Encapsulating the impact of transfer learning, domain knowledge and training strategies in deep-learning based architecture: A biometric based case study

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Abstract

In this paper, efforts have been made to analyze the impact of training strategies, transfer learning and domain knowledge on two biometric-based problems namely: three class oculus classification and fingerprint sensor classification. For analyzing these problems we have considered deep-learning based architecture and evaluated our results on benchmark contact-lens datasets like IIIT-D, ND, IIT-K (our model is publicly available) and on fingerprint datasets like FVC-2002, FVC-2004, FVC-2006, IIITD-MOLF, IITK. In-depth feature analysis of various proposed deep-learning models has been done in order to infer that indeed training in different ways along with transfer learning and domain knowledge plays a vital role in deciding the learning ability of any network.

1. Introduction

Todays world is an era of digitization. Many countries, especially the developed and the developing ones are moving towards cashless economy. In such scenarios, security is of prime concern. Password based authentication is easy to spoof and moreover remembering passwords for different purposes is quite cumbersome. In such situations biometric based authentication provides a reliable source of personal identification. The main aim of this work is to utilize prodigious benefits of deep-learning in solving challenging biometric problems like three class oculus contact lens classification into no, soft and cosmetic lenses and fingerprint sensor identification.

One of the biggest challenges for the biometric-based model is that they are not only investigated and implemented purely for academic purpose but they should be designed in such a manner that is useful in real-world scenarios for large datasets and that too at a reasonable cost. In this paper, we have considered two biometric-based case studies namely three class oculus classification and fingerprint sensor classification for understanding the role of encapsulating transfer learning, domain knowledge and different learning strategies.

1.1. Contribution

Our main contribution includes:

- A generalized hierarchical deep convolutional network (GHCLNet) for three-class oculus classification into no-lens, soft-lens and cosmetic-lens has been proposed. This network works without any pre-processing and segmentation step and works on full holistic contact-lens features.
- A deep-convolutional neural network has been proposed that is capable of detecting input fingerprint sensors.
- An exhaustive deep feature analysis has been done on the two above mentioned biometric based case-studies to understand the real-insights of features learned at different layers.

2. Case Study-A

Broadly contact lenses are classified into two main categories (i) Soft lens or Transparent lens and (ii) Cosmetic or Colored lens. Soft lenses serve as an alternative to glasses and generally is used for correcting vision problems like myopia, hypermetropia, presbyopia and astigmatism while cosmetic lenses are mainly used to enhance and beautify the iris texture. No matter for what purpose contact lens is used, the main concern is that every time lenses are used, it alters the highly unique and discriminative iris textual features. Over the years it has been realized that, performance of the iris recognition system degrades substantially in the presence of the contact-lens and particularly the presence of cosmetic-lens as clearly evident by the work done by [4]. Hence detection of contact lens is must for improving the

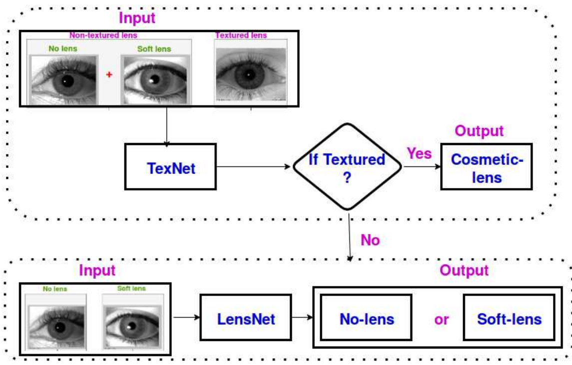

Figure 1. Generalized Hierarchically Tuned Contact Lens Detection Network (GHCLNet) architecture

utility and reliability of iris recognition system for contact lens users. Cosmetic lens changes the texture of the eye both in visible as well as in near infrared spectra and thus can be detected, but differentiating between a soft lens and no lens is still a challenging problem.

2.1. Proposed Model

In our work we have proposed a novel approach for detecting contact lens using a Generalized Hierarchically tuned Contact Lens detection Network (GHCLNet) based on ResNet50[2] model as shown in Fig.1. This network can work on raw input iris images without any pre-processing and segmentation requirement, and this is one of its prodigious strength as it can be easily integrated as a first step into any iris based recognition system to increase its performance. While designing this hierarchical model we have included the expert domain knowledge in its design by utilizing the divide and conquer strategy by dividing the three class oculus classification problem into two subparts.

We have carried out extensive experimentation on two publicly available iris datasets namely ND and IIIT-D and on IIT-K dataset which is not publicly available using four testing strategies: intra sensor validation, inter sensor validation, multi-sensor validation and combined sensor validation (its result is shown in table1) which yields correct classification rate (CCR %) above 95%, 89%, 95% and 95% respectively which is better than the available state-of-the-art [3]. To the best of our knowledge this kind of combined sensor testing has not done by anyone so far and this depicts the highly generalized ability of our network. In order to visualize the features of GHCLNet we have used input reconstruction method that maximally activates the point of interest unit associated with a filter. It is clearly evident from Fig.2 that initial convolutional layers are looking directly at the raw pixels of the input images and thus they are learning low level features like bunch of oriented edges, colours and blobs at different orientations and frequencies

Table 1. Combined Sensor qualitative performance in CCR(%) on the proposed GHCLNet architecture [3]

Dataset	**Agg(CCR%)**
IITK	99.14
ND-I	92.87
ND-II	94.93
IIITD-VISTA	95.69
IIITD-COGENT	95.43

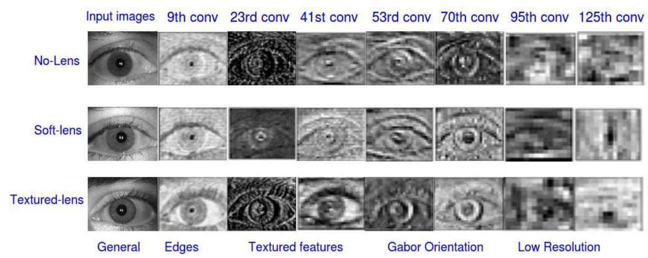

Figure 2. Features learned by different convolutional layers corresponding to no lens, soft lens and cosmetic lens by GHCLNet

which is same as seen by the striate cortex.

Note We have made our trained GHCLNet model publicly available on `https://github.com/vishesh9494/GHCLNet`.

3. Case Study-B

Fingerprint sensors can be classified into various categories e.g. (i) basis of imaging technology they are classified as optical, capacitive and thermal; (ii) basis of user interaction they are classified as press, sweep and non- contacted ones. In such a heterogenous sensor environment, it is crucial to identify the source sensor by which the acquired image is captured. This is essentially required to handle sensor inter-operability issues and further in identifying various attacks on biometric systems, where biometric templates can be modified or mis-used. Another interesting application of sensor identification is in establishing the sequence of commands for law enforcement for identifying spurious activity in online systems. An image can be altered or fabricated during the acquisition phase, transmission or during storage. In order to understand whether the image has been fabricated or not it is necessary to know the source that generates the image. It is commonly known that cross sensor biometric data validation degrades substantially as compared to the intra-sensor validation [1]. Thus it is essential to identify different types of sensors for handling sensor interoperability issues.

3.1. Proposed Model

Deep-Convolutional neural networks are well known for extracting distinctive features. In our recent work, we have

Table 2. FPSensorNet qualitative performance in CCR(%) on various datasets [1]

Dataset	Agg(CCR%)
FVC-2002	98.99
FVC-2004	98.23
FVC-2006	99.73
IIITD-MOLF	100
IITK	99.78

proposed a novel deep architecture for fingerprint sensor classification termed as FPSensorNet as shown in Fig.3 inspired from ResNet50 [2]. To the best of our knowledge, this is the first attempt in which deep convolutional neural network has been used for fingerprint sensor classification. ResNet50[2] network comprises of five main branches. Hence extensive experimentation has been done on more than $80,000$ images from publicly available datasets FVC-2002, FVC-2004, FVC-2006, IIIT-MOLF and IITK fingerprint dataset which is not publicly available. During network training, we have observed the fact that in our network, Branch-2 and Branch-4 of ResNet50 are extremely important for learning discriminant information among different sensors. We have dropped Branch-5 of the model because it is not adding any peculiar information. Table 2 lists our experimental results on various databases under consideration. The proposed architecture yields quite promising results.

Feature Analysis In order to thoroughly understand what our network is learning we did rigorous feature analysis of various convolutional layers as shown in Fig.4 and Fig.5 Features learned by Conv_2 layer are very basic features, but as we move deeper in the network more specific learning has been performed like in Conv_9 layer it has learned sector significance information. Interestingly we have observed that our network automatically learned the state-of-the-art CompCode, and its closely related features at Conv_31 layer. It can be observed that oriented Gabor filter like features are learned at different orientations.

4. Conclusion

The main objective of this paper is to highlight how transfer learning, domain knowledge along with different training strategies, particularly in biometric-domain plays an important role in deciding the output of any deep-learning based model.

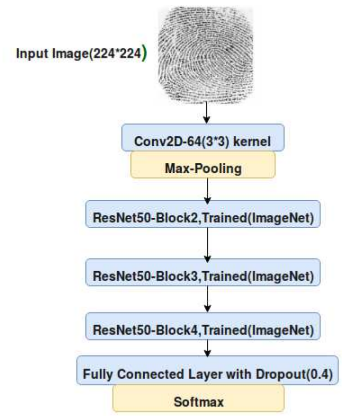

Figure 3. ResNet50 based deep network (FPSensorNet) for fingerprint sensor classification

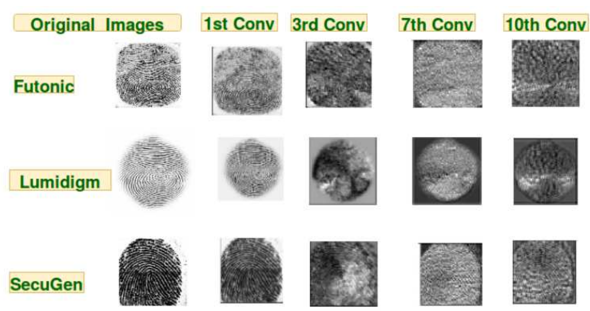

Figure 4. Visualization of different convolutional layers on proposed architecture for fingerprints acquired using (a) Futonic (b) Lumidigm (c) Secugen sensors

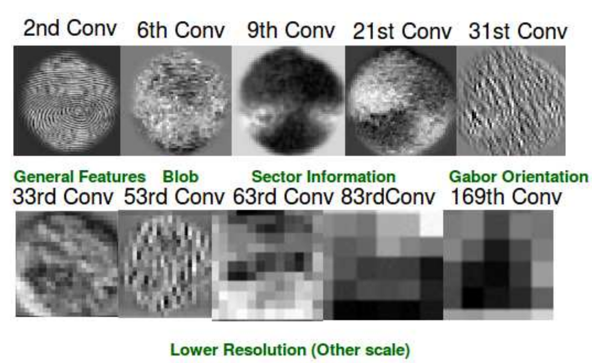

Figure 5. Features learned by Lumidigm fingerprint sensor

References

[1] A. Agarwal, R. Singh, and M. Vatsa. Fingerprint sensor classification via mélange of handcrafted features. In *23rd International Conference on Pattern Recognition, ICPR*, pages 3001–3006, 2016.

[2] K. He, X. Zhang, S. Ren, and J. Sun. Deep residual learning for image recognition. In *IEEE CVPR*, pages 770–778, 2016.

[3] R. Raghavendra, K. B. Raja, and C. Busch. Contlensnet: Robust iris contact lens detection using deep convolutional neural networks. In *IEEE WACV*, pages 1160–1167, 2017.

[4] D. Yadav, N. Kohli, J. S. D. Jr., R. Singh, M. Vatsa, and K. W. Bowyer. Unraveling the effect of textured contact lenses on iris recognition. *IEEE TIFS*, 9(5):851–862, 2014.