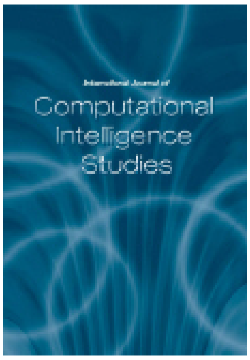


**International Journal of Computational Intelligence Studies**

ISSN online: 1755-4985 - ISSN print: 1755-4977
https://www.inderscience.com/ijcistudies

# Research on intelligent access control technology of face recognition model based on parameter sharing and dense connection

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**DOI:** 10.1504/IJCISTUDIES.2023.10060752

**Article History:**

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|---|---|
| Received: | 11 October 2022 |
| Last revised: | 13 February 2023 |
| Accepted: | 22 September 2023 |
| Published online: | 05 April 2024 |

# Research on intelligent access control technology of face recognition model based on parameter sharing and dense connection

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**Abstract:** This study proposes a laboratory intelligent facial recognition system based on improved CNN, which significantly improves the accuracy of facial recognition by optimising the portrait recognition algorithm, improving CNN calculation and large parameter scale, and utilising perspective projection to improve portrait effect and sample utilisation. The experimental results show that the recognition rate has been improved by 10%, the CPU usage rate is less than 100%, and the model parameters have been reduced by more than 95%. This system can effectively and accurately recognise faces, making it suitable for embedded facial recognition devices.

**Keywords:** convolutional neural network; CNN; face recognition; liveness detection; intelligent access control.

**Reference** to this paper should be made as follows: Xu, Y. (2023) 'Research on intelligent access control technology of face recognition model based on parameter sharing and dense connection', *Int. J. Computational Intelligence Studies*, Vol. 12, Nos. 3/4, pp.255–270.

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## 1 Introduction

With the continuous development of technologies such as artificial intelligence and optical imaging, biometric technology has become important to ensure personal and information security (Tooley, 2020). Compared with voice recognition, fingerprint recognition and other technologies, face recognition technology is utilised widely in intelligent access control, intelligent transportation, fast payment, and other industries because it is simple to use, non-contact, and quick to recognise (Yu et al., 2020; Zhu, 2021). In terms of face recognition for smart access control, due to cost and volume constraints, the traditional PC platform face recognition system is not feasible, while the face recognition system based on embedded devices is small in size and low in cost. More the ground is used in the access control system of residential areas, schools and other places. The access control system combining face recognition technology and embedded technology will have the advantages of both, so the study of their therefore, the study of the combination of both has an important application value and practical significance. At the same time, the existing embedded face recognition system also has many defects and needs to be optimised. The first is that the recognition rate needs to be improved in the case of a single sample or a small number of samples; the second is that the immunity to fraudulent attacks of forged faces is low, which is mainly reflected in the insufficient recognition performance of live faces; in addition, traditional CNN recognition The algorithm has a large amount of calculation and is difficult to apply to the embedded access control system (Wang et al., 2020). PCA is a relatively new algorithm in face recognition, and the advantages of this algorithm are high recognition rate and fast recognition speed. And the convolutional neural network (CNN) has a strong ability of image understanding and judgment. In response to these problems, the research focuses on portrait recognition and face living body detection, and proposes a PCA face recognition algorithm based on portrait enhancement and a lightweight CNN portrait living body recognition model based on a new convolution calculation method.

## 2 Related works

Since CNN has superior modelling powers than traditional neural networks in recent years, it has become widely used in industries like image processing and natural language processing, greatly advancing the technological capabilities of image recognition and intelligent translation. At present, many scholars have applied CNN to many fields and achieved good results. Medical researchers such as Deepa predicted invasive ductal carcinoma by establishing a CNN prediction model. The proposed model is compared and analysed with a variety of models. After evaluation, the prediction accuracy of the proposed algorithm in the invasive ductal carcinoma dataset is maintained at about 92%, the recall rate is 95%, and the prediction accuracy on the BreakHis dataset is accurate. The degree of accuracy remains around 94%, and the recall rate is 96% (Deepa and Senthil, 2022). Saeedi et al. (2021) used the deep learning framework of EEG signal images combined with CNN and LSTM to help early detection of major depression and help patients to treat and hinder early. Experiments show that the CNN-LSTM model has excellent performance in test detection, and its specific mechanism makes the detection accuracy rate as high as 99.24%. Methods for early diagnosis of patients, Jadhav and Inamdar (2022) combined the transfer learning characteristics of CNN with the global feature extraction in the gradient direction, extracted the relevant handwritten characters from the severely deformed MODI documents, carried out relevant learning and training on the established classifier, and finally carried out the transformation in the MODI dataset. Test results showed that the proposed framework has excellent performance in recognising and extracting MODI handwritten characters without changing the data and network. In order to improve the traffic sign recognition performance of ADAS, scholars such as Karthika used the CNN algorithm to classify the detected traffic signs, and used the GTSDB and GTSRB datasets for experiments. The average accuracy is 89.56%, and the recognition accuracy for traffic signs is 86.6%, which proves the effectiveness of the method (Karthika and Parameswaran, 2022). Researchers such as Ouchicha proposed a deep CNN classification algorithm to categorise brain magnetic resonance images of Alzheimer's disease. The model has a dense block residual network, which has stronger global and local capture performance. The model was trained and evaluated through the database. The experimental results showed that the classification of the model was accurate to 98.53%, indicating that this method has certain feasibility in the classification of AD patients (Ouchicha et al., 2022). Researchers such as Mahto developed an algorithm to enhance watermarking to ensure the copyright of images. The research used an improved encryption scheme to encrypt the image, and at the same time integrated the denoising CNN to increase the robustness of the algorithm. It is known from practical applications that this method has a large watermarking capacity, a small amount of calculation, and good imperceptibility and other characteristics to enhance the security of images (Mahto et al., 2022).

Numerous scholars have undertaken in-depth research on the intelligent face recognition of the access control system, and many of them have used CNN. Some face recognition algorithms have accuracy levels that are very near to 100%. The deployment of tag arrays, the elimination of environmental interference, and the establishment of a model to extract spatiotemporal features are all done by Chen et al. (2020) using the RFID method to perceive intelligent access control events in a particular way. They also analyse the correlation between radio frequency signals of access events. In the performance test in the real environment, the comprehensive recognition accuracy of the access control system for volunteers was 97.5%, the height recognition accuracy was 95%, and the weight recognition accuracy was 92.5% (Chen et al., 2020). Ai and Cheng (2018) have designed face detection and face recognition algorithms for the access control security system, and realised the successful application of the PCA algorithm in the system. In practical applications, the access control system accurately detects and recognises faces, providing trustworthy security. Kim et al. (2020) had problems in the recognition rate of face recognition technology, and proposed an access control based on video surveillance technology. The machine learning face recognition system is combined with RFID. In this way, individuals can use RFID features on mobile devices for multi-channel authentication. Under the dual-channel authentication, the protection of security and privacy was improved. Xu et al. (2020) designed a simplified deep CNN in the research of face recognition, which had excellent results in improving the training speed and improving the accuracy of face recognition. Compared with other face recognition algorithms, this algorithm has the highest recognition accuracy in the face database, and its average accuracy was 99.28%. Access control technology has been widely used. Chen et al. (2019) proposed a face template protection technology using multi-label learning. This technology can map faces into LDPC, encode and learn multi-label in LDPC, and output LDPC through noise generated by internal changes in the CNN model. Decoding allows for the implementation of a robust face template protection solution. Simulation experiments are carried out on the PIE and extended Yale B datasets. The error rate of the scheme in the experiment was within 1%, and it had a high real acceptance rate. System security and user privacy protection are effectively guaranteed. Wu and Zhang (2021) proposed a FaceNet network for efficient face detection and recognition based on MTCNN. The experimental results showed that the proposed method in the study was effective in the relevant field and exhibits 99.85% accuracy. Hariri (2021) considered the use of CNN for the recognition of obscured faces during COVID-19 and the results of the study showed the effectiveness of the method, which had a higher accuracy than compared to other methods used as a comparison.

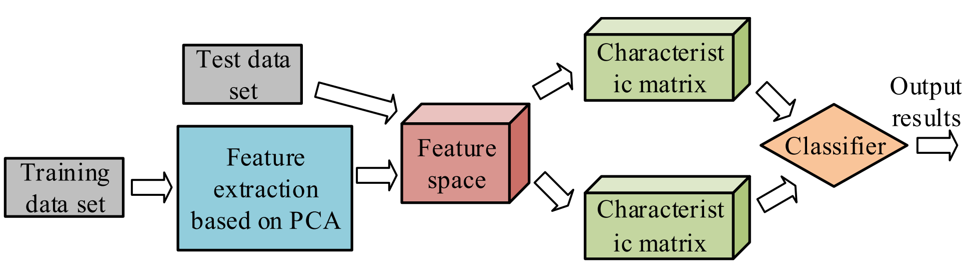
Although there have been significant advancements in the use of CNN and associated research on face recognition technologies for access control, there are still some issues. On the one hand, the calculation scale of the CNN algorithm is usually large and takes up a lot of resources. On the other hand, facial recognition technology for access control is now undergoing research and development and is still in its early stages. The equipment that is currently available is expensive and heavily dependent on network resources. In view of this situation, the research is based on a new convolution calculation method to improve CNN, so that it can be combined with embedded devices to meet the needs of intelligent face recognition in laboratory access control.

## 3 Construction of face recognition model for laboratory access control system

### 3.1 *Design of face recognition algorithm*

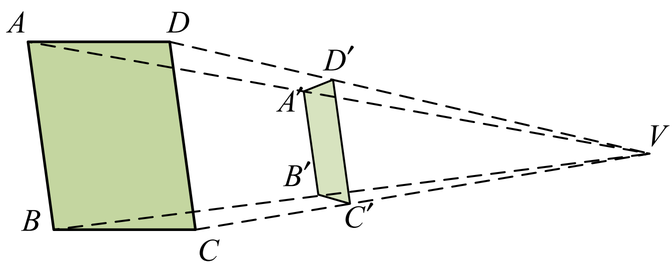
In the face recognition system of laboratory access control, it is very important to correctly match the recognised face image and the system face data. The realisation of this matching process is to extract the image features of the face to be recognised and compare it with the system data on the basis of the system face feature database. Judge whether the face to be recognised exists in the system data according to the threshold of the degree of conformity (Gunawan et al., 2021). The principal component analysis method is one of the most representative face matching methods. Its central concept is to replace facial characteristics with algebraic matrices before using an orthogonal transform-based dimensionality reduction technique [Karhunen-Loeve (KL) transform] will reflect the face. The algebraic matrix of features is converted from high-dimensional to low-dimensional, thereby realising real-time recognition of face features and reducing the amount of data and computation (Zhou and Zhang, 2019). The process of face recognition algorithm using PCA is shown in Figure 1.

**Figure 1** Face recognition algorithm flow using PCA (see online version for colours)




When the PCA face recognition algorithm performs face feature recognition, the spatial structure information of the image will be incomplete, which will lead to a significant drop in the correct rate when recognising non-positive face images. The commonly used solution is to use multi-angle portrait data collection, which greatly reduces the user experience of face recognition, and is difficult to apply when recognising portraits such as ID photos. To this end, perspective projection can be used to enhance the spatial effect of the face image. Perspective projection is a central projection. According to Schall's law, the perspective surface is rotated around the axis by a specific amount so that the previous projection beam changes but the geometric projection on the perspective surface stays the same. This is based on the three points of the perspective centre, the image point, and the target point being on the same line (Bilal, 2019). The effect of perspective projection is shown in Figure 2.

**Figure 2** Perspective projection effect (see online version for colours)




In Figure 2, $V$ represents the viewpoint, and there is a certain angle between the geometric image and the line of sight, so the image on the perspective surface is distorted to a certain extent, and a new geometric image appears. The key to implementing perspective projection is mapping every pixel of the new image produced by perspective to its corresponding pixel in the old image, therefore it is crucial to establish this correlation, as shown in formula (1).

$$\begin{cases} [x', y', t'] = T[r, , s, t] \\ A = \begin{bmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{bmatrix} \end{cases} \tag{1}$$

Formula (1), $(x, y)$ represents the pixel coordinates after perspective, represents $(r, s)$ the pixel coordinates of the original image. And if it is satisfied, $A$ represents the perspective projection matrix. Formula (1) is shown in formula (2) after finishing.

$$\begin{cases} x = \dfrac{x'}{t'} = \dfrac{b_{11}r + b_{21}s + b_{31}}{b_{13}r + b_{23}s + b_{33}} \\ y = \dfrac{y'}{t'} = \dfrac{b_{12}r + b_{22}s + b_{32}}{b_{13}r + b_{23}s + b_{33}} \end{cases} \tag{2}$$

On the basis of obtaining the coordinates of the corresponding pixel points of the four groups of original images and the new image, the perspective matrix can be calculated according to formula (2), and the projection result can be obtained by calculation. By applying perspective projection to non-frontal portraits or flat portraits, the portrait can be enhanced to simulate a face with an inclination angle, allowing for the expansion of a single face sample and improved recognition efficiency. According to the needs of face recognition in the access control system, the four corners of the original face image are respectively simulated by perspective projection to simulate the image of the person's upside-down, downside, left and right head tilt.

### *3.2 Algorithm design of face living body recognition*

Face recognition is a critical component of the face recognition process. Its main function is to judge the authenticity of the portrait to be recognised, exclude fake portraits such as electronic screenshots and masks, and prevent others from impersonating laboratory personnel from affecting the safety management of the laboratory. Therefore, face recognition is very important to ensure the safe operation of the access control system and the safe management of the laboratory. CNNs are a commonly used face recognition algorithm. Similar to a traditional neural network, a CNN consists of three components: input layer, hidden layer and output layer. Some of the nodes are related (Qin et al., 2021). A typical CNN structure is shown in Figure 3.

**Figure 3** Typical structure of CNN (see online version for colours)

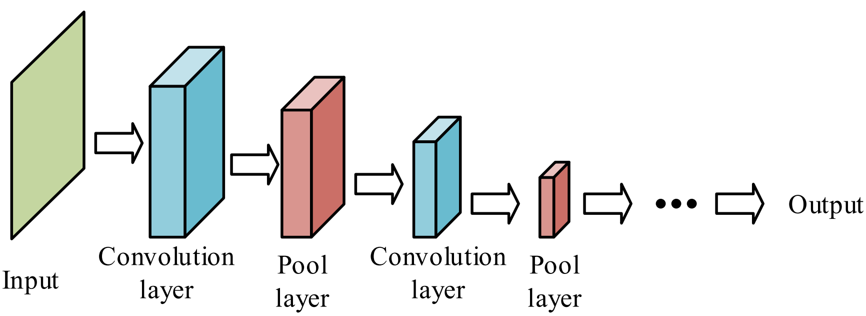
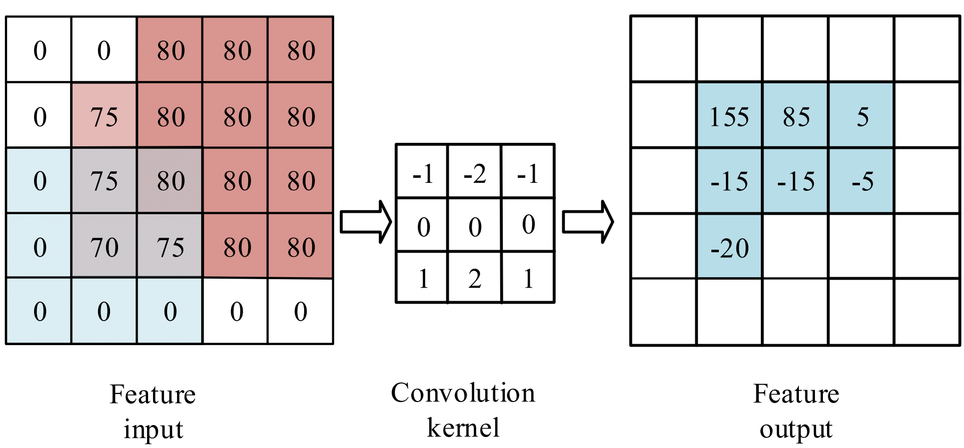



**Figure 4** Convolution operation flow (see online version for colours)




The design of the hidden layer of the CNN is the key part. The convolutional layer, which is the core network layer, is one of three key components of the hidden layer, along with the pooling layer and the fully connected layer. The framework of the convolution layer includes feature output, convolution kernel and feature output. The main operation is to perform convolution calculations by combining the convolution kernel with the input feature map, and the calculation area is generally divided into receptive fields. The convolution kernel is a weight matrix. After the convolution calculation, the calculation result is output as a feature. After the convolution kernel traverses and calculates all the feature inputs, the bias parameter is added on the basis of the calculation result to obtain the final feature image, as shown in Figure 4.

After the input feature image is subjected to the convolution operation, the size is usually reduced. For this reason, the consistency of the input and output image sizes can be ensured by filling the periphery with '0', so the calculation model of the convolution operation is shown in formula (3).

$$O^{k+1}(a,b) = \left[I^k \bullet w^k\right](a,b) + o = \sum_{l=1}^{C_1}\sum_{x=1}^{d}\sum_{y=1}^{d}\left[I_l^k(pa+x, pa+y)\right] + o \tag{3}$$

In formula (3), $k$ represents the current network layer, $I^k$ represents the feature image of the current layer, $O^{k+1}$ represents the feature image of the next layer, $C_k$ represents the number of characteristic input channels of the current network layer, $w$ represents the weight corresponding to the input, $o$ represents the offset, $d$ represents the size of the convolution kernel, $p$ represents the convolution step size, $f$ represents the padding dimension, $(a, b) \in (0, 1, \ldots, D_{k+1})$, $D_{k+1}$ represents the size of the feature image of the next layer, and its calculation is shown in formula (4).

$$D_{k+1} = \left(D_k + 2f - d\right)s^{-1} + 1 \tag{4}$$

The hidden layer of CNN generally adds an activation function as a nonlinear element, thereby solving the problem that the linear pattern of the one-way propagation of the neural network does not match the face recognition, and enhancing the expressive ability of the network. Commonly used activation functions include the Sigmond function, the Tanh function and the ReLU function, where the Sigmond function is shown in equation (5).

$$\text{Sigmond}(x) = \frac{1}{1+e^{-x}} \tag{5}$$

The Sigmond function has a large amount of calculation and a slow convergence speed, which affects the network training effect and easily causes the gradient to disappear. The Tanh function is shown in formula (6).

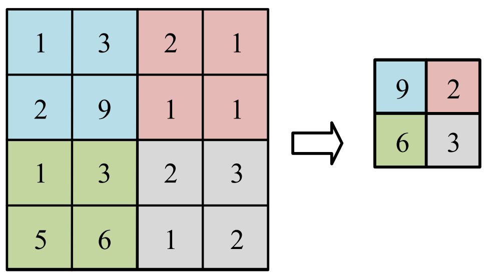
$$\text{Tanh}(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \tag{6}$$

Compared with the Sigmond function, the Tanh function has a certain convergence speed improvement, but the gradient disappearance problem has not been solved. The ReLU function is currently the most widely used, and its mathematical expression is shown in equation (7).

$$\text{ReLU}(x) = \max(0, x) = \begin{cases} x_i & x_i > 0 \\ 0 & x_i \le 0 \end{cases} \tag{7}$$

The ReLU function is currently the most used in neural networks since it has a substantially faster convergence rate and can successfully prevent the gradient from disappearing. The data volume of the CNN continues to increase with the increase of the number of network layers, which significantly deepens the redundancy of the network. Therefore, it is necessary to use the pooling layer to filter the feature results, reduce the amount of data processed by the network, and try to avoid overfitting happened. When calculating the output features of the pooling layer, the same process as the convolutional layer is used to obtain the average eigenvalue or the maximum eigenvalue within the window. In order to avoid the window overlap during the sliding process, set the pooling layer window to 2, 2 × 2 and the stride to 2. After the pooling layer is calculated, the size of the image is reduced by half, as shown in Figure 5.

**Figure 5** Operation process of pool layer (see online version for colours)




The last network layer of the hidden layer is usually designed as a fully connected layer, which adopts the same calculation method to integrate the feature calculation results of the previous network layers. After the above operations, the dimensionality reduction of the output feature is completed, and the spatial dimension is reduced by half. The above process realises the dimensionality reduction process of the output feature map, and the spatial dimension becomes half of the input.

## *3.3 Improvement of CNN algorithm*

Due to the enormous scale of parameters, the CNN requires a lot of resources to operate. And because access control equipment has limitations, it is challenging to achieve high performance. As a result, a lightweight design of the CNN must be implemented. The improved method of the research design is based on the existing MobileNetV2 framework. Based on the standard convolutional layer, the number of input and output channels for the feature needs to be reduced first. The overall network structure parameters are set as shown in Table 1.

Set the input feature image $I$ size of a standard convolutional layer as shown in equation (8).

$$I_h \times I_w \times m \tag{8}$$

Formula (8), and $I_h$ represent the height and width of the input feature image $m$, respectively, and $I_w$ represent the number of input channels of the feature image. The size of the output feature image $O$ is shown in formula (9).

$$O_h \times O_w \times n \tag{9}$$

**Table 1** The overall network structure parameters

| *Operation type* | *Convolution kernel size/step/pad* | *Output dimension* |
|---|---|---|
| Input | — | 227 × 227 × 3 |
| Conv1/BN | 3 × 3/2/0 | 113 × 113 × 32 |
| Conv2/BN | 3 × 3/2/0 | 56 × 56 × 64 |
| Maxpool | 3 × 3/2/0 | 28 × 28 × 64 |
| Conv3/BN | 3 × 3/1/1 | 28 × 28 × 128 |
| Maxpool2 | 3 × 3/2/0 | 14 × 14 × 128 |
| Conv4/BN | 3 × 3/1/1 | 14 × 14 × 256 |
| Max/Pool3 | 3 × 3/2/0 | 7 × 7 × 256 |
| Conv5/BN | 3 × 3/1/1 | 7 × 7 × 384 |
| Conv6/BN | 3 × 3/1/1 | 7 × 7 × 384 |
| Conv7/BN | 1 × 1/1/0 | 7 × 7 × 256 |
| Avepooling | — | 1 × 1 × 256 |
| Fe | — | 256/101 |

Formula (9), $O_h$ represents the height and width of the output feature image $n$, respectively, and $O_w$ represents the number of output channels of the feature image. The size of the convolution kernel of the standard convolutional layer is shown in equation (10).

$$K_h \times K_w \times m \times n \tag{10}$$

Formula (10), and $K_h$ represents the height and width of the convolution kernel, respectively. $K_w$ represents the parameter scale of the convolution kernel largely which determines the parameter scale of the convolution layer, and it can be seen from formula (10) that the parameter scale of the convolution kernel is determined by the number of input and output channels, thus resulting in the parameter scale of the neural network larger. In this regard, the parameter size can be significantly decreased by employing the parameter sharing and dense connection [share and dense (SD)] method, which substitutes a long convolution kernel for mutually independent convolution kernels. In a long convolution kernel, when convolution operation is performed on each input feature image, only a part of the convolution kernel with shared parameters is involved. Under this method, when the height and width of the input feature image are both 1, the long convolution kernel part involved in the convolution operation on the input feature image is shown in equation (11).

$$\left[(1+x\cdot P),(2+x\cdot P),\ldots,(m+x\cdot P)\right] \quad x\in N, x<n \tag{11}$$

In formula (11), $P$ represents the step size in the channel direction. When the length and width of the input feature image are greater than 1, the above convolution operation is repeated for each position. If $P$ it is not 1, the convolution kernel will gradually become larger with the increase of $P$, so as to ensure that the number of output channels remains the same. Therefore, the parameter scale under this method is shown in formula (12).

$$K_h K_w\left[m+P(n-1)\right] \tag{12}$$

Convolutional layers that use parameter sharing have much fewer parameters than conventional convolutional layers. Further adopting depthwise separable convolution, which replaces ordinary convolution and optimises the neural network's parameters and computational scale, all channel features are processed by depthwise convolution, and the processed features are then combined by 1 × 1 convolution. When using this method, the parameter scale of 1 × 1 convolution accounts for a relatively high proportion in the entire network. In this regard, the method of common-phase parameters and dense connection is also used for further optimisation. The parameter scale of 1 × 1 convolution is shown in formula (13).

$$1\times1\times m\times n \tag{13}$$

The optimised 1 × 1 convolution parameter scale is shown in formula (14).

$$1\times1\times\left[m+(n-1)\times P\right] \tag{14}$$

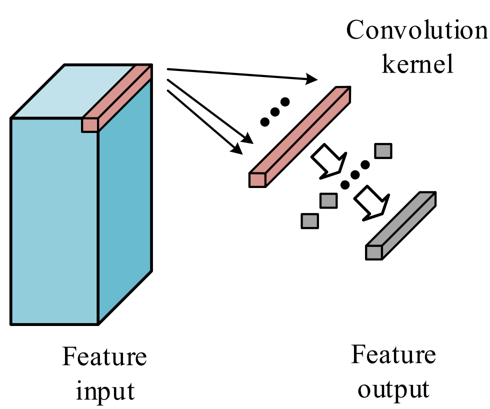
The parameter scale reduced by this method is shown in formula (15).

$$\frac{1\times1\times\left[m+(n-1)\times P\right]}{1\times1\times m\times n}\approx\frac{1}{n}+\frac{P}{m} \tag{15}$$

The optimised convolutional layer is shown in Figure 6.

Compared to the original 1 × 1 convolution, the number of optimised convolution parameters can be reduced by hundreds of times. In addition to improvements for parameter limitations, certain adjustments have been made on the basis of the MobileNetV2 framework. First, the first 1 * 1 convolution of the convolution block is removed to reduce the calculation scale, and the second 1 * 1 convolution block is replaced by a 1 * 1 SAD convolution. In addition, the depth of the network is specified as 1 or 6. Finally, the stride of the SD convolution in the channel direction is also set as a tuning parameter to improve the network, enabling subjective adjustments to the target accuracy or parameter scale. According to the different values, three shared and dense CNNs (SD channel-wise, CNN, and SDC-CNN) are constructed, namely SDC-CNN-S1, SDC-CNN-S64, and SDC-CNN-S192.

**Figure 6** Optimised convolution layer (see online version for colours)



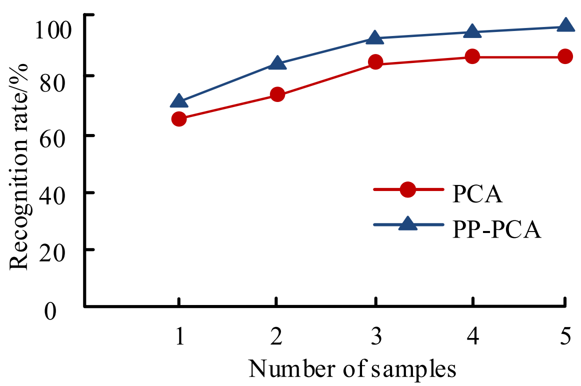
# 4 Performance analysis of face recognition model of laboratory access control system

## *4.1 Performance analysis of PCA face recognition algorithm*

Based on how the laboratory access control system works, a principal component analysis-based algorithm is chosen for face recognition. Perspective projection is then used to improve portraits and make face recognition more accurate. In order to verify the performance of the algorithm, the ORL face database is selected as the training sample to analyse the optimisation effect of the algorithm. The ORL database collected 400 portraits of 40 people, each with ten portraits, and portraits with different angles such as steering and pitch. Firstly, analyse the effect of portrait enhancement, randomly select 40 people with different numbers of portrait samples, and compare the performance of the principal component portrait recognition algorithm (PCA) without portrait enhancement and the principal component portrait identification algorithm (PP-PCA) with portrait enhancement. The training effect, the results are shown in Figure 7.

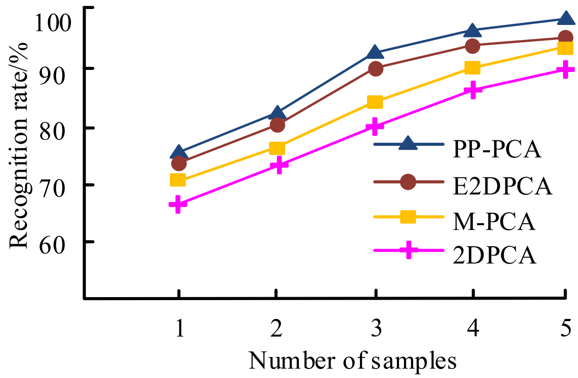
It can be seen from Figure 7 that with the increase of the number of portrait samples, the recognition rates of the PCA and PP-PCA algorithms both improve to a certain extent. Under different numbers of portrait samples, compared with the PCA algorithm without portrait enhancement, the recognition rate of the PP-PCA algorithm with portrait enhancement is increased by about 10%, and when the number of samples is 5, the recognition rate reaches 95%. Therefore, adding portrait enhancement can effectively improve the face recognition effect of the PCA algorithm. In addition, other PCA algorithms including 2DPCA, E2DPCA, and M-PCA are used for horizontal comparison, and the comparison results are shown in Figure 8.

**Figure 7** A analysis of the effect improvement of portrait enhancement (see online version for colours)




According to Figure 8, the recognition rate of each algorithm increases to a certain extent with the increase of the number of samples, and the overall difference is not obvious. When the number of samples is 5, the recognition rate of each algorithm exceeds 90%. In general, the improvement scheme using portrait enhancement has a certain improvement in recognition rate compared with other improvement schemes. Therefore, the proposed method of using perspective projection to achieve portrait enhancement can effectively improve the recognition rate of the PCA based on principal component analysis.

**Figure 8** Comparison of improvement effects of different schemes (see online version for colours)




## *4.2 Improved performance analysis of CNN face recognition model*

In order to verify the performance of the face recognition algorithm designed in the research, the Keras framework in the deep learning framework is selected, and the SD convolution method proposed in the research is implemented using the custom layer method in the framework, thereby constructing the SDC-CNN model. Then, the image recognition performance of SDC-CNN is evaluated using the CIFAR-10 and CIFAR-100 datasets. Both datasets contain 60,000 samples, which are also divided into a test set of 50,000 samples and a training set of 10,000 samples (Gottapu and Dagli, 2020). The training set can be used to train the model after the data has been normalised, and the test set can be used to gauge the model's error rate.

**Table 2** Comparison of test results of different models applied to CIFAR

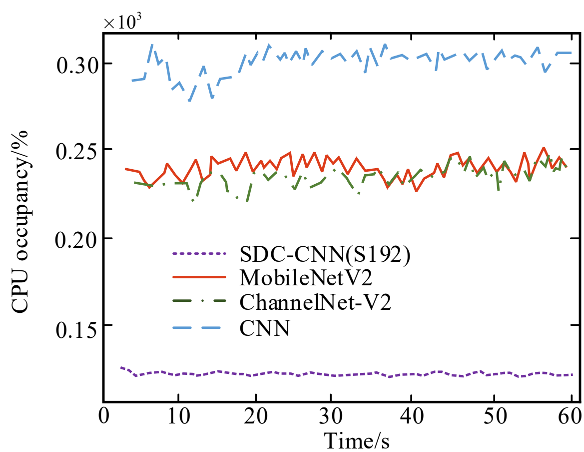
| *Model dataset* | *CIFAR-10* | | *CIFAR-100* | |
|---|---|---|---|---|
| | *Parameters/ 106* | *Error rate/%* | *Parameters/ 106* | *Error rate/%* |
| SDC-CNN (S1) | 0.10 | 11.96 | 0.12 | 30.14 |
| SDC-CNN (S64) | 0.19 | 10.01 | 0.23 | 25.47 |
| SDC-CNN (S192) | 0.35 | 9.10 | 0.39 | 23.65 |
| KSANC | 0.32 | - | 0.32 | 33.49 |
| ResNet | 1.6 | 14.25 | 1.6 | 28.33 |
| ChannelNet-v2 | 1.7 | 12.03 | 1.7 | 24.97 |
| ResNet-164 | 1.8 | 12.54 | 1.8 | 25.74 |
| ResNet with stochastic depth | 1.8 | 11.88 | 1.8 | 25.56 |
| MobileNetV2 | 2.4 | 10.52 | 2.6 | 20.85 |

As can be seen from Table 2, in the CIFAR-10 and CIFAR-100 datasets, the parameter scale of SDC-CNN (S1) is the smallest, which are 0.10× 106 and 0.12 × 106, respectively, which are smaller than MobileNetV2, respectively 95.8% and 95.4%. The parameter scales of SDC-CNN (S64) and SDC-CNN (S192) are also smaller, slightly more than SDC-CNN (S1), but the error rates are reduced by 0.66% and 2.02%, respectively, compared to SDC-CNN (S1). SDC-CNN (S192) has the lowest error rate but larger parameter size, while SDC-CNN (S64) has lower error rate and lower parameter size than all other models. Therefore, the research and design method can effectively compress the parameter scale of the model, and at the same time improve the accuracy to a certain extent. In order to further verify the performance of the SDC-CNN model, the research selects the face dataset ROSE-Youtu of the Rapid-Rich Object Search Lab (ROSE) of Nanyang Technological University to evaluate the face recognition performance of SDC-CNN. The portrait data in ROSE-Youtu comes in the form of facial videos, which contain fake portraits in three different forms: monitors, paper, and masks. Therefore, it is necessary to extract a single-frame video containing portraits and fake portraits from ROSE-Youtu first, and process them according to unified standards. Then the real portraits are used as positive samples and the fake portraits are used as negative samples to train the neural network to build the SDC-CNN (S192) model. Analyse the model's performance in terms of recognition by comparing it to its base model and other models. The equal error rate (EER), accuracy and false positive rate of each model are shown in Table 3.

**Table 3** Comparison of accuracy and misjudgement rates of different models

| *Model* | *Wacelet* | *CoALBP* | *ShuffleNetV2* | *MobileNetV2* | *SDC-CNN (S192)* |
|---|---|---|---|---|---|
| EER/% | 25.4 | 17.9 | 5.12 | 4.76 | 4.24 |
| Accuracy/% | 88.5 | 91.5 | 96.6 | 97.4 | 98.1 |
| Misjudgement rate/% | 11.5 | 8.5 | 3.4 | 2.6 | 1.9 |

**Figure 9** Comparison of CPU utilisation of various models (see online version for colours)




According to Table 3, the live detection model using a CNN has significantly better EER performance than other methods. Compared with ShuffleNetV2 and its basic framework MobileNetV2, the EER of SDC-CNN (S192) is significantly lower, and the recognition accuracy is also improved to a certain extent. The face recognition model's resources are constrained by the access control system, thus it is vital to compare how much CPU each model uses. The CPU usage of each model is shown in Figure 9.

As can be seen from Figure 9, the CPU occupancy rate of the CNN model is the highest, around 300%. Followed by the MobileNetV2 and ChannelNet-V2 models, the CPU occupancy rate is between 200% and 250%. The CPU occupancy rate of the SDC-CNN (S192) model is the lowest, about 70%, and the volatility is small. Therefore, the SDC-CNN (S192) model can be better applied to face recognition in laboratory access control systems with limited resources.

**Table 4** Comparison of face recognition algorithm test results

| *Model* | *Parameters/M* | *Average recognition time/ms* | *Recognition rate/%* |
|---|---|---|---|
| SDC-CNN (S192) | 0.35 | 494 | 98.1 |
| CVSAN | 0.41 | 548 | 96.5 |
| FedFR | 0.39 | 512 | 97.8 |

The study also explores the performance of the algorithms proposed in the study using CVSAN and FedFR as comparisons, both of which are new in the field of embedded face recognition and have been shown to have better performance, the comparison results are shown in Table 4, which includes the statistics of time resources and memory resources included in the computational complexity of the algorithm. It can be seen that SDC-CNN (S192) outperforms the two algorithms used as a comparison in both memory consumption and running time, which are 0.35 M and 494 ms, respectively, and the recognition rates of the three algorithms are comparable, with SDC-CNN (S192) having a recognition rate of 97%, which is slightly higher than the other two algorithms. In summary, the SDC-CNN (S192) proposed in the study can achieve higher face recognition accuracy while occupying fewer resources.

## 5 Conclusions

University laboratories are an important platform for teachers and students to carry out teaching and scientific research activities. It is necessary to introduce information technology to realise the intelligent management of laboratories. Embedded face recognition access control is an effective way to achieve intelligent laboratory management. The key is to achieve accurate and efficient face recognition and live detection. For the face recognition of embedded access control equipment, the traditional CNN has the defects of large parameters and large calculation scales. For this reason, based on the MobileNetV2 framework, a new convolutional calculation scheme is proposed to reduce the parameter size and speed up the calculation speed, and construct the SDC-CNN face recognition model. In order to increase the recognition rate, the portrait is augmented using perspective projection in addition to the PCA face recognition algorithm. Finally, the ORL portrait dataset was used to verify the optimisation effect of portrait enhancement, and the results showed that the recognition rate of PP-PCA was improved by about 10% compared with that before the improvement; the CIFAR-10 and CIFAR-100 datasets were used to verify the effectiveness of the CNN improvement. The results showed that the model can effectively distinguish between real and fake faces, and the number of parameters is greatly reduced. The SDC-CNN (S1) with the smallest parameter scale reduces the number of parameters by more than 95% compared with the basic framework MobileNetV2, and the accuracy is not affected. Finally, ROSE-Youtu is used. The portrait dataset compares the living body recognition performance of other models. The results showed that the EER and correct rate of SDC-CNN (S192) are significantly higher than other models, and the CPU usage is the lowest, which can be better for face recognition in access control systems. However, despite the high accuracy of the algorithm in the recognition of small samples, it exhibits a high possibility of failure in the recognition of large samples, so further optimisation in this area is needed in future rather studies.

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