

Retraction

Retracted: Convolutional Neural Network Face Recognition Method Using Fisher's Criterion

Mobile Information Systems

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

- [1] W. Wang and F. Wu, "Convolutional Neural Network Face Recognition Method Using Fisher's Criterion," *Mobile Information Systems*, vol. 2022, Article ID 1101282, 10 pages, 2022.

Research Article

Convolutional Neural Network Face Recognition Method Using Fisher's Criterion

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In order to further improve the ability of automatic feature extraction of deep learning technology and better solve the problem of system recognition ability declining when the number of training samples is reduced or the number of iterations is reduced, this paper proposes a fisher-based convolutional neural network algorithm, which automatically obtains the structural feature information of a face image with the help of a deep learning algorithm network and then reduces the number of weights with the help of a convolutional neural network to further reduce the complexity of the face recognition model. Through the system test, the verification data shows that the recognition error rate can be controlled at about 10% by extracting 10 of the 14 pictures of each type of face for training. When the training images are reduced, the recognition rate can be further improved.

1. Introduction

Face information is not only the external representation element that can directly express features but also the most natural biometric information. Face recognition technology is a special biometric technology to identify and authenticate individuals with the help of each person's different facial feature information [1]. With the rapid development of science and technology, face recognition technology has been applied to various fields of production and life, such as community access systems, mobile phone unlocking systems, mobile payment systems, and so on. In fact, face recognition and authentication are to carry out image comparison and recognition with the help of naturally taken pictures and system-registered certificate photos, and then provide technical support for intelligent life. The fusion of convolutional neural networks greatly improves the accuracy of classification problems, especially the combination with a face recognition system, which can better distinguish the corresponding attributes of the face and design better optimization functions by obtaining more data. This paper is based on this and further improves the effect of face

recognition by using the Fisher criterion [2]. Figure 1 is a method and process of facial expression recognition based on a convolutional neural network.

2. Literature Review

In recent years, research on face recognition technology has achieved remarkable results. For example, some scholars have proposed the algorithm research of face recognition based on Fisher linear discrimination. First, the mean value of each class of face image is found through the Fisher linear discrimination method, then the distribution matrix in the class and the diffusion matrix between classes are calculated, and finally, the optimal projection value of the face image is found and the face weight is obtained [3–5].

There are also many research studies on face recognition in moving scenes. For example, we studied the face recognition access and control system using a convolutional neural network. In the system, two specific people are allowed to enter after 5 seconds of separate recognition in the video sequence, and the entry is blocked when the presence of external people in the visual area is detected. The

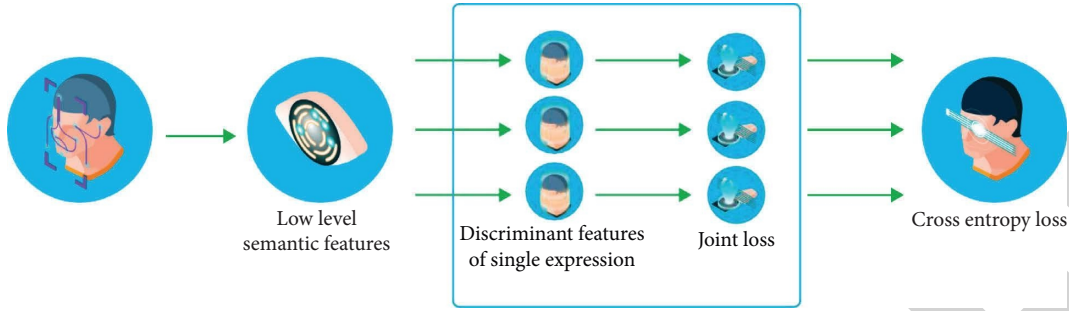


FIGURE 1: A method and flow of facial expression recognition based on a convolutional neural network.

experimental accuracy is 95% with the proposed Fisher vector coding method with binary features. The Fisher vector (FV) coding based on local scale-invariant feature transform (SIFT) is one of the best codings. In order to speed up the calculation time of this method, the FV coding method based on the binary feature has been introduced. By using binary robust independent basic features (brief), this method obtains high efficiency but also loses accuracy. The FV representation of binary features requires appropriate mathematical tools, which are not as easy to obtain as continuous features. Therefore, a new method of FV coding to obtain binary features is proposed, which is still effective and accurate. Experiments also verify that this method has the same good performance as video face recognition obtained by SIFT features [6].

The model-based face recognition method uses facial features to connect with the model and establish a feature model for face recognition. More commonly used models, such as the hidden Markov model, simulate the changes of image features by using a Markov chain. Some scholars have proposed an improved hidden Markov face recognition method. By segmenting the image feature sequence, and then using some observation sequences to calculate the maximum similarity of all hidden Markov models, and selecting the hidden Markov model with high similarity, which effectively reduces the calculation times of the feature vector and improves the speed of face recognition [7–9]. In the research work of deep learning, some scholars have designed a new convolutional neural network structure, which makes full use of the advantages of the spatial pyramid pooling layer, replaces the traditional pooling layer with a spatial pyramid pooling layer, improves the expression of deep features of samples, greatly improves the training speed and the recognition rate, studied the application of the particle swarm optimization algorithm, used PCA technology to extract facial features, and then used the particle swarm optimization algorithm to optimize the parameters of SVM. Experiments on ORL and Yale face databases have achieved high recognition accuracy.

3. Face Recognition Algorithm

3.1. Support Vector Machine

3.1.1. *Linear Support Vector Machine.* First, define the classification hyperplane as follows:

$$w^T x + b = 0. \quad (1)$$

See Figure 2 for details

Define the linear sample set as follows:

$$(X_i, y_i) \quad (i = 1, 2, \dots, N, X \in R^n, y \in \{-1, 1\}). \quad (2)$$

The classification function is as follows:

$$g(x_i) = \text{sgn}(x_i) = \begin{cases} -1, & f(x_i) \leq -1, \\ 1, & f(x_i) \geq 1, \end{cases} \quad (3)$$

where

$$f(x) = w^T x + b = 0. \quad (4)$$

Then the distance between any sample and the optimal hyperplane can be expressed as follows:

$$r = \frac{(w^T + b)}{\|w\|}. \quad (5)$$

The distance between the classification surface and the nearest sample is as follows:

$$r' = \frac{1}{\|w\|}. \quad (6)$$

when r' is the largest, the optimal classification surface is determined, and its corresponding constraints are

$$\begin{aligned} y_i(w^T + b) &\geq 1, \\ i &= 1, 2, \dots, N. \end{aligned} \quad (7)$$

In order to solve the optimal classification surface, Lagrange multiplier method can be introduced, that is as follows:

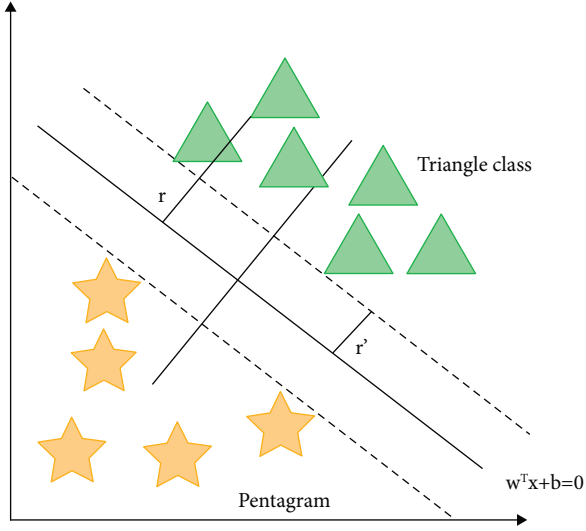


FIGURE 2: Linear separability.

$$L(w, a, b) = \frac{1}{2} \|w\|^2 - \sum_{i=1}^N a_i [y_i (w^T x_i + b) - 1]. \quad (8)$$

Let L calculate the partial derivative of w and b to 0, that is as follows:

$$\begin{cases} \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^N a_i y_i = 0 \\ \frac{\partial L}{\partial w} = 0 \rightarrow w - \sum_{i=1}^N a_i y_i x_i = 0 \end{cases} \quad (9)$$

Then you can get

$$\begin{cases} w = \sum_{i=1}^N a_i y_i x_i \\ \sum_{i=1}^N a_i y_i = 0 \end{cases} \quad (10)$$

The above quadratic function can be solved, and the optimal discriminant function is as follows:

$$g(x) = \text{sgn} \left\{ \sum_{i=1}^N a_i y_i (x_i^T x) + b \right\}. \quad (11)$$

3.1.2. Nonlinear Support Vector Machine. For the nonlinear sample classification problem, the support vector machine uses the kernel function of the input space. While solving the optimal hyperplane, first compare the vectors in the input space and then nonlinear transform the results, which greatly reduces the amount of calculation. Figure 3 shows that the low-dimensional linear separable problem is transformed into a high-dimensional linear separable problem by using a kernel function and then classified by a linear support vector machine [10].

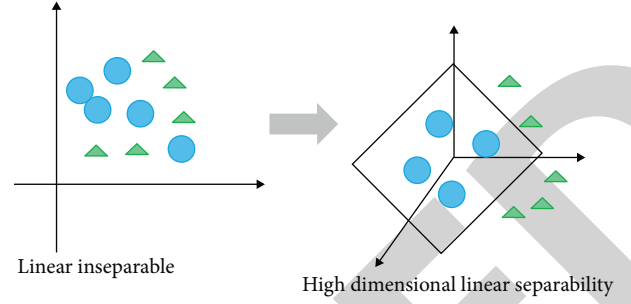


FIGURE 3: Linear indivisibility.

Define the kernel function as $K(x_i, x_j)$, so that

$$x_i^T x_j = K(x_i, x_j). \quad (12)$$

Then the optimal discriminant function is as follows:

$$g(x) = \text{sgn} \left\{ \sum_{i=1}^N a_i y_i K(x_i, x) + b \right\}. \quad (13)$$

Kernel functions mainly include the following:

Linear kernel function:

$$K(x, x_i) = x^T x_i. \quad (14)$$

Gaussian kernel function:

$$K(x, x_i) = \exp \left(-\frac{\|x - x_i\|^2}{\sigma^2} \right). \quad (15)$$

Polynomial kernel function:

$$K(x, x_i) = (x^T x_i + l)^d. \quad (16)$$

3.2. Application of Support Vector Machine Face Recognition. Traditional support vector machines usually use a single core to deal with linear inseparable problems, so the selection of kernel function is a key point. In practical applications, experience or experiments are often used to select the most appropriate kernel function, which will increase the workload. Moreover, the features of data samples may be fused by a variety of features, such as color features, statistical features, geometric features, and so on. The optimal kernel functions corresponding to different features may also be different, so the performance of a single core for complex face image recognition is not high, and it becomes meaningful for multi-core learning and research [11, 12]. Support vector machines have great advantages in dealing with small sample learning problems and have a solid theoretical foundation [13].

4. Depth Convolution Recognition Algorithm Based on Fisher Criterion

4.1. Algorithm Process. To make the algorithm easier to classify, we provide the working force based on the distance between classes, based on the concept of the Fisher test. The formula is as follows:

$$J_1 = \frac{1}{2} \sum_{i=1}^m \sum_{j=1}^m \|h_{w,b} x^{(x,j)} - M^{(i)}\|^2, \quad (17)$$

$$J_2 = \frac{1}{2} \sum_{i=1}^m \sum_{j=1, j \neq i}^m \|M^{(i)} - M^{(j)}\|^2. \quad (18)$$

Equation (17) is the function of measuring class consistency, defined by the sum of the spacing of each model and their class average; equation (18) is the similarity measurement function between classes, which is defined as the sum of the distances of the mean values of all sample classes. $M^{(i)}$ is the average value of class i samples

$$M^{(i)} = \frac{\sum_{j=1}^n h_{w,b}(x^{(i,j)})}{n}, \quad (19)$$

To make it easier to distribute the acquired characteristics of each layer of deep learning in the network, we provide models of working forces with different class and class constraints.

$$J = R + \gamma J_1 - \eta J_2. \quad (20)$$

In the abovementioned formula, R is the cost function of the neural network, and the overall cost function is J . While considering the error, it makes the intra class spacing of samples small and the inter class spacing large [14, 15].

4.2. Multitask Attribute Based Face Analysis. The system diagram of multitask training is shown in Figure 4. First, the databases for each task are preprocessed in the same way and then input into the shared network for training. Finally, they are tested on the corresponding data sets. Table 1 lists the details and usage of each database.

Each layer of a convolutional neural network extracts features. The features at the bottom are more basic, and the more upward, the more abstract the features are. According to our idea, in the network of face attribute analysis, the underlying features should be the same and gradually become different as we go up [16]. Therefore, we use the multitask learning method to combine the face attribute analysis task with the face recognition task, sharing the parameters of the previous convolution layer so that the network can learn more comprehensive content, while the latter full connection layer is separated and classified separately, so that we can learn different features [17, 18].

We use MTCNN for face detection and key point location of all database images, then we use the similarity transformation of five points for image alignment, intercept and zoom to the image size of 256×256 , and finally, divide the image pixel value by 128 after subtracting 127.5, normalize the value to $[-1, 1]$ and input it into the network for training. The experimental platform is Ubuntu 16.04. A total of four NVIDIA Tesla P100 GPUs are used for training. The depth learning tool used is PyTorch, with an initial learning rate of 0.1. The number of pictures trained in each iteration of each task is 256. When the iterative training reaches 20000 and 30000 times, the learning rate will be reduced by 10 times, and finally the training will be stopped when the

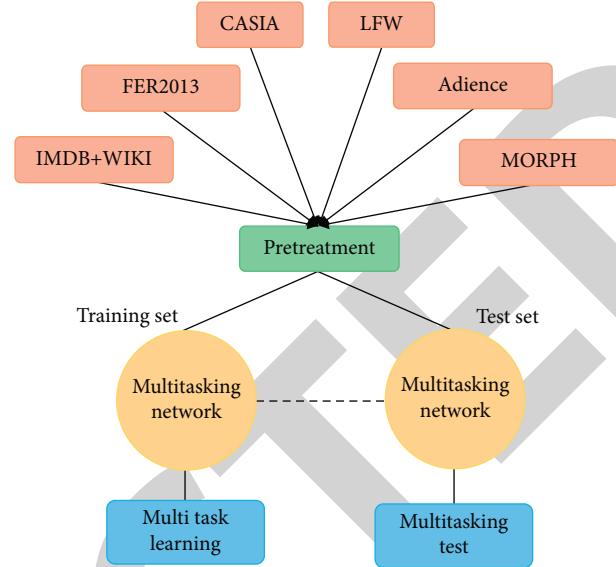


FIGURE 4: Schematic diagram of multitask learning system.

TABLE 1: Database details and usage.

Database	Task	Number of pictures	Use phase
CASIA	Face recognition	494412	Training
LFW	Face recognition	13221	Test
IMDB + WIKI	Gender and age	523088	Training
Adience	Gender and age	26540	Test
MORPH	Age	55213	Test
FER2013	Expression	35884	Training and test

TABLE 2: Weight of loss function for different tasks.

Task	Weight of loss function
Face recognition	1.0
Gender identification	0.9
Age identification	0.9
Expression recognition	0.6

number of iterations reaches 40000 times. The impulse and weight attenuation parameters used in training are 0.9 and 0.0005, respectively. Different tasks assign different loss function weights to them. The details are shown in Table 2.

We also conducted single-task training for these several face attribute analysis tasks and compared them with the multitask learning method. Table 3 is the accuracy rate of face recognition task on LFW. Table 4 is the accuracy rate of gender recognition task on Adience. Table 5 is the accuracy rate of age recognition task on Adience. Table 6 is the performance of age recognition task on MORPH Performance. Table 7 is the accuracy of the expression recognition task on FER2013 [9, 19].

TABLE 3: Accuracy of face recognition task on LFW.

Method	Number of training pictures	Number of networks	Accuracy (%)
DeepFace	4 M	3	97.33
DeepID2+	—	25	99.51
FaceNet	200 M	1	99.67
DeepFR	2.6 M	1	98.88
Baidu	1.3 M	1	99.12
Single task in this paper	0.5 M	1	98.86
Multi task in this paper	0.5 M	1	98.63

TABLE 4: Accuracy of gender recognition task in Adience.

Method	Accuracy
Eidinger	77.4% ± 1.4
Hassner	79.2% ± 0.0
Levi and Hassner	85.6% ± 1.2
Levi and Hassner	86.2% ± 1.2
Single task in this paper	91.2% ± 2.2
Multi task in this paper	92.1% ± 1.6

TABLE 5: Accuracy of age recognition task on adience.

Method	Accuracy
Hassner	45.4% ± 2.4
Levi and Hassner	50.2% ± 5.0
Rothe	55.6% ± 6.2
Rothe	64.2% ± 4.2
Single task in this paper	63.2% ± 5.3
Multi task in this paper	64.1% ± 4.6

TABLE 6: The results of age recognition on MORPH.

Method	MAE mean error
Guo G	3.94
Yi D	3.65
Rothe	3.22
Rothe	2.67
Single task in this paper	3.22
Multi task in this paper	2.91

TABLE 7: Accuracy of expression recognition task on FER2013.

Method	Accuracy (%)
Tang	72.2
Zhou	69.5
Milakov	68.2
Lonescu	67.4
Single task in this paper	70.4
Multi task in this paper	71.3

As can be seen from Table 7, our method has achieved 92% accuracy in gender recognition tasks and also has achieved good accuracy in age recognition and expression recognition tasks. At the same time, the accuracy of multitask is higher than that of a single task, which shows that different face attribute analysis tasks can promote each other. It is worth noting that the accuracy of multitask face recognition decreases slightly, which may be

related to the amount of training data. Because the training data for face recognition itself is enough, adding other databases has a certain impact on it. The weight proportion of the loss function is different between different tasks, which also affects the results. In addition, the classification training of face recognition is divided into many categories, including about 10000 categories. It is a relatively fine classification and has high requirements for accuracy. Adding other databases for training interferes with it [20, 21].

4.3. Face Recognition System Based on Improved Convolutional Neural Network. The traditional convolutional neural network will use the Softmax regression function for regression classification after feature extraction. The classifier can deal with two classification and multiclassification problems, and the calculation is simple. The Softmax classifier can accurately calculate the probability that the sample belongs to each class, so as to determine the class of the sample. In the face database in this paper, the recognition degree of faces is greatly affected by the environment, so this paper selects the support vector machine with a stronger classification ability as the classifier [22].

The face recognition system includes three stages: face image preprocessing; feature extraction of a convolutional neural network; and classification of a support vector machine. The face image preprocessing stage includes image normalization, Gaussian filtering, and image histogram equalization. In order to ensure the consistency of the images, it is necessary to normalize the images. Image normalization includes geometric normalization and gray normalization. Geometric normalization is used to solve the problem of different face sizes and poses due to different image acquisition distances. Gray normalization is used to solve the influence of illumination intensity and light source intensity on the face image. Gray normalization usually includes two steps: gray change and stretching. For example, if the average value of an image is m and one pixel of the image is $f(x, y)$, the standard deviation σ of the image is as follows:

$$\sigma = \sqrt{\frac{1}{n} \sum_{x,y} (f(x, y) - m)^2}. \quad (21)$$

The gray transformation formula of the image is as follows:

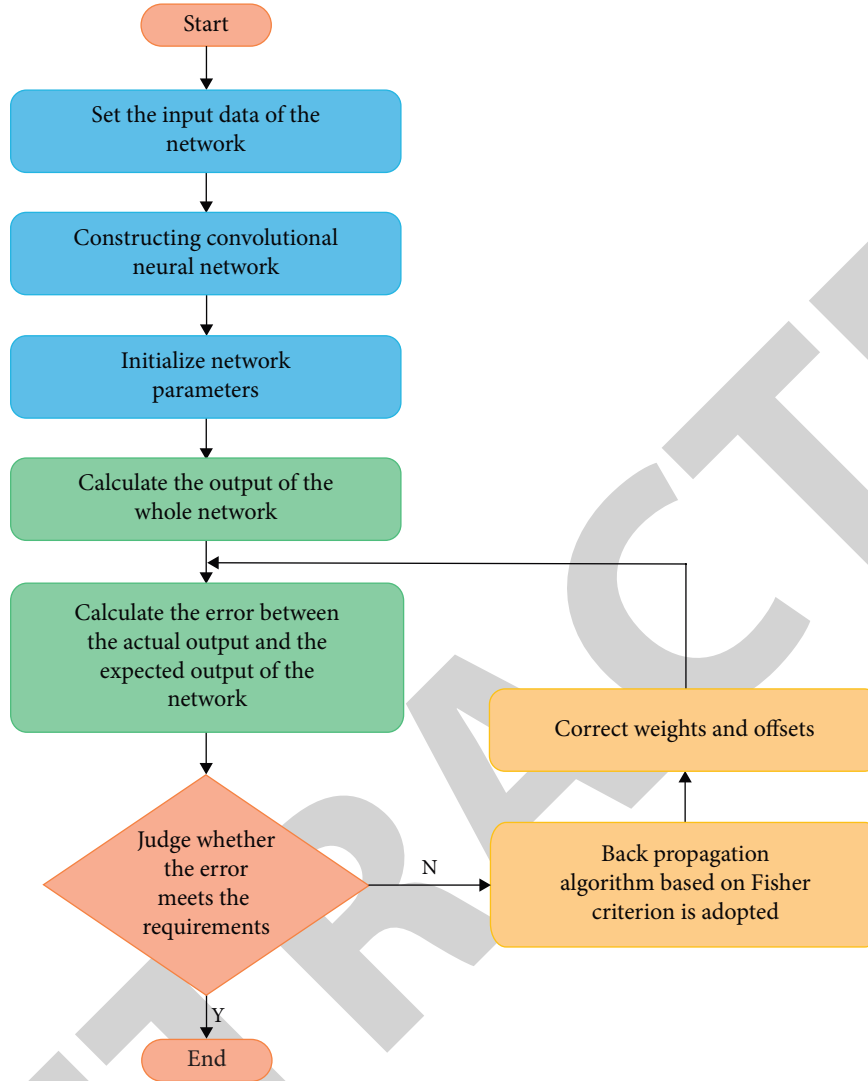


FIGURE 5: Training of convolutional neural networks based on the Fisher criterion.

$$f(x, y) = f(x, y) - \frac{b}{\sigma}. \quad (22)$$

However, the pixel value of the transformed image may not be within the gray value range, so it is necessary to stretch the mapped image to make its pixel values within the range of 0~255. The specific transformation formula is as follows:

$$f(x, y) = \frac{(f(x, y) - \min) \times 255}{\max - \min}. \quad (23)$$

The images used in this paper are gray-scale images, so it is necessary to normalize the gray-scale images to transform the images into the required standard size form. Because there are some noise factors in the face database, which have nothing to do with the research content of the experiment, they will interfere with the extraction of some key information from the image and affect the subsequent image processing work. Therefore, in order to reduce the influence of noise factors on the experimental results, the Gaussian

filtering method is adopted in this paper. Gaussian filtering is widely used in image denoising. This method uses a known convolution check to convolute the pixels of the image, and uses the weighted average gray value in its neighborhood to replace the pixel value of the central point of the neighborhood. It is an efficient process of facial feature extraction based on convolution neural networks [23]. The training flow chart of a convolutional neural network based on the Fisher criterion is shown in Figure 5.

In the training process, the sensitivity of each layer is calculated by the Fisher criterion algorithm, and the increment of weight and bias is calculated to update it. After the convolution neural network is trained, the image features can be extracted. In this paper, a 6-layer convolution neural network is constructed. The input image goes through the convolution operation and sampling operation layer by layer. Finally, a face image is mapped into 120 feature images, and each feature image contains some local information about the original image. The classification stage of support vector machines also includes the training and

discrimination of support vector machines. In the training stage, the image features extracted by the convolutional neural network are normalized and transmitted to the support vector machine for training. In this paper, the kernel function of the support vector machine is a Gaussian kernel function, in which the parameter C and the grid search method are used to optimize the parameters. The grid search method is an exhaustive method of parameter optimization, which is suitable for all parameter optimization problems. The specific implementation method is as follows: first, the penalty factor and the search range of the parameters are selected according to experience; then the different growth directions of the two parameters are extended by using a fixed step size to form a grid shape; and finally, the accuracy is obtained by using the method of cross verification. In the discrimination stage, the sample set to be classified is pre-processed and extracted by the face system, expressed as a feature vector, and input into the trained support vector machine. Finally, the accuracy of face recognition is evaluated [24].

4.4. Experimental Results and Analysis. In order to prove the robustness of the algorithm proposed in this paper, this chapter will carry out a series of experiments on the ORL face database, Yale face database, and AR face database, respectively, and compare this algorithm with classical face recognition algorithms such as the SCNN algorithm, traditional neural network, convolutional neural network, and sparse self-coding network, so as to verify the effectiveness of the convolutional neural network and the support vector machine algorithm based on Fisher criterion.

4.4.1. Introduction to Experimental Database. The ORL face database contains 400 face images of 40 volunteers. These face images include the changes of volunteers' posture, expression, and facial ornaments. The original image size is 112×92 . In the preprocessing stage of the face recognition system, the image needs to be initialized to the size of 28×28 .

The Yale face database contains a total of 165 face images of 15 volunteers. The data set included different changes in volunteers' facial posture, light intensity, and expression. The size of the image is 100×100 , which needs to be uniformly converted to the size of 28×28 .

The AR face database contains 3000 images of 126 volunteers. In this paper, 120 people in the database, 13 images per person, are selected as the database. The database contains the occlusion, expression, and small pose changes of the face. The original size of the AR face image is 768×576 , which also needs preprocessing to reduce the image to 28×28 .

4.4.2. Experimental Results and Analysis of ORL Face Database. The experiment was carried out on the ORL face database. The parameters of the convolution neural network are set as follows: the size of the C1 and C3 convolution kernel is 5×5 , the size of the C5 convolution kernel is 4×4 , the lower sampling layer adopts mean sampling, the sampling window is 2×2 , the network adopts batch training, the

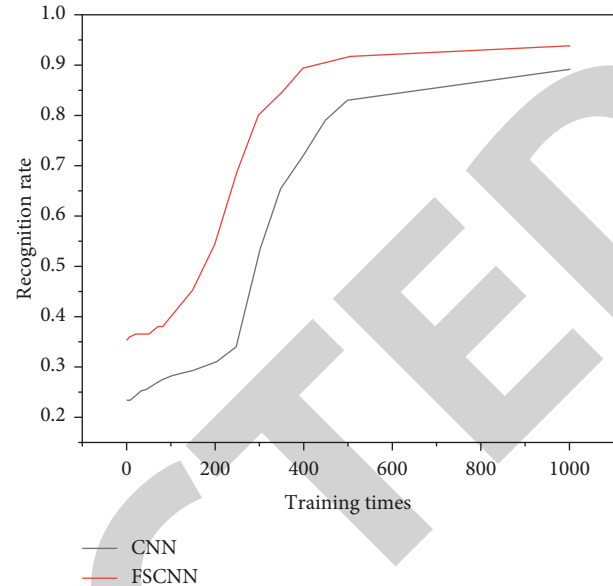


FIGURE 6: Recognition rates of FSCNN and CNN methods under different iteration times.

TABLE 8: The recognition rate of each method in the ORL database under different numbers of training samples.

Experimental method	2	4	6	8
CNN	0.3522	0.4589	0.6833	0.8876
NN	0.1124	0.3056	0.4527	0.5034
SAE	0.1544	0.3244	0.5565	0.7254
SCNN	0.3245	0.5147	0.7143	0.8933
FSCNN	0.5126	0.7389	0.8423	0.9328

activation function adopts a Sigmoid function, the learning rate is 0.01, the values of parameters α and β are 0.02, the network threshold is initialized to 0, and the kernel function selected by the support vector machine is a Gaussian kernel function. Figure 6 shows the comparison of the recognition rate of the algorithm in this paper (FSCNN) and the classical CNN when iterating on the ORL library for different times. From the figure, it can be seen that the recognition rate of the algorithm in this paper is significantly improved and the convergence is better than that of the CNN method.

In order to test the recognition rate of this algorithm under different numbers of training samples, 2, 4, 6, and 8 face images of each type in the ORL library are trained, respectively, and the remaining images are used for testing. The experimental results are shown in Table 8. It can be seen that this algorithm can also obtain high recognition effects with fewer training samples, and the overall recognition rate is stronger than other methods.

4.4.3. Experimental Results and Analysis of the Yale Face Database. The experiment was carried out on the Yale face database, and the parameters are the same as those of the ORL database. Compare the method in this paper with CNN and record the experimental results, as shown in Table 9. From the table, it can be seen that compared with CNN, the

TABLE 9: The recognition rates of CNN and FSCNN with different training times.

Training times	Method	Recognition rate	Increase (%)
500	CNN	0.7741	12.73
	FSCNN	0.9014	
2000	CNN	0.8711	5.05
	FSCNN	0.9216	
4000	CNN	0.9015	2.95
	FSCNN	0.9313	

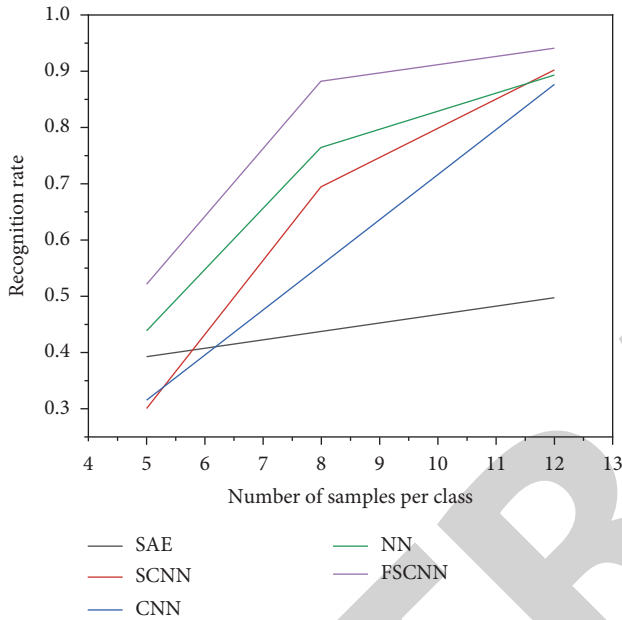


FIGURE 7: The recognition rate of several methods when the number of samples of each type is different.

TABLE 10: Recognition rate of several methods under different samples.

Experimental method	5	8	12
CNN	0.3144	0.5421	0.8731
NN	0.4326	0.7654	0.8929
SAE	0.3895	0.4321	0.4956
SCNN	0.3212	0.6522	0.9126
FSCNN	0.5212	0.6833	0.9412

TABLE 11: The recognition rate of classical CNN and FCNN with different iteration times in the MNIST library.

Training times	Recognition rate (%)		Increase rate (%)
	Classic CNN	Text method	
10	97.23	97.25	0.02
5	95.83	96.74	0.11
1	88.56	89.74	1.18

algorithm in this paper improves significantly with fewer training times; that is, the algorithm in this paper has stronger convergence and can obtain a higher recognition rate with fewer training times.

TABLE 12: The error rates of different methods with different training samples.

Experimental method	Number of samples of each type		
	4	7	10
NN	0.6801	0.3342	0.1123
SAE	0.7228	0.6712	0.5982
SAE2	0.6354	0.4811	0.1956
CNN	0.7731	0.3606	0.1314
FCNN	0.5732	0.3224	0.1294

4.4.4. *Experimental Results and Analysis of AR Face Database.* A comparative experiment was conducted in the AR face database. 120 people with 14 images are selected from the AR database. 5, 8, and 12 images are selected from each type of sample as training samples, and the rest are used as test samples for experimental simulation. The experimental simulation is shown in Figure 7 mentioned above, and the experimental data are recorded as shown in Table 10. From Table 10, it can be concluded that the algorithm in this paper improves significantly when there are few samples, which verifies the effectiveness of the algorithm in this paper.

4.4.5. *Recognition of Different Training times.* 60000 training samples were selected in the experiment, and the training times increased from 1 to 10. The experimental results are shown in Table 11.

The experimental results show that when the training times are more than 10 times, there is no difference between the two recognition rates. When the training times are reduced to only once, the recognition rate of the proposed method is improved by 1.15% compared with the traditional method. When the number of trials is increased, most machine learning methods will improve the recognition rate accordingly, but the more training times, the longer the time will be consumed. However, in practical application, it is required to complete the recognition quickly in a short time. The experimental results show that the algorithm proposed in this paper can better meet the actual needs, especially for handwritten word databases. When the same training times are small, the recognition rate of the method proposed in this paper is significantly improved.

4.4.6. *For AR Database, When the Training Is Different, the Identification Error of Different Methods Is Analyzed.* The database contains color photos of 126 people. Each type of people has changes in light, size, and expression, with a total of 2600 pictures. A total of 120 people are selected, and 14 pictures of each person are tested. During the experiment, 4, 7, and 10 pictures are taken from 14 pictures of each type of people for training, and other images are tested. The experimental results are shown in Table 12.

It can be seen from the results that when 10 images are taken from 14 images of each type of person for training and the rest are tested, the recognition error rate of most methods is 10%, but when the training images of each type of person are reduced, the recognition rate of the improved

algorithm proposed in this paper is higher than that of other algorithms. In other words, when the labeled training data is less, the method proposed in this study is more effective.

5. Conclusion

Face recognition has become a hot topic in our time, and its use plays an important role in many areas. This paper describes the development algorithms for the extraction and distribution of facial expressions and proves the effectiveness of the experimental algorithms. The main role of this sentence is as follows:

- (1) Outreach characteristics are a prerequisite for facial recognition. In this paper, a broken neural network is used to decompose facial features and cannot be repaired by training the network. This paper describes the improvement of the neural network algorithm in this paper because the speed of recognition of neural networks decreases rapidly with the reduction of training standards. The Fisher indicator is used to calculate operating costs and change patterns. In addition, vector technology is used as an alternative to the simple classifier of a convolutional neural network. Experiments have shown that this algorithm has a higher percentage of recognition, improved compatibility, and a better alternative when the model is smaller.
- (2) Due to the limitations of single-core auxiliary vector machines for learning and distribution, this paper provides support for vector machine algorithms with mixed-core operations which integrate important functions into global and local roles. Local education skills will be improved, and international assessment scores will be improved. Supporting vector systems with integrated cores are combined with enhanced neural network systems to improve the overall capacity distribution of the system. The test results also confirm the performance of the algorithm.

In this study, facial recognition based on neural networks and vector support systems was devised to eliminate facial and dividing faces. Facial removal is very important in postoperative work, and the neural network has many advantages over removal features. Therefore, in this article, the disruptive neural network is used as a signal breaker. To improve the neural network performance of commercial products, the author has introduced a neural network dysfunction algorithm based on Fisher procedures, which can reduce the distance between similar models and increase the distance between different models when an error occurs between the actual release and the model. The label should be as small as possible. Face feature classification is a key and difficult point. Feature extraction and feature classification are two functions of a general convolutional neural network. A Softmax classification layer will be added after the full connection layer. Softmax has great advantages in multiclassification, but support vector machines are also very successful in dealing with nonlinear and multidimensional problems and have stronger classification ability.

Therefore, a support vector machine is used for classification and prediction in this paper. The effectiveness of the algorithm in this paper is also verified through experimental comparisons on three face databases: ORL, AR, and Yale.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest.

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