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ADVANCEMENTS IN IDENTITY VERIFICATION: GAIT RECOGNITION AND DENSE NET TRANSFER LEARNING FOR THE FUTURE

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Article Info

Keywords: gait recognition, biometric technology, transfer learning, Densely connected neural networks, DenseNet-based transfer learning, Gait Energy Image, feature extraction, K nearest neighbor classifier, CASIA-B dataset, same-view recognition, robustness, VGGNet network, network model parameters, speed, quality, transfer generated images.

Abstract

Transfer Learning for the Future Gait recognition has emerged as a cutting-edge biometric recognition technology with significant implications for everyday life. This study introduces a novel gait recognition approach, which uses Densely connected neural networks as the foundation for transfer learning, known as DenseNet-based transfer learning. The method begins by incorporating spatial information of gait through Gait Energy Image (GEI) input, followed by feature extraction using DenseNet-based transfer learning. The K nearest neighbor classifier (KNN) is then employed for classification and identification purposes. The proposed method is first tested on the extensive public dataset CASIA-B for same-view gait recognition, yielding impressive results with an average recognition rate of 98.86%. The method also demonstrates strong robustness under varying conditions. When compared to the VGGNet network, the proposed method reduces the number of network model parameters by 448M, or approximately 84.85%. These findings indicate that the proposed approach significantly enhances the speed and quality of gait recognition transfer generated images.

Introduction

In recent years, identity verification has emerged as a critical aspect of security, privacy, and access control in the digital age. With the rapid advancement of technology, it has become necessary to develop more efficient and accurate methods for identifying individuals (Jain et al., 2004). Traditional approaches, such as passwords and security questions, have proven to be increasingly susceptible to cyber threats, while biometric recognition systems, such as fingerprint, face, and iris recognition, have shown promise in enhancing security and privacy (Ross et al., 2006). Among various biometric methods, gait recognition has gained significant attention due to its unique features and potential applicability in various domains (Tao et al., 2019). This paper aims to discuss the

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advancements in identity verification, focusing on gait recognition and DenseNet transfer learning as innovative approaches for the future.

Gait recognition refers to the process of identifying an individual based on their walking style and patterns. This biometric feature is characterized by its non-invasive nature, which enables identification from a distance without the need for direct contact with the subject (Boulgouris et al., 2005). Moreover, gait is considered as a difficult feature to forge or conceal, thus increasing its potential in providing reliable identity verification (Nixon et al., 2005). Previous research has demonstrated the efficacy of gait recognition in various applications, such as surveillance, human-computer interaction, and healthcare (Han & Bhanu, 2005; Wang et al., 2015).Despite the potential advantages of gait recognition, several challenges remain in the development of robust and accurate gait recognition systems. Factors such as varying walking speeds, clothing, footwear, and carrying conditions can affect gait patterns and pose difficulties in achieving high recognition rates (Tao et al., 2019). Furthermore, the high dimensionality of gait data and the lack of large-scale gait datasets have hindered the progress of gait recognition research (Mansur et al., 2017). To address these challenges, recent studies have explored the application of deep learning techniques, such as convolutional neural networks (CNNs), to improve the performance of gait recognition systems (Yu et al., 2017).

One promising approach in this regard is the use of DenseNet transfer learning, a deep learning architecture that has demonstrated success in various computer vision tasks, such as image classification and object detection (Huang et al., 2017). DenseNet is characterized by its dense connectivity between layers, which facilitates gradient flow and feature reuse, leading to improved learning efficiency and generalization performance (Huang et al., 2017). Transfer learning, on the other hand, involves leveraging pre-trained models on large-scale datasets to improve the learning process and performance on new tasks with limited data (Pan & Yang, 2010). By combining DenseNet and transfer learning, it is possible to develop more robust and accurate gait recognition systems that can overcome the challenges associated with dataset limitations and variations in gait patterns (Tao et al., 2019).

Advancements in identity verification, particularly in the area of gait recognition and DenseNet transfer learning, hold great promise for the future of security and privacy applications. By leveraging the unique properties of gait and the power of deep learning techniques, it is possible to develop more effective and reliable identity verification systems that can address the growing needs of the digital age.

2. Related works

Transfer learning is the forefront of research in machine learning. Andrew Ng, a professor at Stanford University, believes that transfer learning will become the next driving force for the successful application of machine learning in the commercial field after supervised learning [7]. Although we have now entered the era of big data, there is a contradiction between big data and weak computing. Traditional machine learning can only rely on powerful computing capabilities, while transfer learning not only can reduce the use of computing resources, but also quickly transfer the knowledge that has been learned to a new field. In transfer learning, not only the training data and test data do not need to meet the conditions of independent and identical data distribution, but also the model in the target domain does not need to be trained from scratch, which can significantly reduce the need for training data and training time in the target domain [8].

Convolutional neural networks have become the most mainstream method in the field of computer vision. The classic networks of CNN are AlxNet, VGGNet, GoogLenet, ResNet, DenseNet. We can use these classic CNN networks as pre-trained models for transfer learning. In 2012, Alex Krizhevsky et al. proposed AlexNet [9], which applied the basic principles of CNN to a deep and wide network. The entire network has a total of 8 layers, the first 5 layers are convolution layers, and the last 3 layers are fully connected layers which using 11 * 11, 5 * 5, and 3 * 3 convolution kernels. AlexNet is the champion of the ILSVRC2012 competition, and the accuracy rate much better than the second place (Its top5 error rate is 15.3%, and the second place is 26.2%). In recent years, AlexNet-based transfer learning methods have been widely used in process industry image recognition [10], fiat currency recognition [11], and so on.

In 2014, Karen Simonyan et al. at Oxford University proposed VGGNet [12], which is runner-up at ILSVRC2014. It has two structures, VGG16 and VGG19.They are essentially the same, except that the network depth is different. Compared with AlexNet, the improvement of VGGNet is mainly to use several consecutive 3 * 3 small convolution kernels to replace the larger convolution kernel in AlexNet and use a deeper network, so that the network learns more complex models and improves parameter efficiency. In recent years, VGGNet-based transfer learning methods have been widely used in gait recognition [3], clothing picture recognition [13], and so on.

Also in 2014, Christian Szegedy et al. proposed GoogLeNet [14] which was the winner of the ILSVRC2014 competition. GoogLeNet cleverly uses the inception network structure, which not only maintains the sparseness of the network structure, but also utilizes the high computing performance of the dense matrix. Although GoogLeNet has 22 network layers, its number of parameters is about 5 million, only 1/12 of the number of AlexNet parameters and 1/36 of the number of VGGNet parameters. It uses computing resources more efficiently, and extracts more features under the same amount of calculation, which improves the training effect. In recent years, the GoogLeNet-based transfer learning method has been widely used in remote sensing image automatic classification [15] and human behavior classification [16]. In 2015, Kaiming He et al. proposed ResNet [17] which was the champion of ILSVRC2015. One of the biggest highlights of ResNet is that the author added residual blocks through the short circuit mechanism. The residual learning between two layers is studied for shallow ResNet, and the residual learning between three layers is performed for deep ResNet. The proposed residual network reduces a series of problems caused by deep networks, such as the disappearance of gradients. It not only enables deeper networks to be trained, but also improves the accuracy of recognition. In recent years, ResNet-based transfer learning methods have been widely used in human protein atlas image classification [18] and face recognition [19]. In 2016, Gao Huang et al. proposed DenseNet [20]. The basic idea of DenseNet is the same as that of ResNet. Its main contribution is to achieve feature reuse through the connection of features on the channel, and establish dense connections between all the front layers and the back layers. DenseNet has a narrower network width, fewer parameters, and less computational cost.It not only alleviates the vanishing-gradient problem, but also achieves better performance than ResNet. DenseNet also won the Best Paper Award of CVPR 2017.In recent years, DenseNet-based transfer learning methods have been widely used in human motion recognition [5] and complex traffic scene language segmentation [6].

According to the current research status at home and abroad, transfer learning based on CNN classic network has been widely applied in various fields that proving transfer learning is effective. In the field of gait recognition, there are few transfer learning methods based on CNN classic network. Therefore, according to the advantages and disadvantages of each classic CNN network, this paper proposes a gait recognition method based on DenseNet for transfer learning. The experimental details are explained in the third and fourth sections below.

3. Proposed method

DenseNet [20] was proposed by Gao Huang et al. in 2016, which is a convolutional neural network with dense connection characteristics. It introduces direct connections from any layer to all subsequent layers, and connects multiple inputs into a tensor through the $Hl(\cdot)$ function [20], then passes to the next layer of the network. The number of feature maps and the number of parameters are greatly reduced through feature reuse, dividing the network into multiple Bottleneck layers, and introducing Transiton layers etc. These improve the computational efficiency and achieve higher experimental performance. In this paper, DenseNet is used as a feature extractor, then fine-tune the model and obtain the recognition results.

3.1 Input Data

The gait energy image [21] is used as the input of the network. The gait energy image obtains each pixel value in the gait by calculating the average value of the pixels of the silhouette in a gait cycle, which effectively maintains the spatial information in the gait sequence. Not only does it save storage space and computation time, it is also less sensitive to the silhouette noise of a single frame. The calculation method is as follows：

$$GEI = \frac{1}{N}\sum_{t=1}^{N} B_t$$

Where N is the number of frames in a single gait cycle, and Bt is the silhouette of the t^{th} frame in the gait cycle. The specific calculation process is shown in Fig. 1.

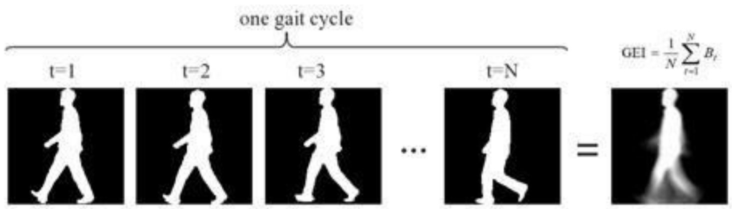

Fig. 1 The calculation process of gait energy image

3.2 Network Structure

The classic convolutional neural network which is density convolutional network (referred to as DenseNet) is used as the basis of our transfer learning. A pre-trained DenseNet model on the ImageNet dataset is loaded and used as a feature extractor. The gait energy image is used as the input of DenseNet to further obtain the gait depth information. In the experiment, there is no need to retrain the model, and the outputs of the fully connected layer and softmax layer can be changed from 1000 categories to 124 categories, so as to adapt to the situation of gait recognition classification problem in this paper, and realize feature transfer. We briefly introduce this network structure in Fig. 2. For more details, may refer to the paper [20]. Where n1,n2,n3,n4 correspond to different values. When [n1,n2,n3,n4] is [6,12,24,16], it is a DenseNet121 structure; when [n1,n2,n3,n4] is [6,12,32,32], it is a DenseNet169 structure; when [n1,n2,n3,n4] is [6,12,48,32], it is a DenseNet201 structure.

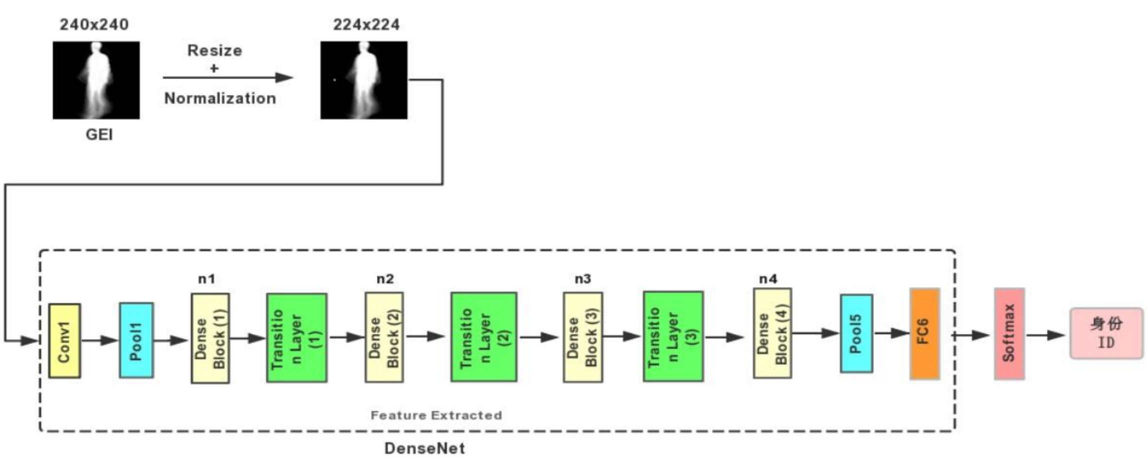

Fig. 2 An illustration of network architecture with 4 dense block

The Dense Block is composed of multiple conv_blocks through dense connections. The input of each conv_block is the connection of all the previous layers. Each conv_block consists of a 1*1 convolution layer and a 3*3 convolution layer. In order to reduce the number of feature maps and improve the calculation efficiency, a convolution layer of 1*1 is introduced. The structure diagram of Dense Block and the structure diagram of conv_block are shown in Fig. 3 and Fig. 4, respectively. In the Dense Block structure diagram, n is the number of conv_blocks, that is, each Dense Block is composed of n conv_block dense connections, where n corresponds to n1, n2, n3 and n4 in Fig.2.

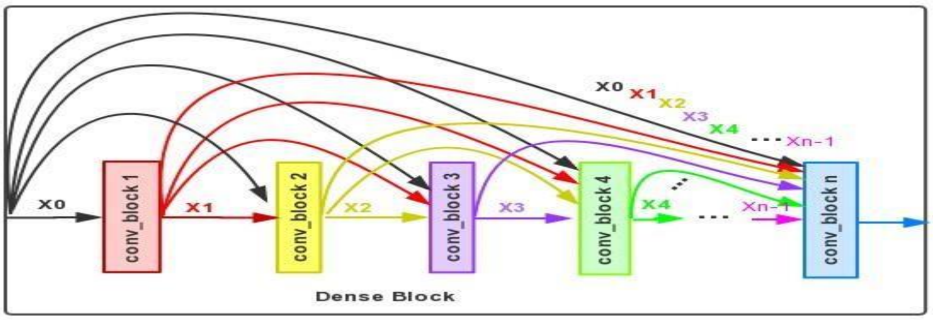

Fig. 3 Dense Block structure diagram, n is the number of conv_blocks, that is, each Dense Block is composed of n conv_block dense connections, where n corresponds to n1,n2, n3 and n4 in Fig.2.

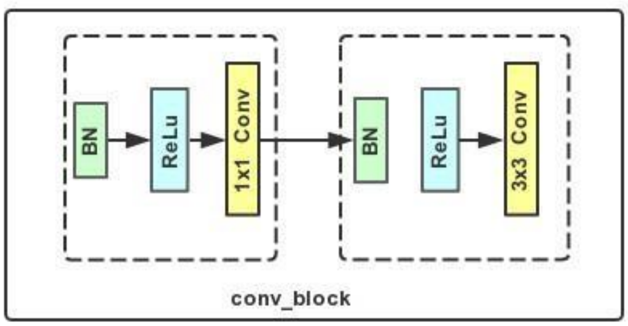

Fig. 4 Conv_block structure diagram

The transition layer consists of a batch normalization layer, a 1*1 convolution layer, and a 2*2 average pooling layer, which is used to reduce the dimensional size of the Dense Block output.

The structure of the Transition layer is shown in Fig. 5.

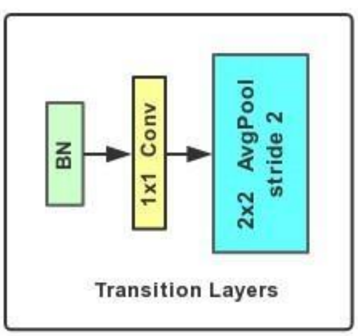

Fig. 5 Transition layer structure

In addition to the above main parts, in front of the first dense block is a 7*7 convolution layer with stride 2 and a maximum pooling layer with 3*3. In the last layer of the network, the softmax function is used to calculate the multi-class cross-entropy loss. In the test phase, the features obtained by DenseNet-based transfer learning are used to classify the identity of the person using the nearest neighbor classifier.

4. Experimental and results

This article uses the Keras open source deep learning framework to build a DenseNet network model for training. The training process includes two stages of training and testing. In this article, experiments I and II were performed and compared with mainstream gait recognition methods.

4.1 DataSet

CASIA Gait Database [22] is a database published by the Chinese Academy of Sciences Automation Research in 2006. It includes a small-scale database Dataset A created in 2001, a multi-view database Dataset B created in 2005, and an infrared database Dataset C. This article adopt the CASIA-B database. CASIA-B [23] is a large-scale, multi-view gait database with a total of 124 subjects, each of whom has 11 views from 0° to 180°, with an interval of 18 degrees. It also provides gait energy image [21] under three different conditions, which are normal walking conditions, carrying a bag condition, and wearing a coat condition. There are 10 sets of gait sequences in total, of which there are 6 groups of gait sequences under normal walking conditions, and both 2 groups under carrying a bag and wearing a coat conditions. Each person has 110 gait sequences. In Fig. 6, we list a sample gait energy image of a person in the CASIA-B database at 11 angles and 3 conditions.

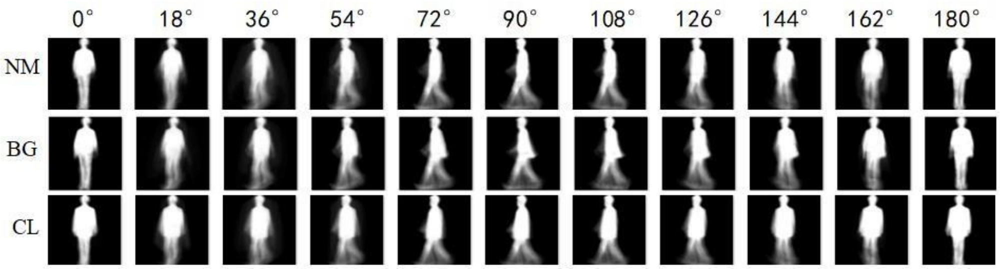

Fig. 6 Sample example of a person's gait energy image at 11 angles and 3 conditions

The image resolution of GEI [21] is 240 * 240 pixels. In this experiment, the data preprocessing uses the data normalization method mentioned in [24]. The pixel value is divided by 255 so that it is in the range [0,1] and resized to 224*224, making it conform to the input picture format of DenseNet network architecture.

4.2 Training

The gait recognition method based on DenseNet transfer learning proposed in this paper is designed and implemented using python script language and keras deep learning framework. The Python version used in this experiment is 3.6.2, and the Keras version is 2.0.5.The main parameters of the computer hardware used in this experiment are as follows: the GPU is GTX 1080Ti GAMINGX with 11G memory, the CPU is AMD Ryzen 5 2600X, the main frequency is 3.6GHz, and the memory size is 32GB.In the experiment, we use the gait sequence of the first 74 subjects as the training set and the last 50 as the test set. All networks are trained using stochastic gradient descent with a batch size of 16 and training of 100 epochs. The other parameters are set to DenseNet [20] trained on the ImageNet [25] dataset. For example, the initial learning rate is 0.1, the weight decay parameter is set to 10^{-4} , and the nesterov momentum [26] is set to 0.9, the dropout rate is set to 0.2.The loss function employs categorical crossentropy. It is worth noting that when using this objective function, the labels need to be converted into a two-valued sequence of the form as (n_samples, n_classes).Therefore, the label y should be adopted a one-hot encoding, converted to an array of the form as (n_samples, 124) with values 0 and 1,where n_samples is the number of gait sequences in the training or testing set.

4.3 Experimental results

In this paper, two experiments were performed to evaluate the rank-1 recognition rate of the CASIA-B dataset. One of the experiments is performed at different angles and different DenseNet network depths under normal walking conditions, the other is performed under three covariate conditions.

4.3.1 Experiment I

In this experiment, under normal walking conditions, the rank-1 recognition rate of CASIA-B data set at 0° -180 ° and three network structures such as DenseNet121, DenseNet169 and DenseNet201 were evaluated, where the gait sequence NM#1-4 serves as gallery and NM#5-6 as probe. Moreover, we compared it with VGGNet-based transfer learning [3] and other traditional methods. The experimental results are shown in Table 1. It can be known from Table 1 that the recognition rate of our proposed gait recognition method of DenseNet-based transfer learning not only exceeds the traditional method, but also exceeds the gait recognition method of VGGNet-based transfer learning. In three network structures, DenseNet201-based transfer learning method has the highest accuracy rate of 98.87%, which is 3.17% higher than VGGNet-based transfer learning [3], and also has fewer parameters than the VGGNet-based transfer learning method. As shown in Fig. 7, DenseNet121 has the least parameters, only 33M, which is about 1/16 of VGG16. In addition, DenseNet201 has the largest number of parameters, only about 1/7 of VGG16, which greatly improve the use efficiency of computer resources.

Method	0°	18°	36°	54°	72°	90°	108°	126°	144°	162°	180°	Mean
DM-GEI[3]	92.0	86.5	82.0	89.5	92.5	93.5	92.0	93.5	94.5	94.5	96.0	91.5
DM-MGEI	85.5	74.5	76.0	85.5	89.5	91.0	89.0	89.5	87.5	92.0	95.0	86.8
DM-GEnI	92.5	90.5	85.5	87.5	91.5	92.0	94.0	92.0	92.5	95.0	94.3	91.6
DM-FDF	93.0	87.5	82.0	88.5	91.5	93.0	91.5	92.5	94.5	94.0	95.5	91.2
DM-GFI	86.0	79.0	76.5	85.0	90.5	91.5	88.5	90.5	94.5	95.5	96.5	88.5
KSPP[27]	95.2	79.8	70.7	84.7	96.2	96.8	94.1	94.4	92.7	93.6	95.2	90.3
VGR-Net[28]	98.3	99.2	99.2	96.7	97.7	97.1	97.9	97.1	96.3	97.0	97.1	97.6
VGGNet[3]	95.4	91.3	92.1	94.2	97.1	97.7	97.7	96.7	95.8	97.5	97.1	95.7
DenseNet121	100	98.4	97.2	97.2	97.6	97.6	98.0	96.8	96.4	98.8	100	98.0
DenseNet169	99.2	99.2	96.8	97.6	98.0	96.8	98.4	97.2	97.6	98.8	100	98.15
DenseNet201	99.6	99.6	97.2	98.0	98.8	98.8	98.8	98.4	99.2	99.2	100	98.87

Table 1: Experimental comparison of Rank-1 recognition rate of CASIA-B data set under the NM condition

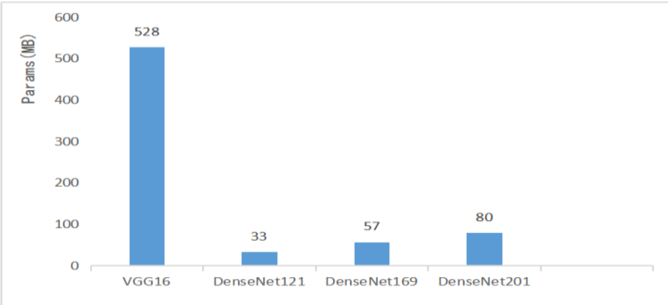

Fig. 7 Comparison of model parameters

4.3.2 Experiment II

In Experiment II, we tested our method under three covariate conditions, namely normal walking conditions, carrying a bag condition, and wearing a coat condition. The settings of the gallery and probe used in this experiment are as follows. Under normal walking conditions, the gait sequence NM#1-4 is used as gallery and NM#5-6 is used as probe, which is also the same as the setting of Experiment I; Under carrying a bag condition, the gait sequence BG#1 is used as a gallery, and BG#2 is used as a probe; Under wearing a coat condition, the gait sequence CL#1 is used as a gallery, and CL#2 is used as a probe. In the experiment, only the recognition rate at 180 ° is tested. The experimental results are shown in Table 2. It can be observed from the table that the recognition rate under the condition of carrying a bag and wearing a coat is not as high as that under normal walking. Both of these conditions have an impact on gait recognition that the effect is less when wearing a coat, and the effect is larger under carrying a bag. The reason is that carrying a bag will occlude part of the gait silhouette, and the features learned by the network are not highly discriminating, which affects the recognition rate.

Table 2: Rank-1 recognition rate (%) comparison of CASIA-B dataset under three covariate conditions

Method	nm-nm	bg-bg	cl-cl
DenseNet121	100.0	85.5	92.0
DenseNet169	100.0	87.1	96.0
DenseNet201	100.0	89.5	98.4

5. Conclusion

In this paper, a gait recognition method based on DenseNet transfer learning is proposed, which uses DenseNet as a feature extractor. The gait energy image is used as a feature to extract gait features, and implements feature transfer. Finally, the nearest-neighbor classifier is used to classify and identify people. This method was tested on the data set CASIA-B, and achieved an average recognition rate of 98.86% in the same perspective. Besides, it was robust to different conditions. The recognition rate of the proposed method is improved by 3.17% compared with the VGGNet-based transfer learning method [3] network. The method in this paper not only reduces the amount of parameters and reduces the storage overhead, but also speeds up the model training speed and improves the recognition rate. In the future, it can be further studied in the following aspects. Further verification and research of the proposed method in other data sets; attempts to fuse DensNet with ResNet to perform feature transfer.

Acknowledgements

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