sgn is the symbolic function, and a^* is the closed value of classification, which can be obtained by any support vector.[30]

If in the case of inseparable linearity, a relaxation term $\psi_j \geq 0$ is added to the constraint condition, which becomes

$$u_j[(e \bullet x_i) + a] - 1 + \psi_j \geq 0. \tag{12}$$

The optimization goal becomes the smallest $\phi(e, \psi) = \frac{1}{2}\|e \bullet e\| + C[\sum_{i=1}^{n} \psi_j]$, where C is a constant that controls the degree of punishment for the wrong sample.

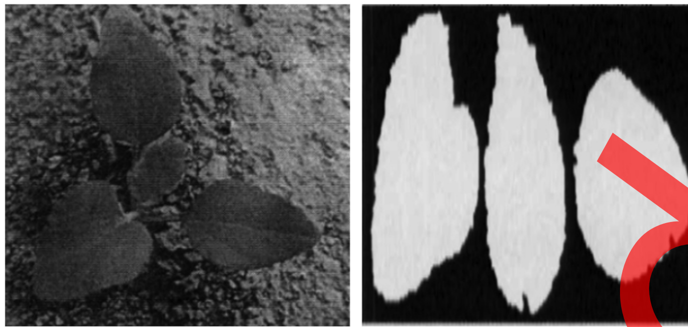
3 Field Weed Recognition Algorithm Based on Machine Learning

3.1 *Extraction and Analysis of Field Weed Shape Characteristic Parameters*

This article considers the selection of two simple regional shape characteristic parameters and circularity, elongation, dispersion, and roundness for the five plants of maize, dentate, reverse branch, cedar, and crabgrass. Four shape characteristic parameters with invariance are used to calculate the shape characteristic parameters of the above plants. The reason for studying these five plants is to facilitate the identification of different plants with similar characteristics and make the results more convincing.

Taking into account the complex background of the soil environment and the overlap of plant leaves, it is difficult to calculate the shape characteristic parameters of a single leaf. Therefore, this paper uses image tools to intercept individual leaves in the plant binarized image, superimpose the intercepted single leaf region images to mark the region, and calculate the shape feature parameters. The results are shown in Fig. 1(a) for an image of a single weed Xanthium, and three images of Xanthium monocotyledon are shown in Fig. 2(b).

Plants have various growth characteristics. For example, even if the day lily of the same weed has different growing seasons or planting areas, its leaf shape will change, making it difficult to extract the characteristic parameters of the leaf shape. This paper studies the selection of mesophytic weeds to analyze and suppress three monocots in each sample of each plant type to



(a) Image of a single Xanthium (b) Binary image of a single leaf

Fig. 1 Shape feature extraction and analysis image. (a) Image of a single Xanthium, and (b) binary image of a single leaf.

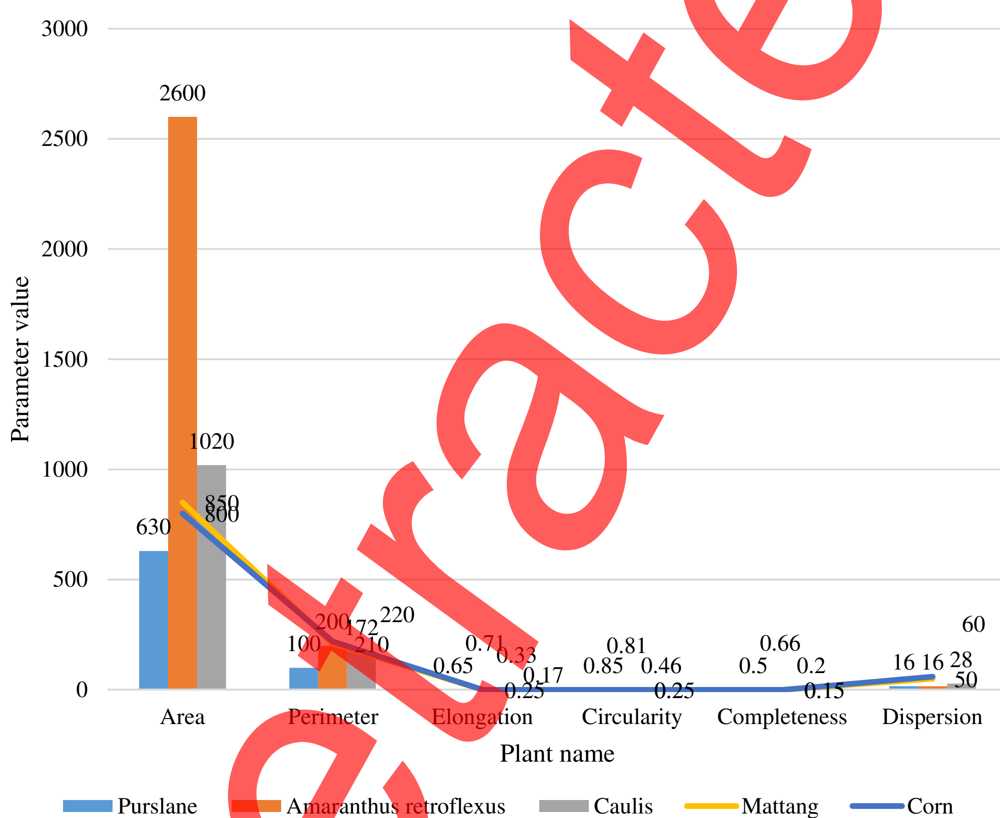


Fig. 2 Plant leaf shape characteristic parameter data.

calculate characteristic leaf parameters. Because leaf shape varies with different growing seasons or planting areas, it is difficult to extract leaf shape characteristic parameters, and it is easier to calculate characteristic leaf parameters by suppressing three monocots. Since roundness is a constant shape characteristic parameter, it is not sensitive to changes in blade ratio. Therefore, in this paper, the characteristic shape parameter of the three leaves of each plant with roundness that is an intermediate value is defined as its characteristic data. The characteristic data of various types of plants are the average value of the corresponding characteristic parameters of this type of plants. The statistical data results are shown in Table 1 and Fig. 2.

The data in Figure 2 is explained by the eigenvalues of different plants. The larger the eigenvalue, the better the recognition effect. As shown in Fig. 2, the characteristic values of different plants vary, with Amaranthus retroflexus having the largest area of 2600, followed by Caulis with 1020, and Purslane minimum 630.

Table 1 Plant leaf shape characteristic parameter data.

Plant name	Purslane	Amaranthus retroflexus	Caulis	Mattang	Corn
Area	630	2600	1020	850	800
Perimeter	100	200	172	210	220
Elongation	0.65	0.71	0.33	0.25	0.17
Circularity	0.85	0.81	0.46	0.25	0.20
Completeness	0.50	0.66	0.20	0.15	0.15
Dispersion	16	16	28	50	60

From the data in the table, it can be seen that the five types of plants all show certain differences in these characteristic parameters, so these characteristic parameters can be used to effectively identify them. Taking into account the different growth periods of plants, the area, perimeter, and other characteristic parameters of plants change differently. Single or multiple dimensionless shape characteristic parameters can be used to identify them. In this paper, the width–length ratio, fullness, and circularity are selected as the feature parameter set. The feature data of wheat is obviously different from that of the four weeds. Among the four weeds, the circularity of the four weeds is dependent on the circularity of spur and antibranch. The roundness of the branch line and the anti-branch line is relatively close, and the distribution range of the remaining feature quantities is relatively clear, making it an effective identification parameter.

Preprocessing, background segmentation, mathematical morphology, and other processing for each type of plant are performed, and the dimensional parameters are calculated. To ensure that the recognition result is not affected by image acquisition hardware equipment and human factors, the nondimensional feature parameters of each type of plant are extracted for comparison analysis, and the results are shown in Table 2 and Fig. 3:

It can be seen from Figure 3 that the width-to-length ratio of the anti-branch is relatively large, ranging from 0.4 to 0.8; the length-to-width ratio of corn seedlings is in the middle, ranging from 0.1 to 0.4; the width-to-length ratio of *P. edulis* is the smallest, below 0.1. Individual sample values for maize and anti-branching are more similar. Therefore, the three plants can be separated using the aspect ratio.

A comparison of the circularity of the three plants is shown in Fig. 4.

From the data in the figure, we can see that the circularity values of dicot amaranth are mainly around 0.6, and the circularity values of corn seedlings and monocotyledonous barnyardgrass are in the range of 0.2 to 0.3 and overlap each other. Therefore, the circularity C is used. Only dicot amaranth can be separated from corn and barnyard grass.

Table 2 The ratio of width to length of corn, purpurea, and amaranthus retroflexus.

Sample	Purslane	Amaranthus retroflexus	Corn
1	0.07	0.63	0.08
2	0.09	0.44	0.21
3	0.02	0.60	0.16
4	0.01	0.64	0.19
5	0.07	0.39	0.14
6	0.14	0.48	0.19
7	0.03	0.66	0.22

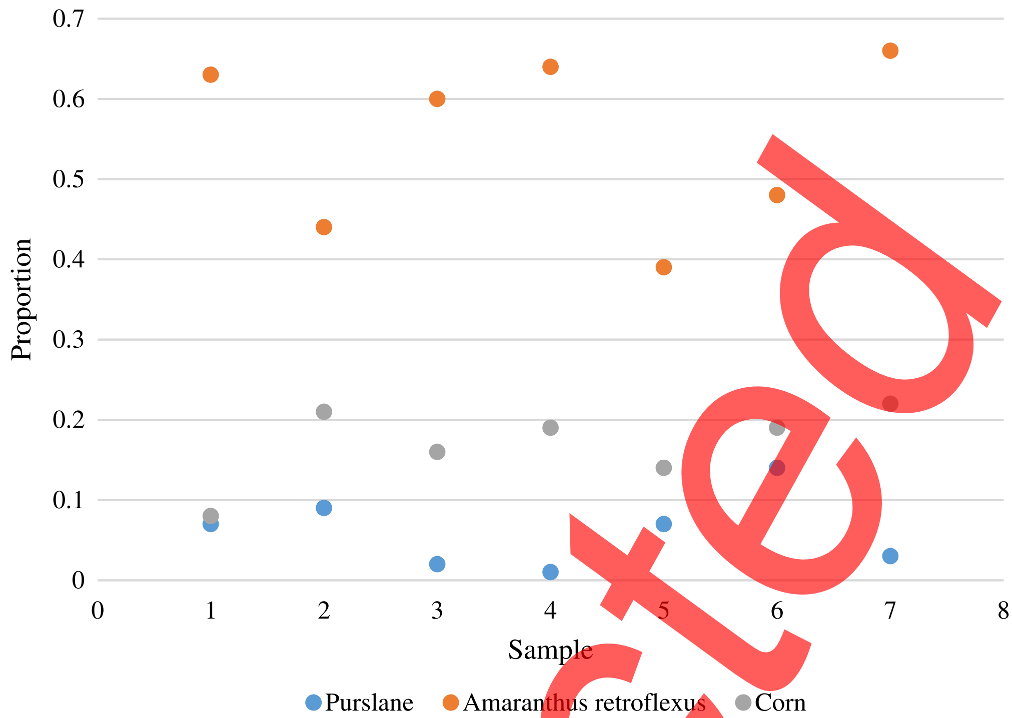


Fig. 3 The width-to-length ratio of corn, purpurea, and amaranthus retroflexus.

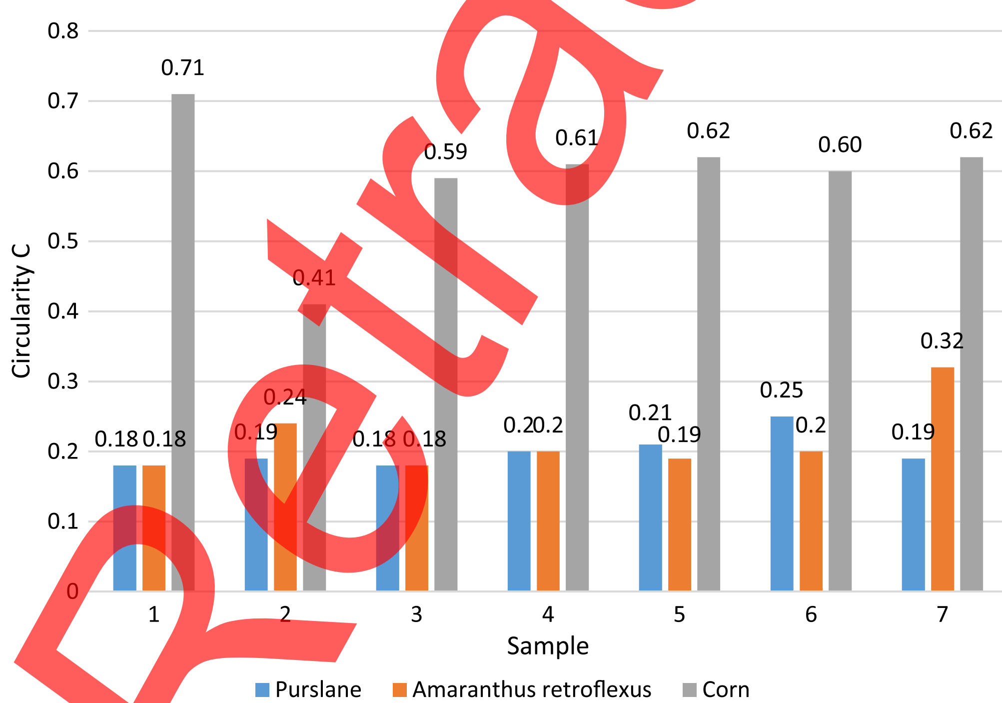


Fig. 4 The width–length ratio of corn, purpurea, and amaranthus retroflexus.

3.2 *Comparison of Feature Fusion Algorithms in Machine Learning*

This paper uses the image feature fusion method to conduct experiments on the Oxfordflower17 and Oxfordflower102 databases and obtains the comparison results of different fusion algorithms as shown in Table 3.

Table 3 Comparison table of the results of different feature fusion algorithms on the database.

Database	Oxfordflower17		Oxfordflower102	
Method	Correct rate	Time (s)	Correct rate	Time (s)
Local Binary Pattern (LBP)	35.74%	26	21.21%	32
Histogram of Oriented Gradients (HOG)	53.42%	37	37.34%	50
Locality-Constrained Linear Coding (LLC)	71.21%	100	56.12%	121
LLC+HOG+LBP	75.43%	653	58.01%	560

In terms of accuracy, it is shown in the data in Figs. 5 and 6 that the LLC feature extraction classification algorithm is significantly better than the HOG feature and the LBP feature on Oxfordflower17 and Oxfordflower102, indicating that the Dense Sift with PCA Dense Sift (DSIFT) feature extracted by the LLC algorithm is effective for weeds. It can be seen from the figure that the LLC feature extraction classification algorithm has good classification ability. Compared with the effect of single feature classification, the feature fusion method is generally better than the single feature extraction method, and the accuracy rate can be increased by 3% to 4%. However, the exception is that, when LLC and LBP features are fused, the accuracy rate does not rise but falls on the basis of LLC, which shows that LBP does not form complementary advantages with LLC features, but instead creates feature redundancy and reduces the classification effect. To put it simply, features produce redundancy because the classification problem is a pattern recognition problem, which uses a feature vector; the feature vector component is a feature, and some features have no impact on the classification whereas others have a great correlation between characteristics.

Figure 7 shows a comparison of the time spent for the various feature fusion algorithms. The abscissa represents different feature fusion methods, and the ordinate represents the time spent by the algorithm, in milliseconds (ms).

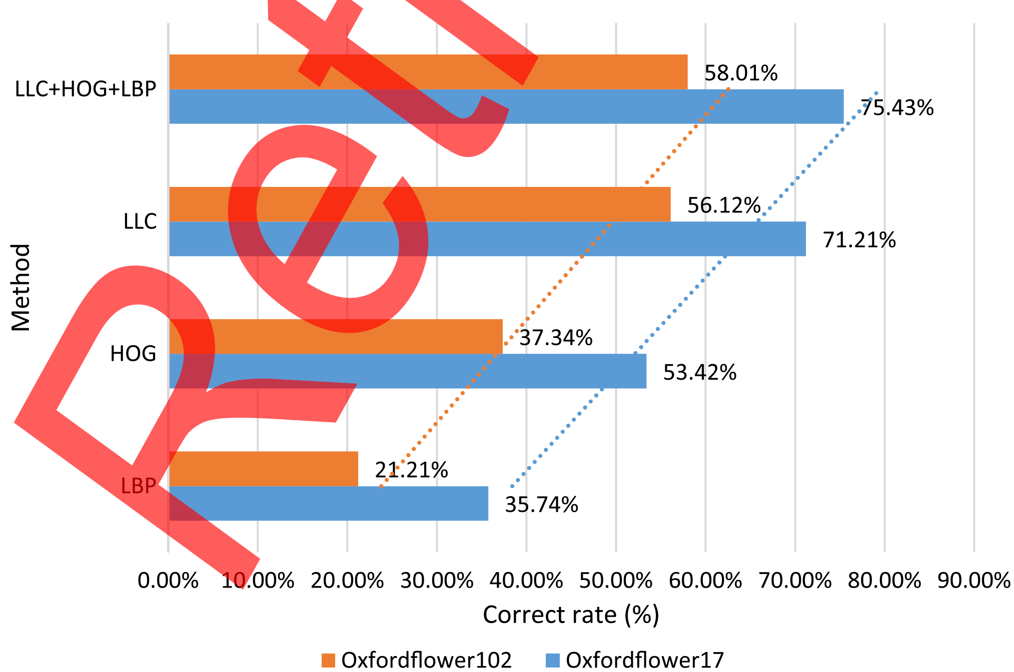


Fig. 5 The accuracy results of different feature fusion algorithms on the database.

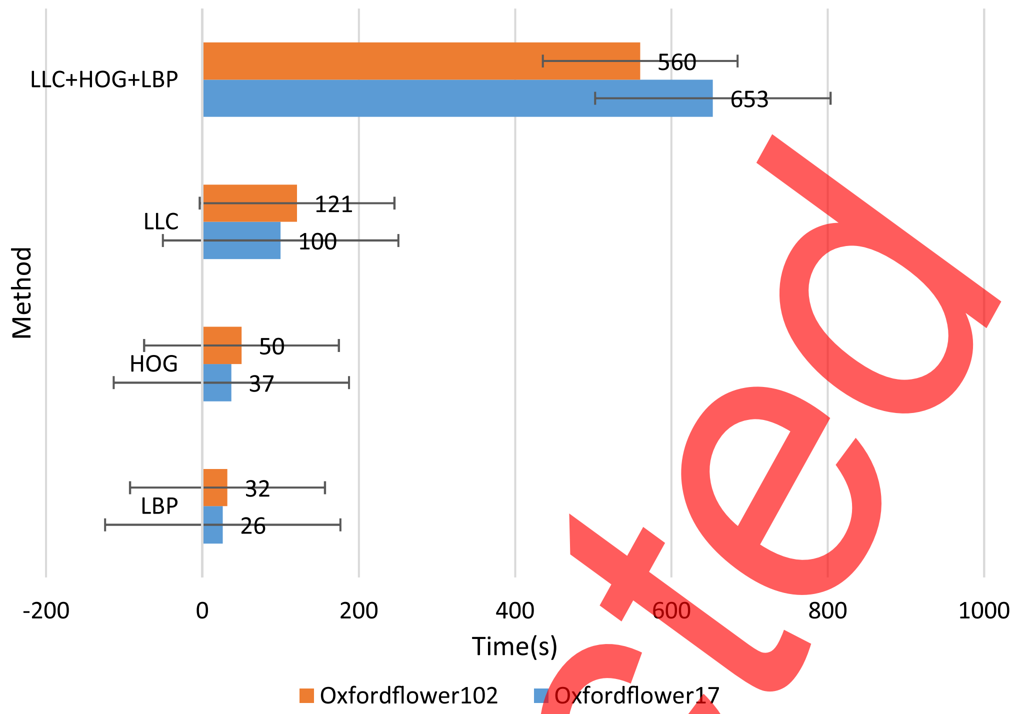


Fig. 6 Time results of different feature fusion algorithms on the database.

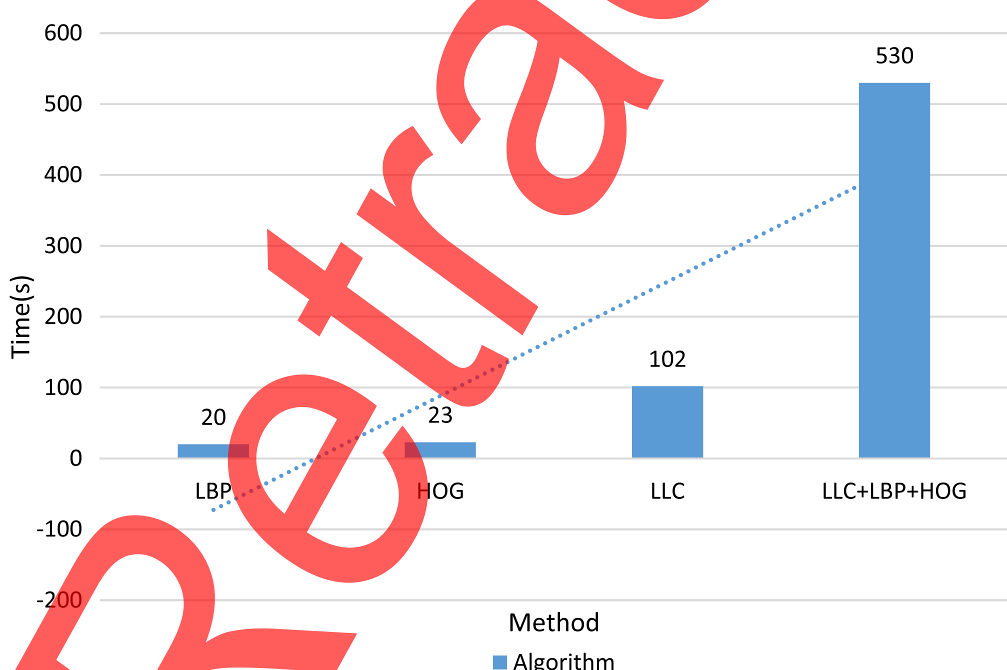


Fig. 7 Time chart of different feature fusion algorithms.

In general, LLC features have a higher accuracy rate for weed image classification and take less time, so they are more suitable for real-time weed recognition tasks. The LLC+LBP+HOG feature fusion method significantly improves the accuracy and has an acceptable time expenditure. It can be applied to some systems that do not require high real-time performance. Although other multifeature fusion methods improve the accuracy rate, they also bring a greater time cost, which will require improvement and optimization in future experiments.

3.3 *Field Weed Identification Verification*

The performance of machine learning is closely related to the training process, and the number of training samples must be appropriate. Too many samples will cause memory to be forgotten. In this paper, the collected field images were screened, and 40 representative independent corn seedlings, 30 barnyardgrass seedlings, and 30 amaranth seedlings images were selected. The morphological characteristic parameters of all leaves were calculated. The aspect ratio, circularity, and first moment invariant data of 20 groups of 80 images were taken as training samples and input into the model for learning and training. The learning rate adopts the variable learning rate with momentum to improve the model's performance. The feature parameters of the remaining 10 groups of 40 images were used as test samples to test the model, and the correct rate of classification and recognition was used as a performance indicator to determine the practicability of the model. The recognition results of the training set and the test set are shown in Table 4 and Fig. 8.

From the data in the table, it can be seen that the machine learning classifier can classify field crops and weeds better and faster; comparing the data shows that an appropriate increase in the number of training samples can improve the accuracy of machine learning recognition.

Table 4 Recognition results of training set and test set.

Sample	Number of samples	Learning rate	Number of iterations	Time-consuming (s)	Number of errors	Correct rate (%)
Training set	80	1.44	130	1.51	1	98.75%
Test set	40	2.04	145	1.57	2	95%

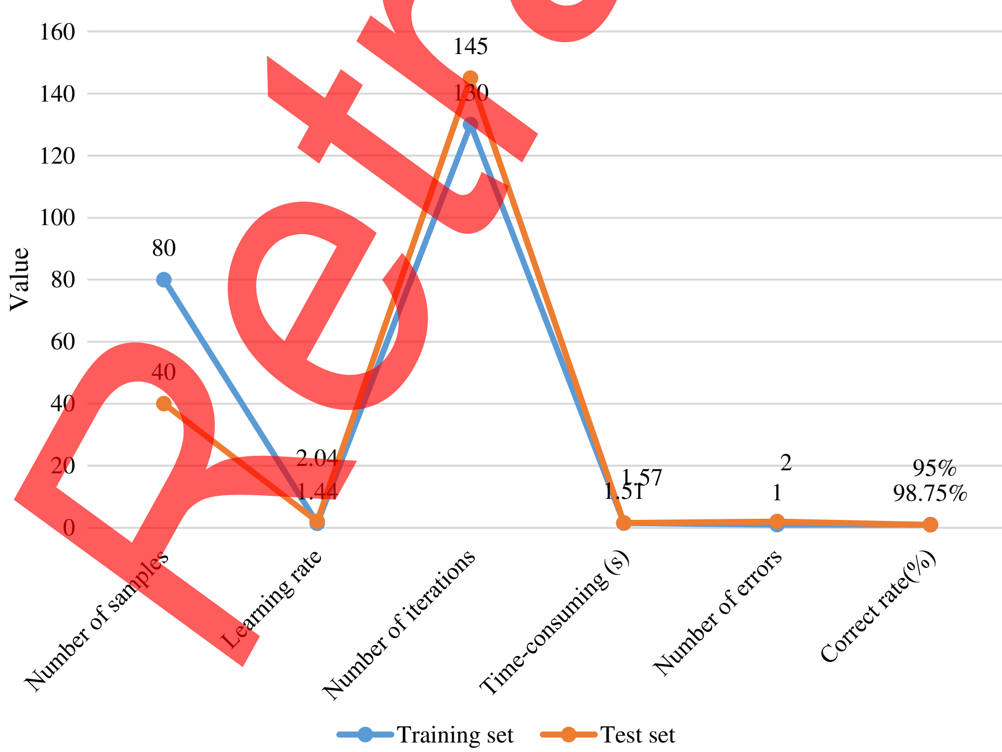


Fig. 8 Recognition results of training set and test set.

5 Conclusions

Based on the in-depth study and summary of the research on the extraction and classification of field weed leaves, this paper studied the identification and classification methods of field corn seedlings and their associated weeds. Taking the static collected images of field crops and weeds as the research object, a series of image enhancement and filtering processing methods were designed, and the morphological characteristic parameters of plant leaves were calculated and analyzed, with multiple characteristic quantities that are conducive to weed recognition being obtained through comparison. Through classifier input, algorithm design and simulation analysis, the article finally achieved a weed identification accuracy rate greater than 97.5%, preparing for subsequent weed positioning and variable spraying. In the field of weed recognition research, the use of weed location; weed characteristics, including shape, color, texture, spectral features; and other methods to identify weeds will become increasingly widespread. However, weeds grow under natural conditions and do not have regular characteristics and morphology as do industrial products. The amount of data available for image processing of weeds is relatively huge. Therefore, for the real-time identification technology of field weeds under real scene conditions in the field, further research work is needed.

With the development of computer technology, more learning methods will be applied to agriculture. For weed recognition, I believe that machine learning can obtain more accurate recognition effects and provide a more powerful technical foundation for the realization of automatic spraying technology.

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