Research Review of Feature Extraction and Classification Recognition of Rice Disease Images based on Computer Vision Technology

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Abstract Diagnosis and recognition of rice diseases and pests, amongst others, are an essential research direction of precision agriculture, which help to effectively prevent and control diseases and pests as well as improve rice yield and quality. Starting with the basic principles and technical routes of feature extraction and classification recognition of rice disease images, this paper expounds characteristics, realization methods and applications of many current feature extraction and recognition methods in China and abroad, analyzes the advantages of and problems in applications of different methods and technologies into recognition of rice diseases and pests, analyzes problems to be solved, proposes corresponding solutions, and looks into the development future of this research.

1. INTRODUCTION
In recent years, as computer technology develops, computer vision technology, with its characteristics such as rapidity, flexibility, low cost, high efficiency, and high precision, has developed into a new technical means for recognition of crop diseases and pests, providing excellent technical support for promotion of green and high yield, stable yield, and high-quality and efficient development of rice. Chinese and foreign scholars have conducted a considerable amount of in-depth research into recognition of rice disease images with computer vision technology, and most researches focus on four aspects: image acquisition, image processing, feature extraction, and classification recognition. Feature extraction and image recognition are crucial links for diagnosis and control of rice diseases, so this paper will explore current researches on feature extraction and classification recognition of disease images in China and abroad to provide reference for follow-up researches.

2. Feature extraction
Image feature extraction is a key step in image recognition, and feature extraction provides feature parameters of images for pattern recognition. The effect of image feature extraction directly determines the effect and precision of image recognition, so how to extract image features with strong representation ability from images remains a key and hot research topic for image processing. Through mapping or transformation, amongst other methods, feature extraction is to extract some features with strong representativeness and nice classification effect from raw feature data, and convert, through mapping or transformation, high-dimensional samples into low-dimensional spaces as well as convert raw features into new features. It not only directly affects the design and classification precision of classifiers and may even influence the feasibility of classification recognition algorithms.
Image features can be roughly divided into four categories: (1) pixel count features; (2) visualization features; (3) algebraic features; and (4) transform coefficient features or filter coefficient features. Color or grayscale histograms are the most common pixel count feature [1]. Visualization features include visual features such as textures and edges. Representative methods of texture analysis include the co-occurrence matrix, the Tamura method, etc; statistics describing texture features can be acquired through the gray-level co-occurrence matrix[2]. Representative differential edge detection operators include the Roberts operator, the Canny operator, the Sobel operator, etc. Algebraic features typically display intrinsic attributes of images, extracted from image matrices; singular value decomposition (SVD), principal component analysis (PCA), linear discriminant analysis (LDA), etc, are all classified into the method of algebraic feature extraction[3]. Through various filter transformations (the Fourier transform, wavelet transform, wavelet packet transform, etc) to images, transform coefficients may be regarded as an image feature, and the transform coefficient feature may be viewed as a feature of secondary extraction [4].

As pathogenic factors may vary, different rice diseases display disease spots in different colors, shapes and textures at positions such as rice roots, stems and leaves. In recent years, as computer vision technology develops rapidly, remarkable progress has been achieved in extraction and recognition of features such as colors, sizes, shapes and textures of target objects in images.

2.1 Color features
As a global feature describing some properties at the surface of target object in an image, the color features depict the surface properties of corresponding scenes in the image or image region, with strong robustness. The most extensively applied models of color features at present include RGB, HSV, YcbCr, HIS, etc. The main method to acquire color features is with the color histogram, which may indicate the proportions of colors in the image, without any need to consider color positions, suitable for complex images.

In Reference[5], in combination with color features of rice sheath blight and for highlighting the region of disease spot, the raw image of leaf disease damages after gray scale transformation is first based on to acquire the distribution of its gray histogram and the statistic result; the cumulative distribution function is taken as the mapping function to realize histogram equalization preprocessing of the image, so that the proportions of gray scales are equalized and thus the image quality is significantly improved, with raised contrast, clear contour details, and distinct disease spot boundaries; moreover, median filtering is applied to the image to protect the edge of target image and filter out the image noise.

Compared with other visualization image features, color features are characterized by vividness, high efficiency, no influence of image translation, rotation or size, and strong robustness, and they are common image features in the field of image recognition. Nonetheless, they cannot well present local features of targets in images, with limitations in the research on agricultural image recognition.

2.2 Texture features
As another type of global features, texture features are different from color features. Not based on pixel points, texture features require statistical calculations in regions containing multiple pixel points. In pattern matching, as regional features, texture features enjoy great advantages and will not lead to matching failure due to local deviations.

Reference[6] adopts microscopy image recognition based on the synergistic judgment of texture and shape features and the decision tree-confusion matrix method. The distance transformation-Gaussian filtering-watershed algorithm method is proposed to separate the adherent rice blast spores. In Reference [7], texture features of leaves with rice diseases are extracted to conduct automatic recognition research on the rice brown spot disease and rice blast, providing new technology and methods for disease recognition.

On the one hand, texture features are an important visual clue and a kind of features that commonly exist in images but are difficult to depict, with advantages such as rotational invariance and strong
noise immunity; on the other hand, as a kind of surface features of object, texture features cannot fully reflect the essential properties of object or lead to high-level image contents. When the image resolution varies, the calculated texture may cause great deviations. Moreover, texture analysis is a highly time-consuming process, and the low execution efficiency of texture feature extraction algorithm itself remains a problem to be addressed in actual applications.

2.3 Morphological features
Distinct from bottom-layer features such as colors or textures, the representation of morphological features must be based on the division of objects or regions in images. The morphological features of image may compensate the uncertainty from color feature extraction. In terms of rice diseases, different disease damages take on different morphs, indicating certain differences. Binarized images often occupy a small space, with clear morphological features, significantly reducing the data size and the computation time.

In Reference [8], targeted at the most obvious feature of rice sheath rot, i.e., the disease spot gradually expands with the aggravation of disease, the edge detection treatment method is adopted to effectively extract the morphological features of the disease and acquire feature parameters. Edge detection may be based on brightness discontinuity, and it is observed that images of disease spots have thin boundaries; experiments show that, for such discontinuity, peak detections with Hough transform can achieve excellent effect. Algorithms for extracting morphological features suitable for classification of spots of rice blast are studied in Reference [9]: based on the extraction of traditional morphological features such as the area and perimeter of disease spot, two new morphological features, i.e., the quantity of disease spots, and the ratio of spot area to spot quantity, are defined; by comparing the effect of extracted morphological features in distinguishing three types of spots, 4 morphological features are finally selected to conduct classification recognition of three types of rice blasts, i.e., acute, chronic, and white-spot ones.

Extraction of morphological features is less demanding, and it is thus extensively applied in early extraction of image features of crop diseases and pests, yet with some problems as well: lack of relatively perfect mathematical morphological models, no complete consistence between the shape information of target and the visual feeling of human eye, which affects the effectiveness of extracted morphological features and increases computational difficulties, remaining difficult research points to be addressed in future.

2.4 Spatial relationship features
Spatial relationship features refer to the relationships of relative spatial locations or relative directions of multiple objects segmented from images, and these relationships can be divided into relationships of connection/adjacency, overlapping/superposition, inclusion/containment, etc.

As some disease spots of rice share highly similar colors, shapes and textures, the three feature parameters alone can hardly differentiate these similar disease spots. For instance, in Reference [10], as for some similar diseases, the three features for rice bacterial blight and sclerotial stem rots, for example, are highly similar, quite difficult to distinguish, but a significant difference in the two diseases is whether the disease-health boundary is clear; damages of rice helminthosporium blight and brown-spot leaf blast both appear in a dotted shape and mostly in brown, and the difference between the two is whether there exist yellow haloes on the periphery; a method is proposed to distinguish between similar disease spots based on the features of disease-health boundary, including color differences inside the spot, at the edge and at the periphery, achieving remarkable effect in recognition precision of some similar diseases.

The application of spatial relationship features may enhance the descriptive and differentiating ability of image contents, but those features are often quite sensitive to rotation, inversion, scale variation, etc. In addition, in actual applications, utilization of space information alone often does not suffice, unable to effectively and accurately represent scene information.
2.5 Multi-feature integration

The aforesaid feature extraction methods are for preliminary acquisition of image features, with different pros and cons. In different actual applications, appropriate methods of image feature extraction may be selected. However, in certain cases, the use of single features for image retrieval or matching often leads to low accuracy in results. Multi-feature integration overcomes the shortcoming that feature extraction with a single method is likely to cause image information loss in a certain aspect and thus leads to incorrect classification; it can relatively completely represent the feature information of images, retain the effective identification information of multiple features integrated inside, eliminate information redundancy to a great extent, and also compress information, favorable to real-time processing and classification of images.

Based on the characteristic that the color of rice disease spot is different from that of normal leaf, in Reference [11], OpenCV is utilized to extract the color features from the HSV space color histogram, and the features of histogram of oriented gradient (HOG) are utilized to describe the local texture and shape features of image; the vectors of two features are integrated to obtain the total length of feature, which is used as an input for the model, and experiments show that this model is characterized by high efficiency, strong robustness, and powerful generalization ability. In Reference[12], feature parameters are extracted from the segmented image, and the HSV color model is adopted to acquire the color features of image; the Hu moment is adopted to acquire the shape features of image, and the gray-level co-occurrence matrix is adopted to acquire the texture feature of image, also with the LLE manifold algorithm for dimensionality reduction of image data and for extracting 3D features; the four categories of features, 23 features in total, constitute feature vectors. Targeted at images of rice sheath blight leaves, the RGB system and the HIS system are adopted in Reference[13] to describe the color feature representation of images of rice sheath blight damage positions; in view that there exist huge differences in thickness and directions of textures between normal tissues and diseased regions of leaves in images of leaf disease damages of rice crops, texture features are utilized to effectively recognize rice sheath blight. In Reference [14], features of spots of three diseases, i.e., rice blast, sheath blight, and bacterial blight, are analyzed to extract 13 different feature parameters in three aspects: colors, shape, and textures; feature parameters are effectively combined to achieve effective recognition of the three diseases. A multi-feature integration method, integrating color features, shape features, texture features, and feature parameters of disease-health boundary, is adopted in Reference [15] to extract features from disease damage images of rice leaves. This method effectively realizes recognition of 15 common leaf diseases of rice, providing technical support for intelligent field diagnosis of rice diseases.

Current researches on feature extraction of rice disease images are mostly based on the following two aspects: (1) Extraction methods is in gradual transition from single feature extraction methods, such as the histogram method to extract disease image features, the gray-level co-occurrence matrix to extract texture features, and the boundary feature method to extract shape features, to comprehensive consideration to multiple features or extraction algorithms of multi-feature integration. Researches on analyses of large numbers of feature parameters, optimization algorithms and feature value extraction have gradually become an important research direction of feature extraction. (2) The extracted target is single, mostly the local disease spot region of rice leaves, affecting global disease research, the extracted time node is single, and most researches do not start until rice disease symptoms appear quite obvious, seriously affecting the real-time performance of image feature extraction. A majority of researches on rice disease images are from the perspectives of image recognition and image processing, lacking consideration to feature extraction from the perspective of rice pathology knowledge. For example, rice blast can be further divided into many forms, such as seedling blast, leaf blast, node blast, neck rot blast, and grain blast, which may develop throughout its growth period, and symptoms may occur at any position. In future researches, it is preferable that multiple extraction time nodes and multiple positions should be selected for feature extraction, so as to provide accurate feature information for different periods of disease outbreak and provide reliable foundation for timely recognition and control of diseases.
3. Classification recognition

3.1 Support vector machines
Support vector machine (SVM) methods are an important classification algorithm of traditional machine learning and a set of classification and pattern recognition methods based on statistical learning theory proposed based on the structural risk minimization principle, and can be extensively applied to statistical classification and regression analysis. A support vector machine is a binary classification model, which maps vectors to a higher-dimensional space, where a maximum hyperplane is built to segment samples; the segmentation principle is margin maximization, and a convex quadratic programming is finally acquired through conversion to obtain solutions. The key of support vector machine methods lies in kernel functions. Vector sets in low-dimensional spaces tend to be difficult to divide, and a solution to that is to map them to high-dimensional spaces; with suitable kernel functions, it is possible to acquire classification functions for high-dimensional spaces.

In Reference [16], 10 images for each of the three types of rice blast, i.e., acute, chronic, and white-spot ones are randomly selected as a training sample set; through comparing the recognition effects of three types of disease spots with multi-class support vector machines with different parameters, the optimal model parameters for support vector machines of disease recognition are determined, and, after model training and classification, disease spots are classified with the voting mechanism. A method of rice sheath blight recognition based on support vector machines is designed and realized in Reference [17], rice sheath blight and healthy rice are selected, respectively, as training samples; the radial basis kernel function is chosen to train the classifier; based on the color and texture features of extracted disease spots and through dimensionality reduction, Lib-SVM is adopted to conduct classification training and testing of extracted feature data, for acquiring the model through training. The disease spot region is separated in Reference [18] a SVM classifier is trained to recognize spots of sheath blight and diagnose the damage grade of sheath blight according to the proportion of sheath blight spot area. Hyperspectral technology is adopted in Reference [19] to build models for healthy and diseased rice recognition; the support vector machine modeling algorithms of four kernel functions (Linear, Polynomial, Radial Basis Function, and Sigmoid) are adopted to conduct classification recognition of rice green smut. The SVM recognition results show that the linear kernel function achieves the best diagnosis performance and performs quite stably.

Support vector machine methods take both training errors and generalization ability into consideration, enjoy unique advantages in pattern recognition problems such as small samples, non-linearity, high dimensions, and local minimums, and may effectively overcome the shortcomings of neural network methods such as difficult convergence, unstable solutions, and poor generalization. Thus, there are great prospects for them to be applied into classification recognition of agricultural diseases and pests. Nonetheless, SVM methods are sensitive to missing data, and provide no general solutions to non-linear problems; moreover, due to dramatic differences in images of diseases and pests among different types of crops, there has been no universal system for recognition classification of crop disease images. During classification of disease spots based on support vector machines, selection of kernel function parameters is currently determined through experiments, which require continuous and in-depth research.

3.2 Artificial neural networks
Artificial neural networks, aka neural networks, are mathematical models for information processing by utilizing structures of connected neural nodes similar to biological brains. Neural network methods have upsides such as massive parallel, distributed processing, self-organization, self-learning, strong noise immunity, and high classification precision, and their ability of classification is especially suitable for applications of pattern recognition and classification, thus extensively applied to recognition of crop diseases and pests in recent years. The BP neural network is an artificial neural network, characterized by advantages such as non-linear mapping, strong generalization ability, and strong fault tolerance.
In Reference [20], texture features and color features of rice leaves are selected; the unique collective computational ability, adaptive learning ability, and strong fault tolerance of BP neural network are adopted to solve the problem of weight adjustment of multilayer feed-forward neural network in solutions to nonlinear continuous functions, successfully recognize the diseased region and normal region of rice blast leaves, and achieve satisfactory recognition effect and nice stability. The BP neural network method is adopted in Reference [21] to train a disease and pest sample for recognizing diseases and pests; the multiple nonlinear regression analysis method is adopted to build an early warning model, and the trend extrapolation method and the exponential smoothing method are combined to build a forecasting model; also, based on the periodicity of disease and pest occurrence, a seasonal exponential smoothing model is built. In Reference [22], three-layer BP networks are used to build a forecasting model to learn and train the sample data; based on the MATLAB neural network toolbox, the Delphi software is utilized to build a simulation system for simulating disease and pest forecasting. Based on the occurrence, damage, temperature, humidity, rainfall, and other meteorological-related characteristics of rice bacterial blight, the characteristics of artificial neural networks with strong mapping ability for complex nonlinear problems are utilized in Reference [23] to build neural network forecasting models for rice bacterial blight, and a BP neural network model with trailm function is adopted to forecast the grade of disease occurrence. In Reference [24], an input matrix and an output matrix are built for disease image features, put into the BP neural network for training; further research on the influence of different parameters in the BP neural network model on the successful recognition rate is conducted in training, and, based on the result, the BPS algorithm is improved to select a network model with the best recognition effect.

In all the references above, image features of research objects are extracted for analysis and research, with certain research results; however, rice disease types are varied and often display multiple composite features including shapes, textures, etc, which post huge challenge for image recognition technology and affect recognition effect. Additionally, the BP neural network is highly sensitive to initial network weights, different weight values for network initialization often converge to different local minimums, affecting training results; moreover, classification recognition with the BP neural network entails a huge amount of computation and low convergence speed, and selection and training of sample instances affect applications of neural networks in image recognition, which shall be an issue requiring subsequent in-depth research.

3.3 Deep learning methods

Deep learning refers to, on multilayer neural networks, an algorithm set of applying various machine learning algorithms to solving image, text and other problems. The core of deep learning is feature learning, aiming to acquire hierarchical feature information through hierarchical networks so as to solve essential difficult problems that would require human design features in the past. Convolutional neural networks are the foundation for deep learning to achieve breakthroughs in the field of computer vision in recent years. On the basis of original multilayer networks, feature learning is added into convolutional neural networks, and connected convolutional layers and dimensionality reduction layers are added before the fully connected layers; artificial selection of features to map into values on multilayer neural networks is shifted to selection by networks themselves. Convolutional neural networks (CNN) do not need to rely on specific features of images for image recognition, and are thus extensively applied to fields such as face recognition, speech recognition, and recognition of crop diseases and pests, with good effect.

In Reference [25], knowledge transfer and deep learning methods are introduced, and the big dataset of ImageNet images and the PlantVillage public dataset of plant diseases, both available online, are taken as the objects for conducting related researches and experiments and expounding the optimal network suitable for problems of crop disease recognition and the corresponding transfer strategies. A deep convolutional neural network model is adopted in Reference [26], and the dataset augmentation technique and the fine-tune method are used for tuning and building of the network; images of eight common rice diseases collected under natural scenes are input into the network model for training and
testing, achieving high recognition precision; different from other methods which exclusively focus on rice leaves or panicles, the images recognized in that paper are scenes of multiple rice plants, which may provide critical technical support for automatic remote diagnosis of rice diseases. Reference[27] proposes the application of deep learning theory into rice disease recognition; a rice disease recognition model is built through the use of deep convolutional neural network; data of three main rice diseases (rice blast, sheath blight, and rice green smut) are normalized, and the deep learning framework Keras is used to perform deep CNN training; through setting of different convolution kernel sizes and pooling functions, researches are made on classification recognition of three common rice diseases. This model is characterized by strong generalization ability, high accuracy, good robustness, and a small loss rate. A convolutional neural network is used in Reference[28] for recognition of rice sheath blight; comparison is also made with the recognition method based on support vector machines, with satisfactory recognition effect. A method of rice green smut is proposed in Reference[29] based on convolutional neural networks; with a model of shallow network structure and learning from AlexNet and VGG, the network structure is improved and optimized, and data augmentation is applied to increase the data size of sample to improve the generalization ability of training results. Softmax is the most common classifier in deep learning and can be viewed as a multi-class logical regression. In Reference[30], the Softmax deep regression classification method is based on to research the technique of recognizing rice blast diseases in cold regions in North China, and a 10-level cross validation method is adopted to effectively recognize three types of rice blast (acute, chronic, and white-spot ones). Reference[31] proposes a rice panicle blast method based on the deep convolutional neural network GoogLeNet; by utilizing its structural depth and width, GoogLeNet learns the hidden high-dimensional feature representations of complex noise hyperspectral images and trains the Softmax classifier in a unified framework, realizing forecasting modeling for panicle blast.

Deep learning neural networks are with multiple layers, great width, strong learning ability, extensive coverage, and good adaptability, capable of solving complex problems. Deep learning is highly dependent on data, with high data-driven ceiling and nice portability, but it is also characterized by shortcomings such as a huge amount of computation, high costs, high software requirements, and complex model design. As deep learning depends on data and its interpretability is not high, problems are likely to occur when the training data are unbalanced.

3.4 Hyperspectral image methods

Hyperspectral images are a new type of remote sensing data, and their data processing methods have become a hot research topic in the field of remote sensing image processing, extensively applied into geology, environment, vegetation, etc. With numerous bands, high spectral resolutions, rich spectral information, and flexible data description and analysis methods, it has been feasible for hyperspectral images to effectively differentiate and identify targets.

In Reference[32], hyperspectral images of leaves and canopies are collected to define the spectral range and acquire the spectral curve of rice leaves. Partial least squares-discriminant analysis is adopted for modeling of different preprocessing spectrums. The MNF algorithm is adopted to extract feature information from raw spectrum data of canopy, and the feature information is based on to build a linear discriminant analysis (LDA) model and a backpropagation neural network (BPNN) discrimination model. In Reference[33], a spectral imaging system is used to collect hyperspectral images of rice leaves at different damage grades after infection with rice blast; hyperspectral images containing only diseases spots are extracted; the maximum intra-class variance method is adopted to segment the gray disease spots; finally, in combination with the 2 parameters of extensibility and damage rate, the rice leaf blast damages are graded. Reference[34] proposes a hyperspectral feature extraction method for detection of rice blast damages, systematically studies spectral feature extraction with Gaussian function fitting, spectral feature extraction with vegetation index, and spectral feature extraction with wavelet approximation coefficient, builds a model for classification discrimination of rice blast damages based on Gaussian fitting parameters, vegetation index, and wavelet approximation coefficient, and realizes precise, non-detective detection of rice blast. For rapid and accurate grading
of rice panicle blast damages, an analysis method of bag of spectrum words (BoSW) model is proposed in Reference [35] to analyze hyperspectral images of rice panicles and automatically judge the degree of panicle blast. In Reference [36], based on hyperspectral imaging technology and stoichiometry and according to the optimal models of spectral dimension and image dimension of hyperspectral images, the content of chlorophyll and the spectral features and image features are combined to build models of backpropagation neural network (BPNN) and linear discriminant analysis (LDA), achieving early detection and recognition of rice sheath blight damages.

As there are a variety of rice diseases and pests, it is highly necessary to build a detailed and complete spectral library and design a dedicated spectral imaging acquisition and analysis system. As rice leaf spectrometry is the basis for canopy spectrometry, with continuous development and improvement of hyperspectral remote sensing technology in future, the spectral technology recognition method will play an increasingly important role in large-scale recognition and control of crop diseases and pests.

| Methods                     | Advantages                     | Disadvantages                        |
|-----------------------------|--------------------------------|--------------------------------------|
| Support vector machines     | Non-linearity, High dimensions | Poor sensitivity to missing data      |
| Neural network              | Large scale parallel, distributed processing, high accuracy | Difficult convergence, large calculation and slow convergence |
| Deep learning methods       | Strong learning ability and adaptability and portability, wide coverage | Large calculation, high cost, high complexity |
| Hyperspectral image methods | Strong data processing ability and flexibility | Large data volume and high information redundancy |

Table 1. Classification and Recognition Method

Current researches on classification recognition of rice diseases are mostly based on the following aspects: (1) a majority of researches are targeted at specific environments and specific disease periods of one or two diseases, when a single classification recognition algorithm is adopted for feature recognition, with big limitations on algorithms and poor robustness; (2) a majority of rice disease recognition systems are offline, standalone, and static recognition under experimental environments, with poor real-time and generalization performance and not high recognition precision, leading to poor effect in actual applications and low recognition efficiency. In future, as mobile communication technology and remote sensing technology advance, online intelligent systems for disease and pest classification recognition, characterized by extensive generalization, strong stability, high precision, and strong real-time performance, will be future research trends, which will also be difficult and hot research topics of image recognition technology for crop diseases and pests in future.

4. CONCLUSION AND PROSPECT

Relatively comprehensive review is made in this paper on methods of feature extraction and classification recognition of rice disease images based on computer vision technology. In the field of feature extraction and classification recognition research, some noticeable research tendencies have also emerged: (1) as each method of feature extraction and classification recognition has some shortcomings and disadvantages, while some theories of emerging disciplines and new technology and new methods are introduced, appropriate feature extraction and classification recognition algorithms are selected based on the object and scope of research, or alternatively, several algorithms are effectively combined and used, seeking the best image classification strategy is the mainstream research trend in the field at present, resulting in better classification effects; (2) with the rapid development of big data, IoT, and artificial intelligence technology, intelligent image segmentation and remote sensing technology, image feature extraction and classification are developing towards digitization, integration, intelligence and standardization. In the real natural environment, intelligent recognition and control of large-scale crop pest image and standardized processing of massive data of pest will be the important research direction of crop pest recognition in the future, and there is still a huge room for improvement in the research of the rapidity, efficiency and robustness of the algorithm.
How to use the image recognition technology to solve the problem of crop diseases and insect pests is of far-reaching significance for the development of modern agricultural production.

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