Research Article

Commodity Price Recognition and Simulation of Image Recognition Technology Based on the Nonlinear Dimensionality Reduction Method

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Dimensionality reduction of images with high-dimensional nonlinear structure is the key to improving the recognition rate. Although some traditional algorithms have achieved some results in the process of dimensionality reduction, they also expose their respective defects. In order to achieve the ideal effect of high-dimensional nonlinear image recognition, based on the analysis of the traditional dimensionality reduction algorithm and refining its advantages, an image recognition technology based on the nonlinear dimensionality reduction method is proposed. As an effective nonlinear feature extraction method, the nonlinear dimensionality reduction method can find the nonlinear structure of datasets and maintain the intrinsic structure of data. Applying the nonlinear dimensionality reduction method to image recognition is to divide the input image into blocks, take it as a dataset in high-dimensional space, reduce the dimension of its structure, and obtain the low-dimensional expression vector of its eigenstructure so that the problem of image recognition can be carried out in a lower dimension. Thus, the computational complexity can be reduced, the recognition accuracy can be improved, and it is convenient for further processing such as image recognition and search. The defects of traditional algorithms are solved, and the commodity price recognition and simulation experiments are carried out, which verifies the feasibility of image recognition technology based on the nonlinear dimensionality reduction method in commodity price recognition.

1. Introduction

In order to solve the problem of dimensionality disaster and effectively deal with high-dimensional data, data dimensionality reduction technology appears. When dealing with high-dimensional data, people naturally consider the possibility of projecting these data into low-dimensional subspace without losing important information about some characteristics of the original variables [1]. Data dimensionality reduction technology is a process of mapping data from high-dimensional space to low-dimensional space, which can best maintain the structure and compactness of data so as to obtain the low-dimensional representation of high-dimensional data. High-dimensional data usually contains redundant information and noise so that we cannot accurately obtain the information we want when processing data, which is often disturbed by the redundant information in high-dimensional data [2]. Through data dimensionality reduction technology, we can effectively remove the mixed information in high-dimensional data so that we can obtain the useful information we really want to extract so as to effectively solve the problem of dimensionality disaster.

The dimensionality reduction algorithm has the following two classification methods, which are divided into feature selection and feature extraction according to different features; according to the relationship between data, it can be divided into linear dimensionality reduction and nonlinear dimensionality reduction [3]. In the former classification method, feature selection is to select some important attributes of all data attributes to represent the original data and ensure that the data is not lost and retain the maximum amount of information as much as possible; feature selection has many applications [4]. In pattern recognition, it can be used to remove hybrid information so as to reduce

computational complexity, save time cost, and improve efficiency; feature extraction is to use new features to represent the original features after feature selection, that is, to integrate the features of the original data through transformation [5]. Finally, it will come down to the problem of solving eigenvalues and eigenvectors. According to different processing methods, feature extraction is divided into global dimensionality reduction and local dimensionality reduction [6]. Global dimensionality reduction is to consider the global information of data and treat all data as a whole; local dimensionality reduction is to focus on local information processing of data, and the purpose is often to effectively extract local information [7].

Traditional dimensionality reduction methods include redundant information and noise. When processing data, they cannot accurately obtain the desired information and are disturbed by redundant information. In order to better complete the image recognition, dimensionality reduction of high-dimensional images is the key technical link before image recognition. Because the computational complexity of the image after dimensionality reduction has been significantly reduced, the storage space has been significantly saved. Although the linear dimensionality reduction method can reduce the dimension of high-dimensional data by finding the linear transformation matrix through the performance target, the high-dimensional face image will have obvious nonlinear manifold characteristics due to factors such as illumination, expression, and posture. However, after data dimensionality reduction, the nonlinear features of the original data will be lost, resulting in data distortion after feature extraction, which reduces the image recognition rate. This paper presents an image recognition technology based on the nonlinear dimensionality reduction method, which reduces the computational complexity, improves the recognition accuracy, and is convenient for further processing such as image recognition and search. The defects of traditional algorithms are solved, and the commodity price recognition and simulation experiments are carried out, which verifies the feasibility of image recognition technology based on the nonlinear dimensionality reduction method in commodity price recognition.

The sections of this paper are arranged as follows. Section 1 summarizes the research background and significance of this paper. Section 2 introduces the related work. Section 3 analyzes the image recognition technology based on the nonlinear dimensionality reduction algorithm and discusses the implementation way of image recognition technology based on the nonlinear dimensionality reduction algorithm in commodity price recognition. Section 4 makes an experimental analysis, and Section 5 summarizes the full text.

2. Related Work

At present, most dimensionality reduction algorithms deal with vector data, and some dimensionality reduction algorithms deal with high-order tensor data. The reason why the reduced dimension data representation is used is that the original high-dimensional space contains redundant information and noise information, which causes errors

and reduces the accuracy in practical applications, such as image recognition [8]; by dimensionality reduction, we hope to reduce the error caused by redundant information and improve the accuracy of recognition.

This technology has been continuously studied by many scholars in the past few decades, and many classical dimensionality reduction algorithms have been proposed. Among them, the traditional dimensionality reduction algorithms include linear discriminant analysis (LDA) and principal component analysis (PCA). The PCA algorithm is the most commonly used linear dimensionality reduction method. Its goal is to map high-dimensional data to low-dimensional space through some kind of linear projection and expect the maximum variance of data in the projected dimension so as to use fewer data dimensions and retain the characteristics of more original data points [9]. However, PCA belongs to unsupervised dimensionality reduction algorithms and does not consider the category information in the sample, so Fisher proposed the LDA algorithm. LDA is one of the most classical supervised dimensionality reduction algorithms. The algorithm minimizes the intraclass divergence matrix and maximizes the interclass divergence matrix and then decomposes the eigenvalue into a mapping matrix according to the Fisher criterion and then uses this mapping matrix to decompose the high-dimensional space; the data is projected into low-dimensional space to reduce the dimension of samples, but the traditional LDA algorithm has a defect, that is, the small sample problem; the number of training samples is required to be much larger than the sample dimension, so the calculated intraclass divergence matrix is not an irreversible matrix. In order to overcome the problem, researchers have proposed many corresponding improvement methods [10]. Some scholars have proposed two-dimensional linear discriminant analysis, which uses the image matrix to construct the intraclass divergence matrix and interclass divergence matrix so as to overcome the problem. Then, the maximum interval criterion (MMC) is proposed, which takes the difference between the interclass divergence matrix and the intraclass divergence matrix as the criterion so as to avoid solving the inverse matrix of the intraclass divergence matrix and solve the problem theoretically [11].

With the development of computer technology, radiofrequency identification technology has developed rapidly. This technology uses radiofrequency signals to transmit information. When used, it is a noncontact method [12]. Radiofrequency technology can also be used for commodity identification. It is similar to the way that barcodes are printed on the outer package of each commodity. It is necessary to affix electronic labels on the outer package of each commodity, which is a type of tag that corresponds to a kind of commodity, and the electronic tags of different kinds of commodities must be different. After the electronic tag is installed on the commodity, the wireless signal communication is carried out through special equipment to complete the commodity price identification. The commodity price identification in this way does not require manual scanning like barcode identification, although it improves the automation of commodity identification to a certain extent.

However, when multiple commodities are settled together, multiple labels send signals at the same time, which inevitably leads to interference between signals, resulting in unsatisfactory accuracy of settlement of multiple commodities; moreover, in order to realize commodity identification, each commodity needs to be attached with an electronic label, which is essentially just a form of barcode label, regardless of label cost or labeling; the labor cost of signing is very high, and the label cannot be recycled [13]. Most goods in convenience stores have little profit space and cannot bear the additional cost brought by using the label. Therefore, commodity recognition based on this method has not been widely promoted. With the increase of image acquisition channels, the difficulty is reduced, and the development of computer hardware equipment based on computer vision image recognition technology has been greatly improved [14]. The commodity price recognition of image recognition technology based on the nonlinear dimensionality reduction method has become a highlight and is gradually put into use.

3. Image Recognition Technology Based on the Nonlinear Dimensionality Reduction Method

3.1. Nonlinear Dimensionality Reduction Method. This section briefly introduces a modification of the Laplacian eigenmap dimensionality reduction method that keeps the eigenstructure of the high-dimensional data manifold unchanged. Given the dataset $X = \{x_1, x_2, \cdots, x_n\}$ with capacity n in d-dimensional space, for the convenience of description, also note $X = \{x_1, x_2, \cdots, x_n\} \in R^{D \times N}$ and note that the neighborhood of the X_i point is U_i, $i = 1, 2, \cdots, N$.

Step 1. Select a neighborhood for each point.

$$U_i = \left\{ x_j \middle| \delta(i,j) \le \frac{\delta_{\min}(i) + \delta_{\min}(j)}{\lim_{n \longrightarrow \infty} \sum_{i,j=1}^{n}(i+j)}, \quad i,j = 1, 2, \cdots, N \right\},$$ (1)

where $\delta(i,j)$ is the Euclidean distance between two points x_i and x_j.

$$\delta_{\min}(i) = \text{Inf} \left\{ \sum_i \middle| \delta_i - \sum_j \delta_{ij} \middle|^2 \right\}.$$ (2)

Step 2. Generate a matrix using the selected neighborhood.

$$\zeta_{ij} = \begin{cases} 1, & j = 1, \\ -\lambda \dfrac{U_i + U_j}{\sqrt{|U_i||U_j|}} + \left| \dfrac{U_i}{U_j} \right|, & j \in U(i), j \ne i. \end{cases}$$ (3)

Step 3. Calculate the minimum D eigenvectors $(y_1, y_2, \cdots, y_d)$ of the Laplacian matrix, which corresponds to the embedding result of X in d-dimensional space. For simplicity, this paper selects $d = 1$. For $M \times N$, the image is segmented and

recorded as $P_k[C_k, 2^k]$. It divides the original image into C blocks, the size of each block is $2^k \times 2^k$, and the interval between two adjacent rings is 2^{k-1}. The dataset with the capacity of C_k in 2^{2k}-dimensional space can be obtained.

Represent the maximum integer not exceeding z, use the nonlinear dimensionality reduction method to reduce the dimension of high-dimensional data, obtain the low-dimensional feature expression vector $\alpha \in R^{C_4}$ of the original graph, and further identify the problem [15]. Learn the center point of each kind of image feature expression vector, and take it as the representative of this kind of image for the recognition process. First, obtain each image X_i and the high-dimensional dataset X_i, $i = 1, 2, \cdots, N$, under segmentation P_4, and then reduce the dimension of X_i to obtain the C_4-dimensional feature expression vector α_i, $i = 1, 2, \cdots, N$. Calculate the center point of each type of image and record the capacity of each type as V_i, if

$$A_i = \left\{ \alpha_1, \alpha_2, \cdots, \alpha_{V_i} \right\} \in R^{C_i \times V_i}, \quad n = \frac{|X|}{T},$$ (4)

represents the set of feature expression vectors of class i image data, and then its center point α_0^i satisfies

$$\alpha_0^i = \arg \sup_{\alpha^\tau \alpha = 1} \left\{ \alpha^\tau \left(\sum_{j=1}^{V_i} \alpha_j \alpha_j^\tau \right) \alpha \right\}.$$ (5)

It is easy to see that α_0^i is the maximum eigenvector of matrix $\sum_{j=1}^{V_i} \alpha_j \alpha_j^\tau \in R^{C_4 \times C_4}$. Given an image, under segmentation P_4, first calculate its feature expression vector, and then calculate α, identifying that it belongs to the class with the greatest similarity.

3.2. Commodity Price Recognition Based on Image Recognition Technology of the Nonlinear Dimensionality Reduction Algorithm. Based on the defects of data dimensionality reduction algorithms, a new nonlinear dimensionality reduction method is proposed. Firstly, the linear supervised LDA algorithm is used to find the nearest neighbor of each sample point, and then the local embedding features of the training set in low-dimensional space are obtained by calculating the local reconstruction weight matrix in the LLE algorithm [16], and finally, according to the characteristics of high-dimensional nonlinear images, the low-dimensional features of new samples are obtained by calculating the training set and its low-dimensional features. In this way, the algorithm can well establish a clear mapping between new sample points and their low-dimensional features through the relationship between high-dimensional space and low-dimensional space [17]. The implementation process of the nonlinear dimensionality reduction algorithm is shown in Figure 1.

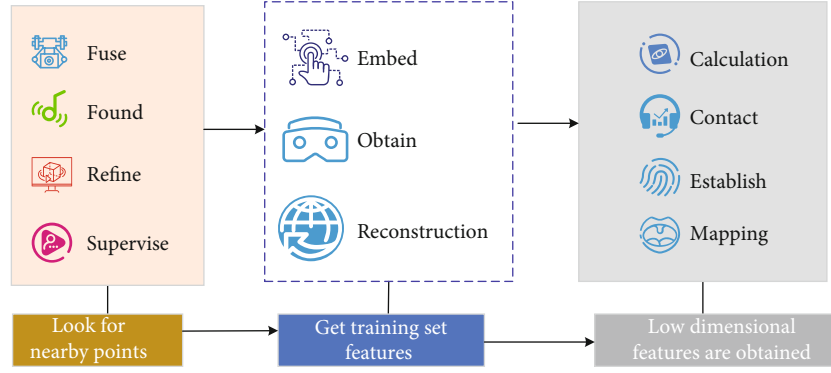The implementation process of the algorithm is as follows:

FIGURE 1: Implementation process of the nonlinear dimensionality reduction algorithm.

(1) The k nearest neighbors of each sample point are obtained by the linear discriminant analysis (LDA) algorithm. The process of finding the nearest neighbor of the sample points is as follows: firstly, the LDA subspace A is obtained by reducing the dimension of the training set X. Then, two points X_i and X_j are arbitrarily selected in the high-dimensional space, and the distance between these two points is defined as the Euclidean distance between their corresponding LDA feature points [18]. Finally, the K adjacent points of each sample point are selected by the newly defined Euclidean distance

(2) The LLE algorithm is used to calculate the local reconstruction weight matrix. The low-dimensional local embedding features of the training set are obtained, and the local reconstruction weight matrix is calculated by using the second and third steps of the LLE algorithm. In this step, the calculation of the local reconstruction weight matrix is still completed in the original high-dimensional space, which can not only ensure the nonlinear structure of high-dimensional data but also obtain the low-dimensional local embedding feature of training set X

(3) According to the training set X and the low-dimensional feature y obtained in the previous step, the low-dimensional feature corresponding to the new sample is calculated. For an image with obvious high-dimensional nonlinear fluidity structure such as commodity price, since the relationship between the points in the local neighborhood of its high-dimensional space and low-dimensional space remains unchanged, the low-dimensional embedding feature of the new sample point can be calculated as long as the neighborhood relationship between the new sample point and the training set X can be obtained. Figure 2 shows the flow chart of modeling

4. Experimental Results and Analysis of Commodity Price Identification

The experimental environment configuration of this paper is as follows: the CPU is Intel Core i7, the memory is 8 GB, the
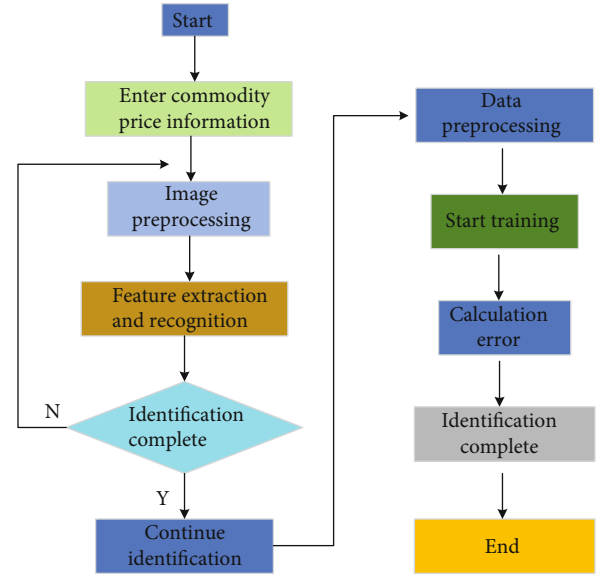

FIGURE 2: Flow chart of modeling.

operating system is Windows 10, and the experiments are carried out under the environment of the MATLAB operating platform. In order to make better use of the color space features of the image to identify the image, the HSI color space mentioned above is used to extract the features of the image H channel, S channel, and I channel, respectively. At the same time, the commodity image is recognized by using the secondary classification combination method mentioned above. In addition, a large number of experiments are carried out on different classification methods, such as traditional image recognition technology and image recognition technology based on the nonlinear dimensionality reduction method, to compare the correct recognition rates of various methods. Through the analysis and comparison of the experimental results, an image recognition method with a good recognition effect is determined to recognize the supermarket shelf commodity price in practical application and verify the effectiveness of the image recognition technology based on the nonlinear dimensionality reduction method in this paper.

4.1. Simulation of Dimensionality Reduction Results of Nonlinear Data. In the real world, many datasets are
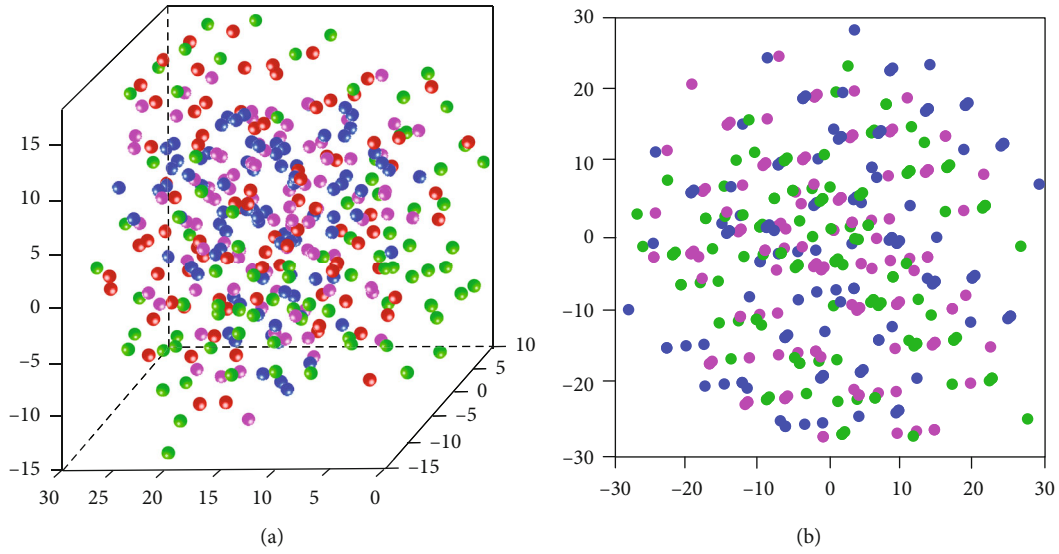
(a)

(b)

FIGURE 3: Datasets and dimensionality reduction results.

nonlinear structures, such as image data, statistical data, and spatial data. In order to make up for this deficiency, many effective nonlinear data dimensionality reduction methods have been studied, such as the equidistance mapping method, local linear embedding method, and Laplacian feature mapping method, and have been successfully applied in the research fields of image analysis, data mining, and computer vision [19]. The basic idea of dimensionality reduction of nonlinear datasets is based on multidimensional scaling analysis and strives to maintain the geodesic distance between two points, that is, to maintain the internal geometric properties of data points, to ensure that the Euclidean distance is used to replace the geodesic distance between close points, and to approach the geodesic distance between distant points with a short path. The main purpose of the algorithm is to find the low-dimensional manifold embedded in the high-dimensional space by using the multidimensional scaling analysis algorithm and preserve the inherent nonlinear geometry of the data through the geodesic distance.

Figure 3(a) shows a dataset containing 1000 data points, which is a dataset obtained after sampling from a surface in three-dimensional space and has a typical nonlinear structure [20]. Taking the neighborhood parameter as 10 and applying dimensionality reduction processing, the two-dimensional representation is shown in Figure 3(b). It can be seen that in the results obtained by PCA dimensionality reduction, the two ends of the surface overlap with its interior, which cannot be distinguished, indicating that it cannot reveal the nonlinear manifold [21]. The IsoMax dimensionality reduction results successfully reflect the internal local distribution structure of data.

4.2. Effectiveness Analysis of Commodity Price Identification. This section will use the simulation experiment of image recognition to verify its effectiveness, record the relevant experimental results, analyze and compare the experimental results, and select the image recognition method with the

best recognition effect as the method of commodity price recognition. In order to verify the effectiveness of the classification and recognition method, firstly, the traditional image recognition method and the image recognition technology based on the nonlinear dimensionality reduction method are used to identify the price in the commodity library under different feature dimensions. The following are the experimental results, as shown in Figure 4.

It can be seen from the results in the figure that the recognition effect of image recognition technology based on the nonlinear dimensionality reduction method is more than one percentage point higher than that of traditional image recognition technology, and the highest recognition rate is 87.65%. The reason is that the image recognition technology based on the nonlinear dimensionality reduction method uses the error coding theory in communication technology and has a certain error correction ability. Therefore, the image recognition technology based on the nonlinear dimensionality reduction method is better than the traditional image recognition technology, and its recognition effect has been improved to a certain extent. At the same time, it can also be found that the image recognition technology based on the nonlinear dimensionality reduction method has improved the image recognition rate in the process of increasing the feature dimension of the image from 10 to 30. However, when the image feature exceeds 30 dimensions, the image recognition begins to decline. When the image recognition rate is 30 dimensions, it has better recognition results. The image recognition rate of traditional image recognition technology also increases first and then decreases with the dimension. When the image feature is 25 dimensions, the recognition rate is the best. Similarly, the traditional image recognition technology, image recognition technology based on the nonlinear dimensionality reduction method, and linear discriminant analysis method can be combined, and then the new combined image recognition method can be used for recognition experiments. In order to verify the effectiveness of this method, the following
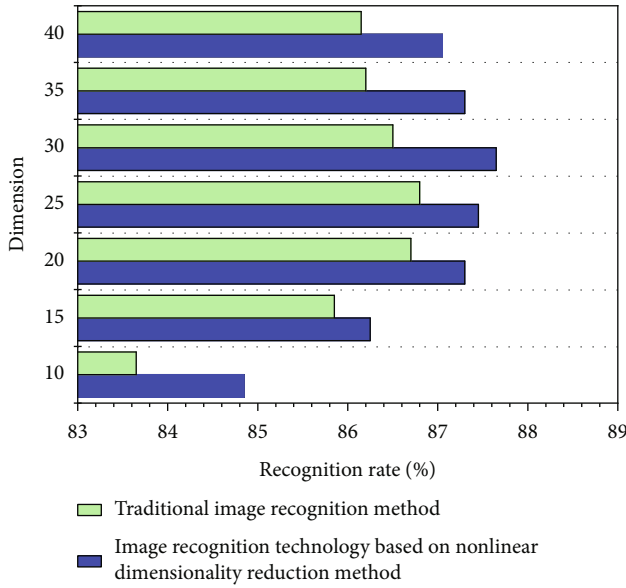
FIGURE 4: Comparison of recognition results under different feature dimensions.

FIGURE 5: Comparison of recognition rates of different feature dimensions after optimization.

figure also lists the image feature extraction using LDA. Then, the experimental results of image recognition using traditional image recognition technology and image recognition technology based on the nonlinear dimensionality reduction method are shown in Figure 5.

It can be seen from the above figure that when image recognition is carried out through traditional image recognition technology and image recognition technology based on the nonlinear dimensionality reduction method, the image features extracted by the LDA method have a better recognition effect than those extracted by PCA, and the overall image recognition rate has been improved to a certain extent, the highest image recognition rate using traditional image recognition technology is 87.80%, and the highest image recognition rate using image recognition technology based on the nonlinear dimensionality reduction method is 88.85%. Compared with the method of extracting image features using principal component analysis, the correct recognition rate of images is improved by about one percentage point, and the recognition effect of image recognition technology based on the nonlinear dimensionality reduction method is still higher than that of traditional image recognition technology. At the same time, the accuracy of image recognition varies with the change of the image feature dimension. When the feature dimension increases from 10 dimensions to 25 dimensions, the recognition rate increases with the increase of the feature dimension. After exceeding 25 dimensions, the recognition rate of images begins to decrease gradually. Therefore, when the feature dimension of the image is 25 dimensions, traditional image recognition technology and image recognition technology based on the nonlinear dimensionality reduction method have the highest recognition rate.

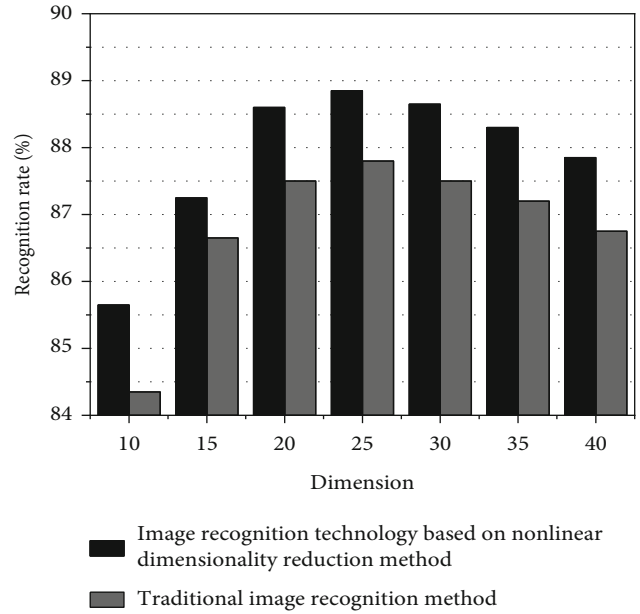*4.3. Efficiency Analysis of Commodity Price Identification.* From the above two groups of experimental data, we can compare the experimental results by using different classification methods so as to select a more suitable method for image recognition. At the same time, we can improve the image recognition rate through different image feature extraction methods, but the efficiency of image recognition is not high enough. In order to identify commodity prices more accurately and improve the accuracy of price recognition, the recognition efficiency of image recognition algorithms is further improved based on the original image recognition method. The recognition results are shown in Figure 6.

As can be seen from the figure, compared with using a single classifier, the image recognition effect of using the convolutional neural network (CNN) as a secondary classifier has been further improved. PCA is used as the image feature extraction method, and then the secondary classification image recognition composed of the convolutional neural network and traditional image recognition technology has the highest recognition rate of 88.60%, while the secondary classifier combined with the convolutional neural network and error correction classifier SVM has the highest recognition rate of 90.55%. At the same time, the change of the image recognition rate of the two image recognition methods with the increase of the feature dimension is basically the same. It can be seen from the broken line diagram that when the feature dimension of the image increases from 10 to 25 dimensions, the image recognition rate is also improving. After exceeding 25 dimensions, the feature dimension continues to increase, and the image recognition rate begins to decline slightly. Therefore, when the photograph characteristic dimension is 25 dimensions, the fine photo attention impact can be obtained. Of course, the linear discriminant evaluation technique can additionally be used to extract the HSI spatial points of color photos rather than the essential aspect evaluation method, and then the two
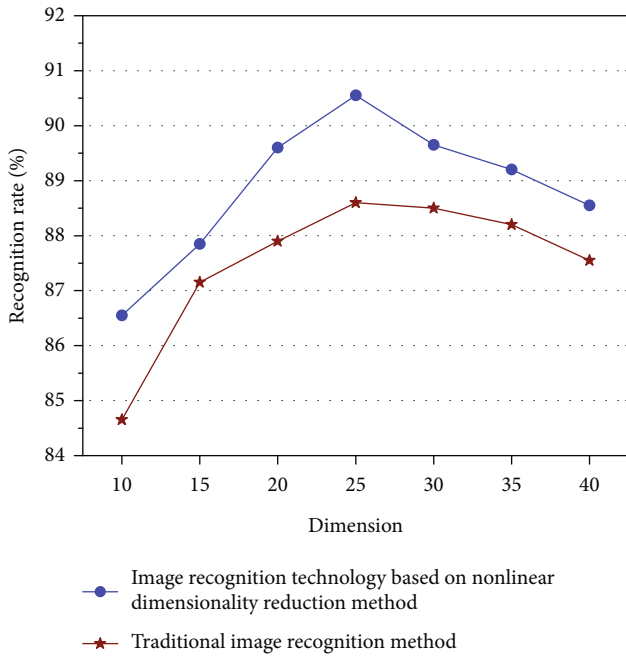
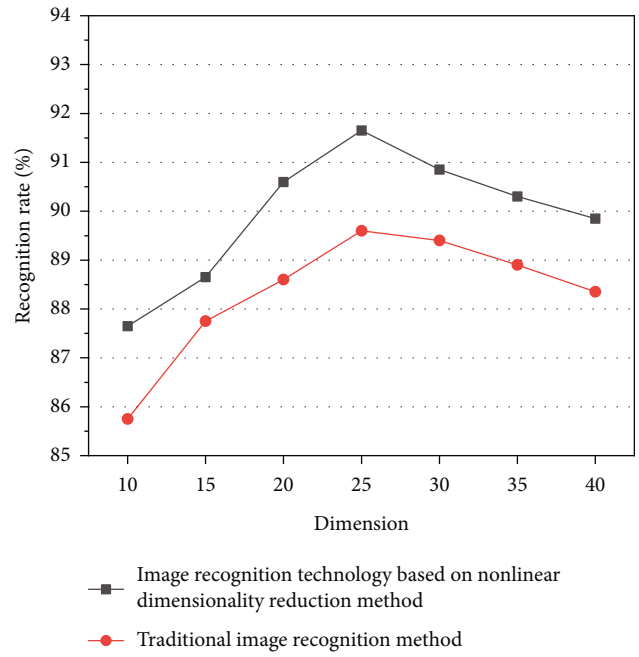FIGURE 6: Efficiency analysis of commodity price identification.

FIGURE 7: Efficiency analysis of commodity price identification.

blended secondary classification techniques can be used for picture recognition. The recognition results of the secondary classification image recognition method are shown in Figure 7.

The experimental results show that compared with the PCA feature, taking the LDA feature as a feature vector and using a secondary classifier have a higher recognition rate and a better recognition effect. The secondary classifier composed of the convolutional neural network and image recognition technology based on the nonlinear dimensionality reduction method has a better effect than using traditional image recognition technology for secondary classification, and the image recognition rate is improved by 1%-2%. The secondary classification image recognition method achieves the best recognition effect when the image feature dimension is 25 dimensions. In order to identify the recognition rate of different image classification methods under different feature dimensions, as shown in Figure 8, the highest image recognition results of all image recognition methods under different feature dimensions are listed.

According to the experimental results in the above figure, the following conclusions can be drawn: among the four methods combined with different feature extraction methods and two secondary classifiers, the secondary classifier composed of the convolutional neural network and image recognition technology based on the nonlinear dimensionality reduction method has a better recognition effect, and the image recognition rate of the two features is higher than that of the other secondary classifier; on the other hand, using the same classification method for image recognition, the correct recognition efficiency of LDA features is higher than that of PCA features. Therefore, using the LDA method to extract HSI spatial color features and using the secondary classification method composed of the
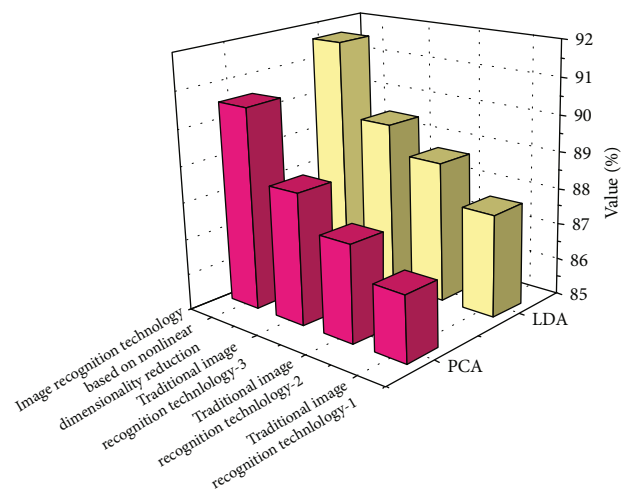

FIGURE 8: Analysis of commodity price recognition results under different feature extraction methods.

convolutional neural network and image recognition technology based on the nonlinear dimensionality reduction method, the image recognition effect is the most ideal.

4.4. Comparison of Accuracy of Different Commodity Price Models.
Considering that the commodity prices of different varieties may be affected by different factors, whether these effects can be eliminated when training the model needs further verification. Therefore, this section carries out experiments from the following two aspects: first, train different models for different varieties; second, train a general model for all varieties. The training sets are randomly selected according to different proportions to train the three prediction models A, B, and C, and then the three trained models are tested, respectively. Figure 9 is a comparison diagram of

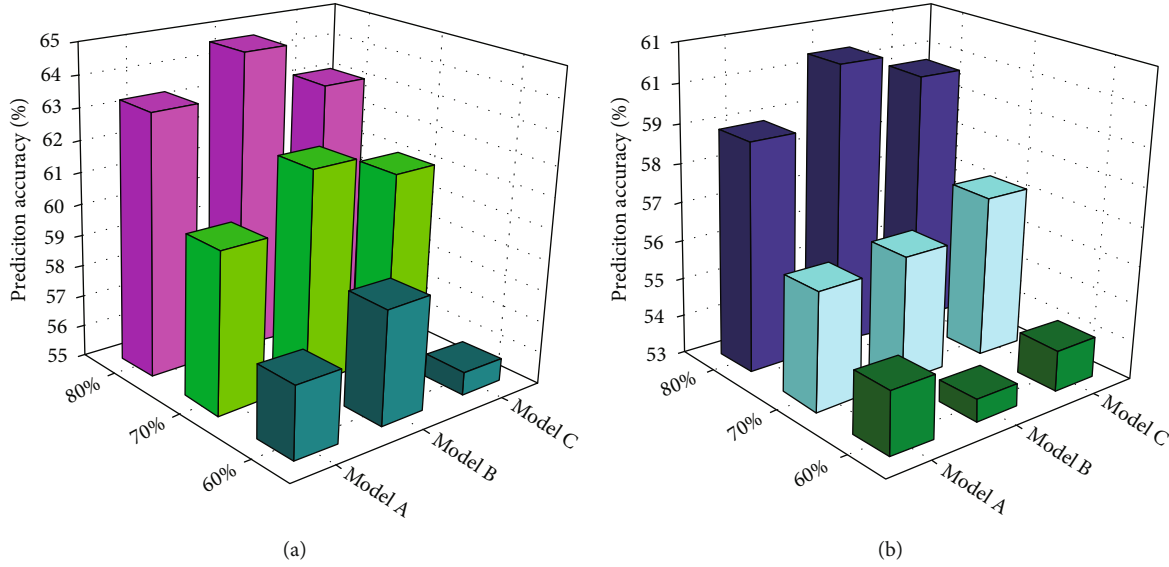(a)   (b)

FIGURE 9: Comparison of prediction accuracy between the special model and the general model.

the accuracy of prediction using three special models when the proportion of the training set is 60%, 70%, and 80%, respectively. Three kinds of datasets are fused into a large dataset to train the neural network model. Figure 9 is a comparison diagram of the accuracy of prediction using the general model when the proportion of the training set is 60%, 70%, and 80%, respectively.

As can be seen from Figures 9(a) and 9(b), the prediction accuracy of the model increases with the increase of the proportion of the training set. Under the same proportion of the training set, the prediction accuracy of the three varieties is almost the same, but the prediction ability of the special model is obviously better than that of the general model. This shows that the effect of different models trained by different varieties is better. Experiments and analyses are carried out on models with different wavelet periods.

5. Conclusion

This paper proposes a new solution to the problem of commodity price recognition; that is, the nonlinear dimensionality reduction method of high-dimensional data is introduced into image recognition. The eigenstructure of the high-dimensional dataset can be found by nonlinear dimensionality reduction to obtain the feature expression vector of a single image so as to transform the high-dimensional recognition problem into the recognition problem of the relatively low-dimensional feature expression vector. Compared with common methods, this consideration has the following characteristics: convenient and fast calculation and small storage capacity. It can fully mine the intrinsic information of image data and omit a large amount of redundant information. Each image can be processed independently. It can greatly improve the recognition effect of common methods. Thus, this expression of image data can be widely used in recognition, search, and other aspects. This method can reduce the complexity of calculation, improve

the accuracy of recognition, and facilitate further processing such as image recognition and search. The defects of traditional algorithms are solved, and the commodity price recognition and simulation experiments are carried out, which verifies the feasibility of image recognition technology based on the nonlinear dimensionality reduction method in commodity price recognition. In order to make the existing image recognition technology mature, economically and practically, in-depth research is carried out from the following aspects: further developing a more comprehensive and systematic database, looking for a more scientific algorithm according to the characteristics of each part of the recognition system, and improving the recognition rate as the focus of future research.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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