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Research Article

Fingerprint Pattern Classification by Using Various Pre-Trained Deep Neural Networks

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Abstract

Biometrics technology is very important in terms of security issues like the identification of personal identity. Many solutions have been offered regarding biometric technology such as eyes-iris recognition, face recognition and vein pattern recognition. Moreover, one of the today's most important authentication methods is fingerprint recognition. Each fingerprint has different pattern of ridges, valleys, deltas and cores. Those pattern types indicate unique fingerprints such as arch, left loop, right loop, tent arch and whorl. The issue of fingerprint pattern recognition is a crucial prior step to speed up the matching process of fingerprint recognition systems. Therefore, an accurate pattern recognition method is always needed, especially for large fingerprint databases. Besides traditional methods, recently, CNN is mostly used for fingerprint pattern recognition and there are many studies in the literature which achieve high recognition rates. In this study, we propose an automated tecnique toward fingerprint classification using various pretrained CNNs Xception and NasNetLarge in order to increase recognition rates. We performed experiments using NIST Special database 4 and we achieved 97.3 98.5% recognition rates respectively, which are the best scores up to now, for four categories: arch, right loop, left loop and whorl. The models was also tested into 5 fingerprint classes which arch and tented arch were seperated as two different classes with the recognition rate of 91.5% and 90.2% respectively.

Keywords: Fingerprint recognition systems, Deep learning, Convolutional Neural Network, Pattern recognition, Henry classification system.

Onceden Egitilmis Cesitli Derin Sinir Aglari Kullanarak Parmak İzi Örüntü Siniflandirma

Öz

Biyometri teknolojisi, kişisel kimlik tespiti gibi güvenlik konuları açısından oldukça önemlidir. Göz-iris tanıma, yüz tanıma ve damar örüntüsü tanıma gibi biyometrik teknoloji ile ilgili birçok çözüm sunulmuştur. Dahası, günümüzün en önemli kimlik doğrulama yöntemlerinden biri parmak izi tanımadır. Her parmak izinin kendine özgü sırt, çukur, delta ve çekirdek model örüntüsü vardır. Bu örüntüler lasso(ilmek), ark(yay) ve wirbel gibi benzersiz parmak izi tiplerini oluşturur. Parmak izi paterni tanıma sorunu, eşleştirme sürecini hızlandırmak için çok önemli bir ön adımdır. Bu nedenle, özellikle büyük parmak izi veritabanları için her zaman doğru bir örüntü tanıma yöntemine ihtiyaç vardır. Geleneksel yöntemlerin yanı sıra son zamanlarda parmak izi örüntü tanıma amacıyla daha çok CNN kullanılmaktadır ve literatürde yüksek tanıma oranlarına ulaşan birçok çalışma bulunmaktadır. Bu çalışmada, tanıma oranlarını artırmak için önceden egitilmis Xception ve NasNetLarge CNN mimarilerini kullanarak parmak izi sınıflandırmasına yönelik otomatik bir teknik öneriyoruz. NIST Özel veritabanı 4'ü kullanarak deneyler yapildi ve dört kategori için: yay, sağ lasso, sol lasso ve wirbel, şu ana kadarki en iyi puan olan %97.3 ve % 98,5 tanınma oranlarina ulaştık. Ayrıca model, yay ve fitilli yay iki ayrı sınıfa ayrılarakta test edilmiş ve 5 sınıf için % 91,5 ve %90.2 tanınma oranına ulaşılmıştır.

Anahtar Kelimeler: Parmak izi tanıma sistemleri, derin öğrenme, Evrişimli Sinir Ağı, Örüntü tanıma, Henry sınıflandırma sistemi.

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1.Introduction

Security solutions for biometrics continue to grow as the likelihood of hacking increases due to the advancement of IT technology, since current authentication methods do not effectively protect an individual's personal information. To decide if they belong to a specific individual, biometrics technology is used to extract human features and behavioral details.

Two forms of such technology exist. The first is used to authenticate a user using 1:1 matching by authentication with a database. The second is used to identify the user using 1:N matching through a search of their information in the database. This form uses the biological characteristics of the person such as face, iris, shape of hand, shape of ear, gate, fingerprint and voice. Such biometric information varies from individual to individual and does not change over the years. There is also a benefit because, unlike with other current authentication methods, there is no chance of memorization or exposure. Fingerprint detection has become the most commonly advertised of the different forms of biometric authentication services.

In 1684, when Neemia Couture of England first discovered that human fingerprints vary from one another, contemporary fingerprint comparison technology began. A taxonomy of fingerprints was later introduced by Henry in 1900. The fingerprint classification is based on characteristics such as, endings, bifurcations, ridges, cores, deltas and flow, right loop, double loop, left loop, whorl, and arch according to the flow. Fingerprints are categorized into 3 major groups: loops, whorls and archs. Shrestha at al.[1] indicated that 60-65% of the fingerprints are categorized as loops, 30-35% of fingerprints are encountered as whorls and 5 -10% of them are defined as arch fingerprints.

Korea has nearly 41 million images in its archive of fingerprints. A correct classification of the images is needed to find a match out of such a large number of fingerprint images.

In the next section, we discuss previous works for our task. Section 3 presents the details of our methodology and dataset. Then, we report our results. Final section presents our conclusion.

2. Related Literature

For the histogram derived from a fingerprint file, Kang et al. [2,3] suggested an efficient preprocessing approach for evaluating a threshold value using neuro-fuzzy method or a neural network. After extracting the ridge information in 16 directions using the Markov model for preprocessed fingerprint images, Jeong and Lee [4] classified them with 88% accuracy while changing the Markov model value using a genetic algorithm.

The most significant flaw in current studies is the thinning needed to obtain ridge direction data. Noise is introduced by thinning, such as twigs that were not present in the original shot. Additional image processing should be used to minimize such noise. In this research, using a convolution neural network, we attempt to classify fingerprints without a thinning method (CNN).

Krizhevsky et al. [5], suggested by Hinton's Supervision team, won the ImageNet Large Scale Visual Recognition Competition (ILSVRC) by a factor of 16 percent over the second-place team in 2012. Deep learning gained prominence after that, and it is now used in a number of areas, including identification and classification. A fingerprint recognition method using the deep learning method was proposed by Wang et al.[6]. In an updated version of the neuro-fuzzy method, Bae et al.[7] classified fingerprints.

A research combining an ensemble approach was performed by Peralta et al.[8] using an improved Alexnet model. Various other experiments have since been carried out. To boost the consistency, preprocessing is applied to an input fingerprint image [9]. By collecting and studying image characteristics using a CNN, fingerprint classification is then carried out.

3. Material and Method

3.1. Dataset

Labelled fingerprint datasets are rarely open to public access. Therefore it is not easy to handle these kind of special datasets. In this work, NIST (National Institute of Standards and Technology) Special Database 4 fingerprint dataset is used for training and test purposes. This dataset has 5 group of fingerprint patterns which are: arch, right loop, left loop, tented arch and whorl. Each group has 400 labelled fingerprints, belong to 50 people. One example for each fingerprint pattern is given in Figure 1. Although each person has different fingerprint, the similarity of fingerprint patterns provide scientists to assign a test fingerprint to a fingerprint pattern. This operation makes the actual classification easier and faster.

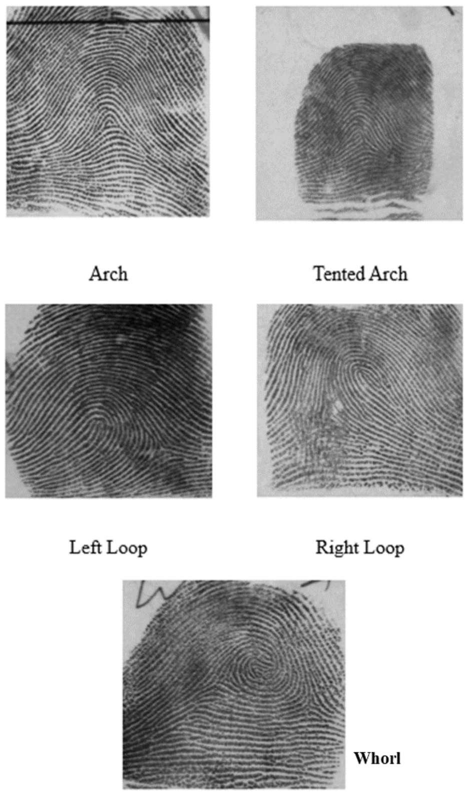

Figure 1. Fingerprint patterns

3.2. Proposed Method

In order to remove the effect of different lighting conditions, each fingerprint image in the dataset is normalized. In this study we two different deep learning structures. The first one is using the pre-trained CNN network: NasNet-Large as the base layer.

This model is a state-of-the art CNN model which achieves the best classification accuracy on image-based datasets [10]. The other layers following the base layer are given in Table-1. Furthermore, the training parameters are provided in Table-2. Another pre-trained CNN architecture used in this study is Xception model. The structure of this model after the base layer is similar to the first one.

The fingerprint data is first shuffled and then randomly divided into training and test sets prior to training. 75% of fingerprint images are assigned as training set and 25% is assigned as test set. The training is implemented by using Keras on Python environment.

Table 1: Layer description of CNNs.

Layer (type)	**Output Shape**
NasNet-Large / Xception	(None, 331, 331, 3)
NasNet_function / Xception_function	(None, 8, 8, 2048)
GlobalAveragePooling2D	(None, 2048)
Dropout	(None, 2048)
Dense	(None, 4)

Table 2: Training parameters of CNNs.

Parameter	**Value**
optimizer	Adam
loss	categorical_crossentropy
shuffle	True
Number of epochs	300
batch_size	64

4. Results and Discussion

We have evaluated the proposed network with NIST database. The confusion matrixes for 4 classes and 5 classes are given in Tables 3 and 4. The left bottom corner of each table provides the general accuracy which are very promising for fingerprint pattern recognition among other studies in the literature. This is since we use a state-of-the art pretrained model which is very successful for image classification-based problems.

In Table 3 and 4, we provide the precision and recall scores as well. The best recall score for 4 classes case is achieved by Whorl and Right Loop classes and the best precision is by Whorl. Similarly, in 5 classes case, the best recall and precision scores are handled for Whorl. Since delta and core patterns are lost in worn and bad quality fingerprints CNN model does not classify these fingerprints correctly regardless of fingerprint types.

Table 3: Confusion matrix for 4 classes for NasNetLarge.

		NIST Special Database 4				recall
Target Class	Arch	98	1	1	0	0,98
	L. Loop	1	99	0	0	0,99
	R. Loop	1	0	98	1	0,98
	Whorl	0	1	0	99	0,99
		Arch	L. Loop	R. Loop	Whorl	0.985
	precision	0,98	0,98	0,98	0,99	
		Predicted Class				

Table 4: Confusion matrix for 5 classes for NasNetLarge.

	NIST Special Database 4					recall
Arch	94	1	0	5	0	0,94
L. Loop	1	94	1	4	0	0,94
R. Loop	0	0	96	3	1	0,96
T. Arch	9	5	3	83	0	0,83
Whorl	0	2	0	0	98	0,98
	Arch	L. Loop	R. Loop	T. Arch	Whorl	0.91
Prec.	0,90	0,92	0,96	0,87	0,98	

In Table 5 we compare our result with some other studies which have implemented their methods on NIST database. According to this benchmark, our study achieves the best accuracy. Another successful study conducted in [18] achieves 97% for the same 4 classes on FVC dataset.

Table 5: Benchmark result on NIST Dataset

Study	Accuracy (%)
Candela et al. [11]	88,6
Karu et al. [12]	91,1
Jain et al. [13]	91,2
Yao et al. [14]	93,1
Zhang et al. [15]	95,3
Liu et al. [16]	92,1
Ruxin et al. [17]	91,4
Proposed (Xception)	97,3
Proposed (NasNetLarge)	98,5

5. Conclusion

In this study, we propose a model which uses a state-of-the-art pretrained convolutional neural network. By using this model, we classify the fingerprint patterns which was put forth by Henry. This classification issue is crucial in terms of grouping fingerprints prior to matching. Therefore, a faster matching can be possible.

We have achieved promising accuracy rates for the NIST database. This shows that using the pretrained CNN models is a good solution to solve the fingerprint pattern classification problem.

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