Research on Gender-related Fingerprint Features, Extracting Fingerprint Features Using Autoencoder Networks for Gender Classification

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Research Article

RESEARCH

Research on Gender-related Fingerprint Features,Extracting fingerprint features using autoencoder networks for gender classification

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Abstract

Background: Fingerprint is an important biological feature of human body, which contains abundant biometric information.At present, the academic exploration of fingerprint gender characteristics is generally at the level of understanding, and the standardization research is quite limited.

Methods: A robust approach is presented in this article, Dense Dilated Convolution ResNet Autoencoder, to extract valid gender information from fingerprints. By replacing the normal convolution operations with the atrous convolution in the backbone, prior knowledge is provided to keep the edge details and the global reception field can be extended.

Results: The results were explored from three aspects: 1) The efficiency of the DDC-ResNet. 6 typical automatic feature extraction methods with 9 mainstream classifiers for a total of 54 combinations are evaluated on our dataset and provide unbiased experimental details. Experimental results demonstrate that the combination of our approach outperforms other combinations in terms of average accuracy and separate-gender accuracy. It reaches 96.5% for average and 0.9752(males)/0.9548(females) for separate-gender accuracy. 2) The effect of fingers. It is found that the best performance of classifying gender with separate fingers is achieved by the right ring finger. 3) The effect of specific features. Based on the observations of the concentrations of fingerprints visualized by our approach, it can be inferred that loops and whorls (level 1), bifurcations(level 2), as well as line shapes (level 3) are connected with gender. Finally, we will open source the dataset that contains 6000 fingerprint images.

Conclusions: The results are demonstrated that autoencoder networks are a powerful method for extracting gender-specific features to help hide the privacy information of the user's gender contained in the fingerprint. Our experiments also identified three levels of features in fingerprints that are important for gender differentiation, including loops and whorls shape, bifurcations shape, and line shapes.

Keywords: Deep learning; Fingerprint; Gender Identification; 54 Combinations' Testbed; Feature Visualization

Background

Fingerprint gender identification aims to extract gender-related features from an unidentified fingerprint to recognize one's gender information. It can be divided into two stages, namely extracting as well as classifying [1–8], in which the former step is of great significance since the effectiveness of gender identification, is primarily determined by the sufficiency of gender-related features. Nowadays, classifying ridge-related features extracted manually has achieved fairly good results, reaching an overall accuracy for 90% for average [8–10]. High performances, however, depends strongly on the manual extraction of features from well-selected regions [11]. These methods have major shortcomings, such as high error, weak robustness, and high labor consumption. So far, with the growing popularity of machine learning and deep learning, automatic feature extraction has become a major foucus.

To realize the automatic feature extraction, considerable work has been done. In machine learning, methods such as DWT, SVD, PCA as well as FFT are extensively used [3, 12, 13]. For deep learning based methods, including deep autoencoder neural networks such as VGG and ResNet,etc have been investigated. [14].

Although numerous algorithms have been proposed, there are still 2 major challenges. First, traditional approaches aquire excessive labor consumption and lack automation. Second, the automatic feature extraction method lacks robustness, which only concerns regions instead of considering the global field. Figure 1 shows the difference between the normal automatic feature extraction method and the deep neural network with global reception consideration. The latter can divide the feature space normatively. Besides, private datasets with disparate data distributions and sizes will directly influence the accuracy,and fingerprint information contains a lot of noise, resulting in low recognition accuracy. Thus, because of the above challenges, we propose a global feature extraction method to improve the efficiency of gender classification.

Figure 1 General automatic gender classification methods preview
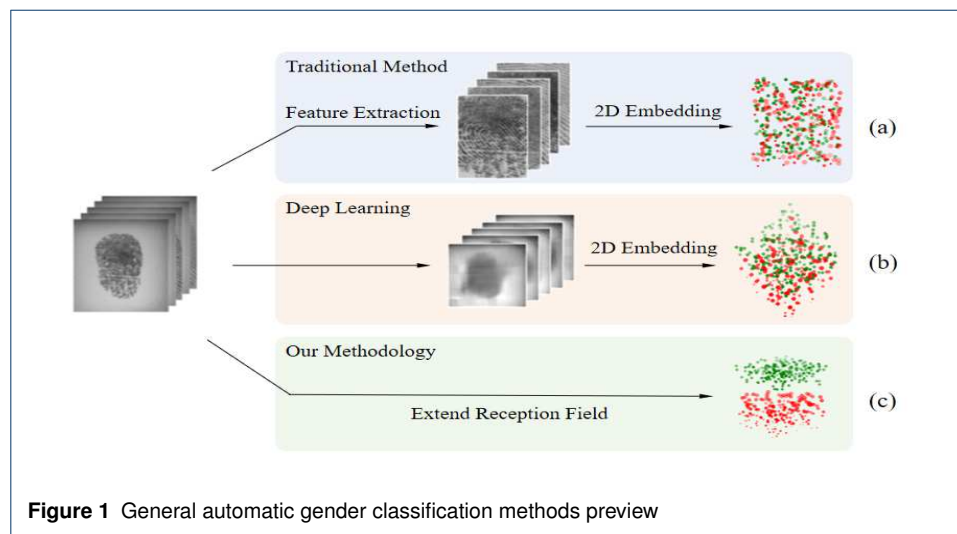
Related Work

Previous discussions have demonstrated that gender-related features have a significant impact on fingerprint gender identification. In this section, we will first go through the evo-

lution and then review the progress in recent years in a conclusive table, which is shown in Table 1.

In 1999, Acree [15] manually counted ridges in specific areas on the fingerprint epidermis, showing that ridge count can determine the gender. Then in 2003, the mean epidermal ridge breadth has been proposed to identify gender [11]. Similarly in 2006, Badawi [10] manualy extracted ridge counts, ridge thickness to valley thickness ratio(RTVTR), and white lines count to determine the gender using a neural network as a classifier. Later, Gungadin [16] found a threshold of the ridge density 13ridges/25mm^2 in 2007, which determines the gender as male when the ridge density is lower than the threshold. In other words, the female has higher ridge density is probably due to they have lower ridge breadth [11].

Owing to the inevitable error and high manpower consumption of manual feature extractions, automatic fingerprint extraction has been proposed. In 2012, ridge features have been analyzed in the spatial domain using FFT, 2D-DCTT, and PSD [12], reaching an accuracy of 90% for females and 79.07% for males, respectively. In the same year, Gnanasivam [3] proposed a method using DWT and SVD as the feature extractor. In 2014, Marasco [13] utilized LBP and LPQ on texture features and used PCA to reduce the features, then the kNN classifier was applied to the extracted features.

In 2017, Gupta [4] applied discrete wavelet transformation to extract fingerprint features, and then output to back propagation neural network for gender classification, and finally obtained 91.45% classification accuracy. In 2018,Shehu [17] employed CNN models, specifically ResNet-34, were trained using transfer learning technique, to complete the feature extraction for fingerprints, and achieved a combined classification accuracy of 75.20%. Since the presence of the deep convolution autoencoder neural network, deep learning has been widely applied in the feature extraction task especially in the biometric recognition field [14].

Contributions of this paper

The main contributions of this study are as follows:(1) We propose a feature extraction method of fingerprint that takes global features into account. For existing typical automatic feature extraction methods and classification methods, we make comprehensive comparisons with fair implementation details. (2) We make a comprehensive comparison to test the efficiency of our method. The finger with the richest gender-related features is detected using the highest performance method. Finally, we visualize the concentrations using the selected method, which indicates the regions with the highest contributions and their corresponding specific features in the gender identification task. (3) We will finally open source the dataset since the open-source datasets in fingerprint gender classification are limited.

Experimental Results

In this section, we first introduce our dataset and adopted implementation details. In the experimental stage, factors that affect gender-related features will be analyzed comprehensively to provide some useful conclusions.

Experimental Setup
Dataset

The fingerprint dataset used in experiments is obtained from ZK fingerprint acquisition equipment (Figure 3) with 500 dpi, containing 200 persons(102 females and 98 males) and

Table 1
The overview of the previous methods.

Year	Publisher	Feature Extraction	Classifier	Results	Dataset
1999	Acree [15]	Ridge counting manually	Threshold	Female ridge density is higher	Own dataset contains 400 subjects
2003	Kralik [11]	Mean epidermal ridge breadth	Threshold	Ridge breadth is 9% greater in males than in females	Own dataset contains 60 subjects
2006	Badawi [10]	RTVTR, white line, ridge thickness	Neural Network	Average 88.8%	Own dataset contains 220 subjects
2007	Gungadin [16]	Counting ridges in the upper portion of the radial border	Threshold	Ridge density of male's fingerprint tend to be less than or equal to 13ridges/25mm^2	Own dataset contains 500 subjects
2011	Arun [9]	Ridge count, ridge density, white line and RTVTR	SVM with RBF kernel	Overall 96%	Own dataset contains 150 male and 125 female images
2012	Kaur [12]	FFT, DCT, PSD	Threshold	90% for female & 79.07% for male	Own dataset contains 220 subjects
2012	Gnanasivam [3]	DWT+SVD	KNN	91.67% for male & 84.69% for female	Own dataset contains 357 subjects
2014	Marasco [13]	LBP and LPQ descriptor	KNN	Overall 88.7%	Own dataset contains 494 subjects
2014	Gupta [4]	DWT	ANN	Overall 91.45%	Own dataset contains 55 subjects
2016	Abdullah [1]	Ridge count, ridge density, white line and RTVTR	J48	Overall 96.28%	Own dataset contains 296 subjects
2016	Abdullah [18]	Ridge count, ridge density, white line and RTVTR	MLP	Overall 97.25%	Own dataset contains 300 subjects
2017	Sheetlani [19]	DWT	CNN	Overall 96.60%	Own dataset contains 80 subjects
2017	Ashish Mishra [5]	minutiae, incipient ridges	SVM & NN	76.06% for SVM and 83.7 % for female	NIST
2018	Wedpathak [8]	Ridge count & RTVTR	ANN	88% for male & 78% for female	Own dataset
2018	Shehu [17]	ResNet-34	CNN	73.98% for female & 76.42% for male	Own dataset contains 369 subjects
2019	Alam [20]	DWT+SVD	KNN	91.25% for male & 88.96% for female	Own dataset contains 42 subjects
2019	Rekha [6]	Gabor filter	KNN, SVM, Naive Bayes	\	\
2021	DDC-ResNet(Ours)	Autoencoder	CNN	**97.52%** for male & **95.48%** for female	Dataset contains 200 subjects

6000 images. Each finger is collected 3 times to guarantee the quality of the fingerprint image.

Implementation Details

In the preprocessing step, we resize each fingerprint image to 256x256 and normalize it to $[0, 1]$. $Train : Test$ ratio is $4 : 1$, No repetitive finger is guaranteed in both the training set and test set.

In the feature extraction stage, for DWT, each fingerprint goes through eight levels of decomposition. For SVD, each fingerprint image vector is of size 256. In VGG-Net, we apply the VGG-19 network in which 8 blocks are utilized. Each block contains 2 convolutional layers and a batch of normalization layers. ResNet-18 is applied and each block contains a residual block to prevent the vanishment of gradients. The DDC-ResNet, by replacing the normal convolutional layers with dilated convolutional layers in ResNet, lowers the loss of valid edge features [21]. To keep the fairness, these three types of feature extraction networks are of the vector size $[-1, 512]$ in the last layer. Here we set the batch size to be 10, and the iteration numbers are 10K. The optimizer we adopt is Adam, in which the learning rate is 3×10^{-4}. Inspired by Maas [22], the leaky relu is used as the activation function. All the codes are realized with the framework TensorFlow [23] in python. Hardware utilization includes GPU with NVIDIA TITAN Xp, and CPU with 2.8GHz, 32GB in RAM.

In the classification progress, the Adaboost is used with the $n\_estimator = 100$, $learning$ $rate = 0.01$, $max\_depth = 7$, and $subsample = 1.0$. In SVM, the linear kernel is utilized with the function LinearSVC in the default configuration, $C = 100$ and $gamma = 0.5$ are set when applying RBF and polynomial kernels. The parameter k in kNN is set to be 1. J48 algorithm is conducted in WEKA software with the default settings [24]. The CNN classifier is comprised of 3 fully connected layers with the leaky relu activation. Classification algorithms except J48 and CNN are all conducted in scikit-learn [25].

Effect of Methods

To evaluate the effect of different methods on gender-related features, we make a benchmark for the combinations of 6 feature extraction methods coupling with 9 classifiers to compare their average and separate-gender accuracies, as shown in Table 2. In terms of the average accuracy, the DDC-ResNet extractor outperforms other extraction methods when matching with different classifiers. For the classifiers, the Adaboost, SVM with the polynomial kernel, and CNN are more outstanding. On the contrary, the SVM with the linear kernel seems not qualified for the extracted features with high dimensional space in the gender identification task. Regarding the separate-gender performance, most of the results show more correct predictions in males than in females, especially for DWT+SVM[3]. The difference is more than 10%, which is agreed with the [7, 26], suggesting that fingerprints of males contain richer gender-related features in some aspects. To make a more comprehensive analysis, we also evaluate the time consumption of each combination when feeding different batch sizes of data. The result is shown in Table 4. In general, deep learning extractors consume more time than machine learning, and SVD extractor consumes the least time. However, FFT behaves oppositely which is because the transformation does not reduce the feature size. In summary, the combination of DDC-ResNet and CNN outperforms other combinations, reaching an average accuracy of 96.50% and separate-gender accuracy

of 0.9743/0.9324. Moreover, males contain richer gender-related features than females. After evaluating the performance of various methods with all test fingers, we will explore how specific fingers influence the gender identification results below.

Table 2
The upper value in each cell represents *average accuracy* (%), and the under value shows separate gender accuracy, meaning *male accuracy/female accuracy*

	FFT	DWT	SVD	ResNet	VGG	DDCResNet
Adaboost	85.280	91.494	92.096	92.068	94.138	94.253
	0.8337/0.8719	0.9531/0.8768	0.9294/0.9125	0.9334/0.9080	0.9464/0.9364	0.9350/0.9501
SVM[1]	65.827	70.001	66.552	69.302	72.454	73.844
	0.6895/0.6270	0.7280/0.6720	0.6839/0.6471	0.7202/0.6658	0.7208/0.7283	0.7366/0.7403
SVM[2]	82.604	88.275	86.506	85.502	88.506	89.576
	0.7935/0.8586	0.9144/0.8511	0.7910/0.9391	0.8210/0.8890	0.8192/0.9509	0.8260/0.9655
SVM[3]	87.310	88.735	91.609	91.713	94.713	**95.333**
	0.8653/0.8809	0.9452/0.8295	0.9248/0.9074	0.9220/0.9123	0.9590/0.9353	**0.9743/0.9324**
KNN	92.202	90.460	88.230	92.529	93.563	92.759
	0.9346/0.9094	0.9187/0.8905	0.8917/0.8729	0.9072/0.9434	0.9428/0.9285	0.8865/0.9687
J48	73.912	90.394	76.667	90.460	88.220	89.344
	0.7224/0.7558	0.8977/0.9102	0.7296/0.8037	0.8979/0.9113	0.9195/0.8449	0.8921/0.8948
CNN	87.220	91.360	92.413	93.333	93.678	**96.500**
	0.8814/0.8630	0.9455/0.8817	0.9350/0.9133	0.9463/0.9204	0.9423/0.9313	**0.9752/0.9548**
ID3	78.931	90.344	89.770	90.460	90.459	91.494
	0.7682/0.8104	0.8727/0.9342	0.8856/0.9098	0.9149/0.8943	0.9099/0.8993	0.9159/0.9140
LDA	88.498	87.192	89.721	82.106	89.385	93.599
	0.9012/0.8687	0.8693/0.8745	0.9411/0.8443	0.7966/0.8455	0.9047/0.8830	0.9461/0.9259

Effect of Fingers

After studying the effect of varing methods on gender-related features, we further explore the effect of each finger. We divide the testing fingerprints into 10 sets, each set of which corresponds to a specific finger containing 660 fingerprint images. We apply the DDC-ResNet coupled with CNN(best performance method above) to test the 10 sets, as listed in Table 3. The result indicates that for each specific finger, the right ring finger(R2) shows the highest accuracy, reaching 92.455%. For 5 pairs of fingers, ring fingers outperform other pairs, reaching an accuracy of 91.413%. For the overall hand, the right hand achieves a higher accuracy than the left hand, which reaches 87.872%. To better understand the effect of fingers on gender-related features, more careful studies will be carried out in the following part.

Effect of Features

To further research on gender-related features, we apply the grad-cam [27] technique to visualize the heat maps, seeing which part contributes most. Specifically, based on earlier results, we visualize testing fingers by using the DDC-ResNet extractor. The overview of

Table 3
Estimate performance of each finger(%), in which F_x represents Finger x. The index from 1 to 5 means little finger, ring finger, middle finger index finger and thumb respectively. And the $F_{average}$ represents the average of their fingers.

Hand	Types of Finger(F_x)					
	F_1	F_2	F_3	F_4	F_5	$F_{average}$
Left	88.291	90.371	87.152	82.819	83.455	86.418
Right	85.864	**92.455**	91.363	86.455	83.224	**87.872**
Average	87.078	**91.413**	89.258	84.637	83.340	\

Table 4
The running time of each combination, each cell means time consumption (s) when feeding 10/100/1000 batch size of data.

	VGG	ResNet	DDCResNet	DWT	SVD	FFT
Adaboost	3.213/3.959/19.677	3.776/4.213/20.581	6.456/6.86/26.100	0.184/2.652/18.693	0.165/1.786/14.445	0.130/3.994/280.162
SVM[1]	3.176/3.905/16.530	3.739/4.159/17.434	6.419/6.806/22.953	0.160/2.013/15.674	0.147/1.292/13.010	0.184/3.207/48.925
SVM[2]	3.176/3.905/16.960	3.739/4.159/17.864	6.419/6.806/23.383	0.143/2.412/15.108	0.153/1.292/12.967	0.029/1.688/147.075
SVM[3]	3.176/3.905/16.902	3.739/4.159/17.806	6.419/6.806/23.325	0.296/1.609/16.883	**0.146/1.291/12.944**	0.028/1.665/143.031
KNN	3.180/3.904/16.602	3.743/4.158/17.506	6.423/6.805/23.025	0.198/1.059/18.370	0.162/1.294/12.889	0.030/1.393/89.841
J48	3.184/3.927/16.331	3.747/4.181/17.235	6.427/6.828/22.754	0.184/1.477/15.854	0.148/1.296/12.791	0.858/4.822/201.731
CNN	3.189/3.903/15.963	3.752/4.157/16.867	6.432/6.804/22.386	0.139/1.749/17.110	0.156/1.300/12.756	1.200/4.190/341.870
ID3	3.176/3.920/16.629	3.739/4.174/17.533	6.419/6.821/23.052	0.142/1.842/15.556	0.1467/1.291/12.897	0.062/1.756/43.519
LDA	3.176/3.901/16.292	3.739/4.154/17.196	6.419/6.801/22.715	0.148/1.466/16.770	0.147/1.292/12.967	0.138/2.478/41.830

visualization is exhibited in Figure 2, It can be seen that concentrations are mainly on or around the center of fingerprints. Detailed observation is shown in Figure 3. The concentration covers the whorl part which belongs to the pattern features of level 1. Further observation reveals that bifurcations are gathered in concentration regions. However, we exclude the sweat pores around the bifurcations since other parts containing more remarkable sweat pores have not received attention. We also find that the concentration regions prefer to be continuous parts. Therefore, it is not hard to say that the foundation of recognition is complete ridges, which explains the reason for manual extraction of minutiae features in well-selected continuous regions.

Conclusion and Future work

This paper proposes an effective network considering the global reception field in the gender classification task, which is realized by replacing normal convolutions with dilated convolution in the extraction method. The experiment thoroughly explores the efficiency from three aspects. First, comparing our method with various methods with fair implementation details in our dataset. 6 typical automatic feature extraction methods like DWT, SVD, VGG, and our method coupling with 9 mainstream classifiers such as Adaboost, kNN, SVM, CNN, etc. a total of 54 combinations are evaluated. Experimental results reveal that the combination of our extractor with the CNN classifier outperforms other combinations. For average accuracy, it reaches 96.50% and for separate-gender accuracy, it reaches 0.9752(males)/0.9548(females). Second, we investigate the effect of fingers by classifying gender using separate fingers, and find the best-performing finger is the right ring finger,

Figure 2 Overall heatmaps

Figure 3 Concentrations in heatmap
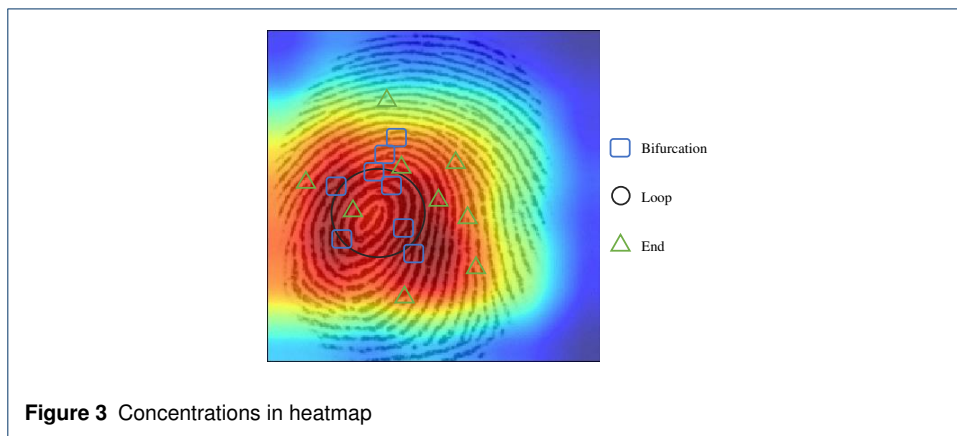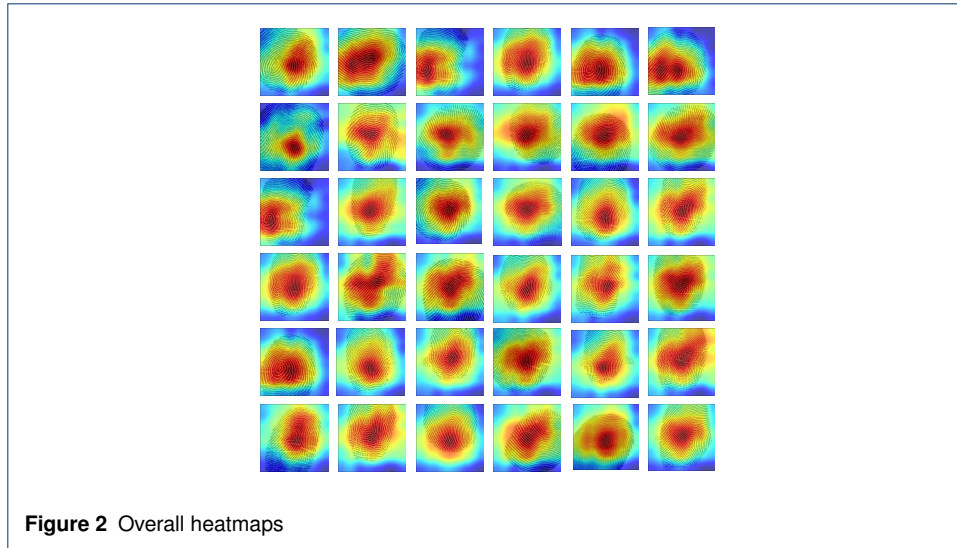
which reaches an accuracy of 92.455%. Third, we study the effect of features by visualizing concentrations of fingerprints. Depending on the analysis, loops/whorls (level 1), bifurcations(level 2) and line shapes(level 3) may have a close relationship with gender. This work not only comprehensively explores the efficiency of the proposed method, but also provides a way to observe fingerprint identification features much closer. These specific features will be quantified in the future to further explore the impact on fingerprint recognition.

Overview of Feature Extraction and Classification Algorithms

In this section, we will introduce our approaches and the implementation principles of automatic feature extraction methods. In addition, we will outline the classification methods utilized in this paper.

Feature Extraction

Discrete Wavelet Transformation

Wavelet has been extensively applied in feature extraction, soft-biometrics recognition, and denoising, etc. It decomposes an image into sub-bands containing frequency and orientation information to represent the valid signals. Specifically, a fingerprint image is decomposed into 4 sub-bands at one level, namely low-low(LL), low-high(LH), high-low(HL)

and high-high(HH) which is shown in Figure 4. Typically, the LL sub-band will be decomposed repeatedly since it is thought to represent the most energy, and k refers to the repeat times. If k is set, (3*k)+1 sub-bands are available. The energy of each sub-band is calculated by equation 1, which will be used as a feature vector for gender classification(E_k), where $X_k(i,j)$ represents the pixel at the position i and j on the kth level. W and H represent the width and the height of the sub-band, respectively.

$$E_k = \frac{1}{WH} \sum_{i=1}^{W} \sum_{j=1}^{H} |X_k(i,j)| \tag{1}$$

Figure 4 Discrete Wavelet Transform for the fingers's gender classification
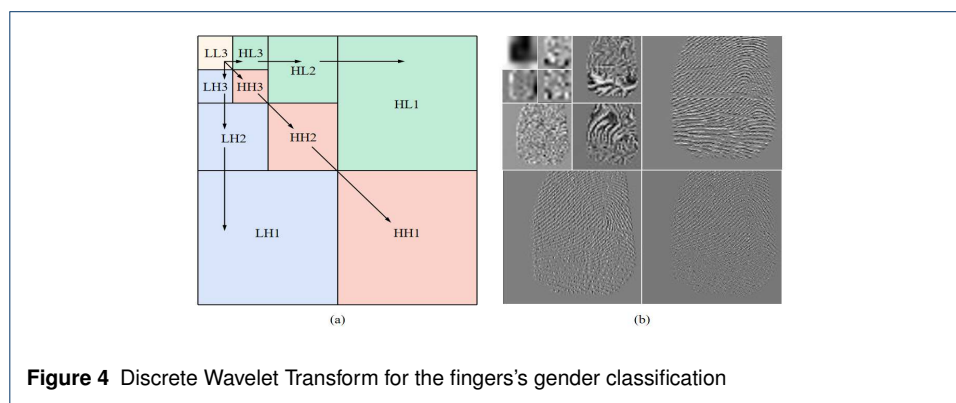
Singular Value Decomposition

The fundamental of the SVD is that any rectangular matrix can be transformed into the product of three new matrices. Specifically, given a fingerprint image matrix A with H rows and W columns, it can be factored into U, S, and V by using equation 2, where $U = AA^T$ and $V = A^T A$ and S are diagonal matrices that contain the square root eigenvalues with the size of H by W, which is stored for gender classification.

$$A = USV^T \tag{2}$$

Fast Fourier Transform

The FFT is used to transform a fingerprint image into the frequency domain. The transformed vector contains most of the information in the spatial domain and is used for gender classification. It is presented in equation 3, where M and N represent the height and width of the fingerprint image, k and l represent frequency variables, respectively. $0 \leq$ m, k $\leq$ M-1, $0 \leq$ n, l $\leq$ N-1.

$$F[k,l] = \frac{1}{\sqrt{MN}} \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} f[m,n] e^{-j2\pi(\frac{mk}{M} + \frac{nl}{N})} \tag{3}$$

Our method

Autoencoder neural networks can be divided into the encoder and decoder. Concretely, in the encoder step, the low dimensional data will be compressed into feature vector in high

dimensional space, and the decoder step is to reconstructs the original data without redundant features. The general equation is described in 4. where f is the activation function(In this work, we utilized leaky Relu), the W is the parameter matrix, and b is a vector of bias parameters. The feature vector can be optimized by minimizing the distance between the original data and the reconstructed data, and used for gender classification. Our method utilizes ResNet as the backbone, and uses the atrous convolution operation to replace the normal convolutions, as shown in Figure 5. In the block res we utilize atrous rates as 1, 2 and 5 to prevent the gridding effect. [28].And we put the feature vector output from the final convolution layer in the decoder into the classifier for classification.
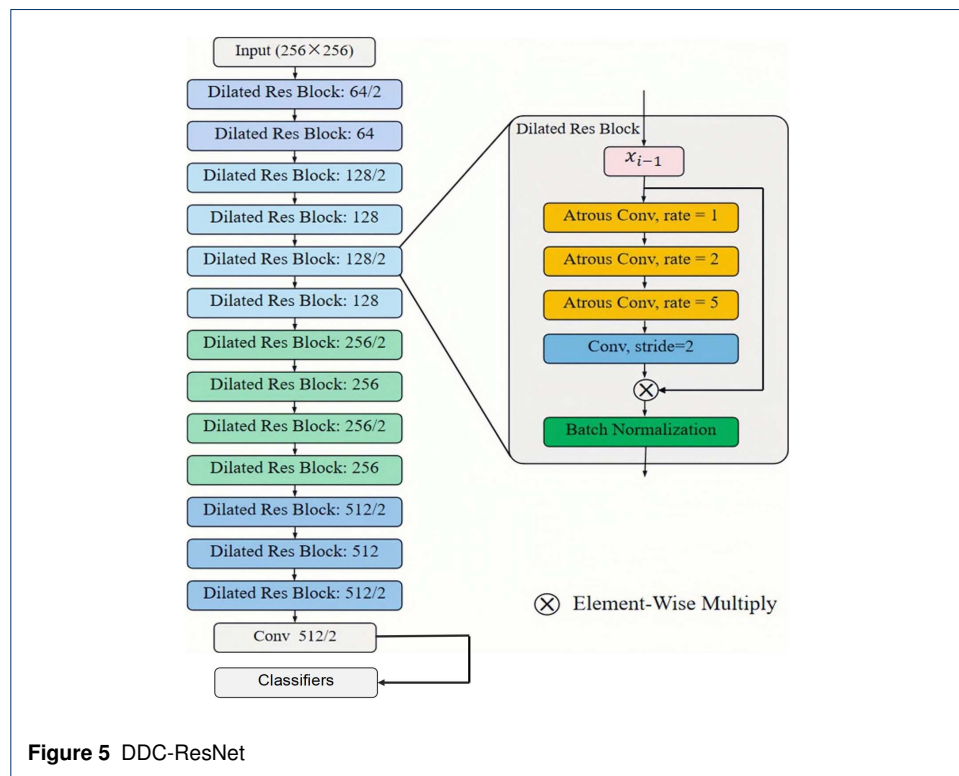
$$y = f(Wx + b)$$
$$x' = f(W'x + b)$$

(4)

Figure 5 DDC-ResNet

Gender Classification

To ensure fairness of experiments, we adopt commonly used 9 classifiers in gender classification problem, which are CNN, SVM(3 kernels), kNN, Adaboost, J48, ID3, and LDA. Among them the 3 kernels in SVM refer to linear, radial basis function, and polynomial, respectively. CNN is comprised of fully connected layers. These are all mainstream algorithms used in classification tasks. We threrfore only highlight their implementation details in the experimental result section and more details of the methods are presented in experimental setup section.

Gender Classification

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Abbreviations
FFT:Fast Fourier Transform;DWT:Discrete Wavelet Transform;VGG:Visual Geometry Group Network;SVM:Support Vector Machine;LDA:Linear Discriminant Analysis;KNN:K-nearest Neighbors;CNN:Convolutional Neural Network;PCA:Principal Component Analysis.

Availability of data and materials
The datasets used in the study are available from the corresponding author upon request.

Declarations

Ethics approval and consent to participate
The study was approved by Shaanxi University of Science and Technology. All 200 persons who provided fingerprint were fully informed of the purpose and protocol of the study and gave written consent to provide fingerprint information for scientific research and publication only.The authors declare that all experiments were performed according to the ethical principles and the data will not be used in any scenario other than scientific experiments.

Competing interests
The authors declare that they have no competing interests.

Consent for publication
Not applicable.

Authors' contributions
QY, QM, LH, CJ and LY contributed to the study concept and design.CJ and LH were involved in the acquisition of data.QY, QM, LH and CJ have contributed to the writing of the manuscript. All authors read and approved the final manuscript.

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