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Matching of Contact and Contactless Fingerprint Using CNN model

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Abstract: Matching of contactless and contact fingerprints has increased its attention in recent days. There have been only a few attempts to match contactless and contact-based fingerprints using Convolutional neural network (CNN) model. We collected a publicly available dataset of contactless and their corresponding contact-based fingerprints from Hong Kong Polytechnic University. The dataset consists of 3,120 contactless fingerprints and corresponding contact fingerprint images from 260 fingers of 6 impressions each. Due to the difference in nature of acquisition of both contact and contactless fingerprint first, we pre-process both the fingerprints to enhance the image quality. We train the CNN model using both fingerprints. In our work, we used the Sequential CNN model to increase the accuracy of matching contact and contactless fingerprint images.
Key Word: contact-based fingerprints, contactless fingerprints, Convolutional neural network, Matching.

I. INTRODUCTION

Biometrics is used as practical means of identifying and authenticating individuals.It is a technique for instantly identifying someone based on physical andbehavioral traits. They are employed in the fields like law enforcement, healthcare, in forensic applications which includes criminal investigations, as well as in the civilian sector for border access control systems, national identity card validation, authentication processors,and airport security. Facial, signature, iris, voice, and eye vein recognition factors of biometrics areemployed in some situations because there is less trust in the uniqueness of the identifiers and they are simple to forge.Fingerprints are the most essential sort of physiological human biometrics, which is incredibly distinctive to each individual. Fingerprints are the most extensively employed biometrics. During the fourth or fifth month of pregnancy, a person's fingerprints grow. Unless a person is wounded in an accident, their fingerprint patterns remain relatively the same throughout their lives, therefore the important acceptance factor of the fingerprint is stability. Unlike other factors that can alter significantly with age, disease, and other conditions, fingerprints do not change over the course of a lifetime.

From figure 1 we can define a fingerprint as a collection of ridges and furrows. The continuous dark pattern flow in the fingerprint is called ridges and the light area between ridges is called furrows. Fingerprint has some unique points on the ridges which are known as minutiae points.

Fig 1. Fingerprint Image

Numerous types of fingerprint scanners have been developed over the years. The majority of fingerprint scanners that we use today are contact fingerprint scanners, which make direct contact with user’s finger. Contact-based fingerprint sensors have to cope with sensor surface noise, fingerprint deformation due to improper placement, and hygienic concerns. Contactless fingerprint Scanners support users with touch less fingerprints, which have more security, hygiene and overcomes the limitations of the contact-based fingerprint.

Deep learning is a subset of machine learning. Due to its ability to handle enormous amounts of data, it has emerged as a particularly important approach in recent years. It is multi-layered neural network that learn from vast amounts of data. Deep learning technologies showed remarkable success in classification, feature representation and image recognition. In recent years, deep learning is used for biometric recognition.Convolutional neural network (CNN) is the most well-known and often utilized type of deep neural network among many others. There is less attempt to match contact to contactless fingerprints using CNN models. In our work, we are using Sequential CNN model.

II. LITERATURE SURVEY

Few researchers are worked on matching of contactless and contact-based fingerprints, some of their research contributions are described below.

Lin and Kumar [1] proposed a modelthat accurately aligns important minutiae features utilizing a robust thin-plate spline (RTPS) and a deformation correction model (DCM).To extract minutiae-related ridges, the traditional minutiae extraction algorithm is used. They used PolyU contactless to contact-based fingerprint datasets. They got a 15.35% of equal error rate and 60.39% rank-1 accuracy using minutiae with RTPs +DCM.

Chenhoa Lin and Ajay Kumar [2] created a framework that is trained by multi-siamese CNN using fingerprint minutiae, respective ridge map, and specific region of ridge map. By performing multi siamese model on the dataset, they got a 7% of equal error rate and 64% of rank-one accuracy.

Steven et al [3] matched both contact and contactless fingerprints using minutiae and texture feature. Segmentation, enhancement, scaling and deformation correction are the pre-processing techniques used. To overcome the non-linear distortion of contactless and contact fingerprints, they used thin-plate-spline deformation correction model. On the PolyU dataset, they got an equal error rate of 0.30% by deep print and verifier 12.0 implementation.

Ali Dabouei et al [4] worked on the perspective distortion of contactless fingerprints by combining a rectification and a ridge network. In order to reduce the environmental variations of contactless fingerprint they used ridge entrance model. The proposed model achieves an equal error rate of 7.71% and rank -1 accuracy of 61.01%.

Peter wild et al [5] worked on fingerprint pre-processing using skin-mark finger segmentation, finger image enhancement, and resolution estimation. They used filtering based on NFIQ 2.0 quality measure. They got a true accept rank of 95.5%-98.6% and a false accept rank=0.1%.

III. METHODOLOGY

The block diagram of the proposed contact and contactless fingerprint matching approach is illustrated in the figure 2. First, we collect the contact and contactless fingerprints from the dataset and pre-process both the fingerprint images. The dataset was next divided into 70%of train, 10% of validation and 10%of test data**.** The data is trained and the validation data is validated using a CNN model. The test data are then predicted.

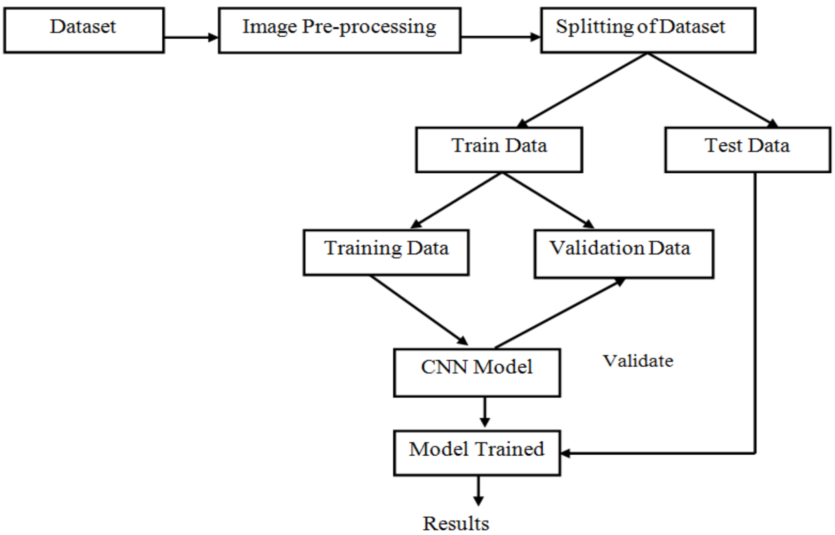
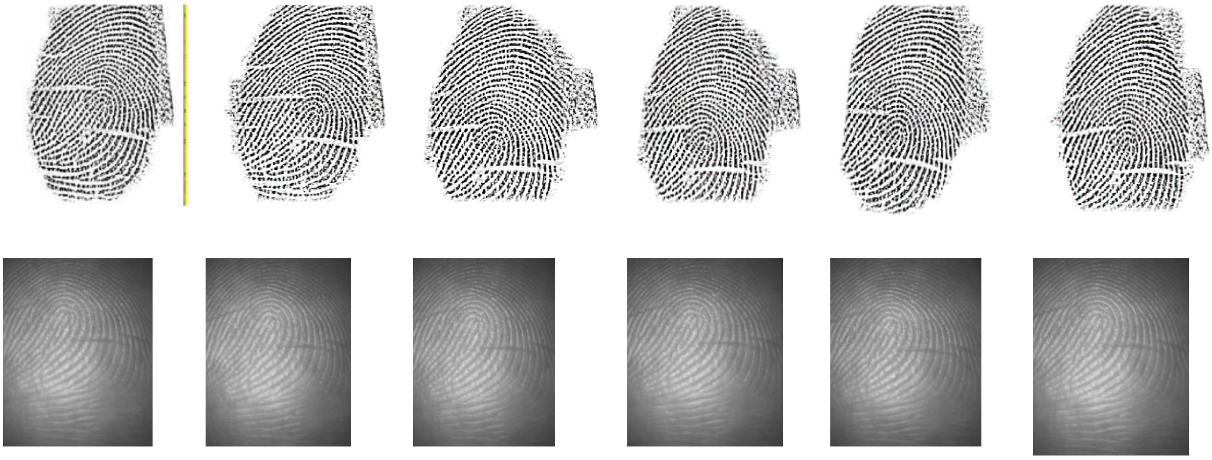


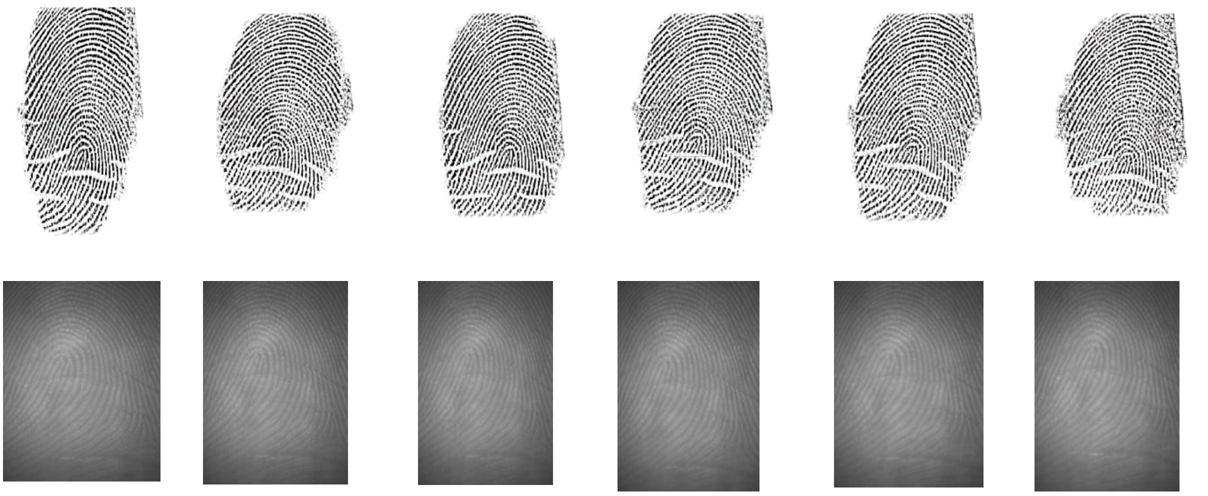
Fig 2. Block diagram for contact and contactless fingerprint matching approach using CNN models.

Dataset

The data was acquired from Hong Kong Polytechnic University "Contactless 2D to Contact-based 2D Fingerprint" Image Dataset [6]. The Dataset consists of 3,120 contactless fingerprints and corresponding contact fingerprint images from 260 fingers of 6 impressions. The contactless 2D fingerprint images and corresponding contact fingerprint images are acquired from a digital CMOS camera and URU fingerprint reader. Figure 3aindicates contact and contactless fingerprint of image 1and 3b indicates contact and contactless fingerprint of image2. The size of each contact fingerprint image is around 64.00kb and contactless fingerprint images are around 79.00kb. The resolution of each contact fingerprints are 328*356 and contactless fingerprints are 350*225.



a. Contact and contactless fingerprints



b. contact and contactless fingerprints

Fig 3.contact and contactless fingerprint images.

IMAGE PRE-PROCESSING AND AUGMENTATION

The images should be pre-processed before being input into the model,as raw photos are never precise and processing them through a model decreases the model's accuracy. In most CNN models pre-processing step takes 80% of the work and it largely depends on the quality of the image. Because contact and contactless fingerprints are distinct in nature, images from the same finger will seem significantly different,therefore it is necessary to perform image pre-processing. To improve the CNN model's accuracy, we will pre-process the images. The pre-processing technique used in the proposed work is image enhancement using Adaptive Histogram Equalization.

Image Enhancement

The method of adopting strategies to accentuate fingerprint images to simplify the identification of ridge valley structures is known as fingerprint image enhancement. Generally, Image enhancement is used to highlight certain information about an image or remove unnecessary information from the images.Figure 4, shows the raw Contact and Contactless fingerprint images. In order to improve the visual of an image, we used an adaptive histogram equalization pre-processing technique. This technique addresses two problems: one concerns undesirable physical characteristics such as scars, blurring, wrinkles, skin pores, and emerging ridges; the other concerns visual contrast issues such as lack of dynamic range.

The contrast of fingerprint images is improved by adaptive histogram equalization (AHE).Compared to conventional histogram equalization, the adaptive method is different. To scatter the brightness of images, AHE computes several histograms, each one corresponding to a distinct area of the image.It works wonders for enhancing local contrast and defining edges in various areas of an image. Figure 5, represents the enhanced Contact and Contactless fingerprint images.

Fig 4. Before enhancement of Contact and Contactless fingerprint image.

Fig 5. Adaptive histogram equalization of Contact and Contactless fingerprint image.

DATA AUGMENTATION

A data augmentation strategy is used to increase the volume of the dataset by altering the existing data, as we know deep learning models require more data for training. Stated that CNN[9] can classify images in different orientations. Some of the data augmentation techniques are flipping, rotation, shearing, cropping, zooming in, zooming out, and changing the contrast or brightness. The images in the dataset was small in number, therefore we carried data augmentation for good performance of the CNN model. To increase the volume of the dataset we carry out minor changes to the existing data. In our study, we used to rotating the images by 90 degrees clockwise. Figure 6 and 7, represents the contactless and contact fingerprint images obtained after rotating 90 degrees clockwise for 3 times. The rotation procedure will rotate the pixels out of an image frame and leave the area of the frame with no pixel data since the image dimensions are not retained.

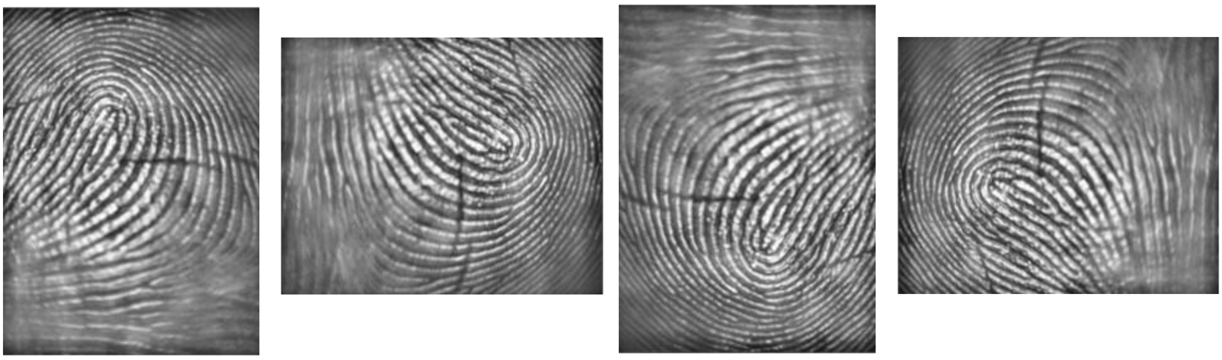


Fig 6. The contactless fingerprints are turned 90 degrees clockwise with relation to the prior one.

Fig 7. The contact fingerprints are turned 90 degrees clockwise with relation to the prior one.

CNN MODEL

A CNN is a deep learning neural network designed to analyze a structured array of data and is an artificial neural network used for image/object recognition and categorization.Deep Learning uses a CNN to identify objects in an image.CNNs are employed in a wide range of applications, includingcomputer vision, image processing. These tasks includes segmentation, localization, video analysis, the detection of impediments in auto-driving cars, and natural language processing. In today's fast growing domain CNN's play a vital role. The design components in input images, such as borders, colours, shapes, including eyes and faces, are very well detected by CNNs. The convolutional neural network algorithm's fundamental objective is to convert data into easier-to-process formats while preserving crucial properties for determining what the input represents. This qualifies them as excellent choices for dealing with large datasets. The CNN algorithm can recognize more complicated shapes, since it consists of many convolutional layers stacked on top of one another. Multiple convolutional layers pull essential features from data that is organized in a grid-like format.

We used a sequential CNN model, where each layer connects to previous and following layers. Figure 8, represents the proposed sequential CNN architecture. The model encompasses four convolutional layers, four Batch Normalization Layer, four Leaky Relu Layer, four Max pool Layer, one Flatten Dense and SoftMax layers.A convolutional layer is the essential component of a CNN. It has a selection of filters, whose settings must be given during training. The filters are smaller than the image. A convolution's receptive area's pixels are all combined into a single value. Convolution layer shrinks the size of the image and combine all the field data into a single pixel. Batch norm is a normalisation method that occurs between layers of a neural network. It is done in mini-batches rather than using the complete data set. We considered batch size as 32. By leveraging faster learning rates and expediting training, it facilitates learning. Leaky Rectified Linear Unit, often known as Leaky Relu, is an activation function that is based on Relu but it has a tiny slope for negative values rather than a flat slope. By employing pooling layers, the size of the feature map is decreased. The maximum element is chosen from the feature map area by the max-pooling layer. The feature map with the most noticeable features is the output of the max-pooling layer. Generated two-dimensional arrays from feature maps are transformed into a single continuous vector using the flattened layer. Based on the output of convolutional layers, dense layers are utilised to classify images. Instead of using relu, sigmoid, tanh or other activation functions at the very last layer, we use softmax activation. The softmax activation layer converts the output of the neural network to a probability distribution.

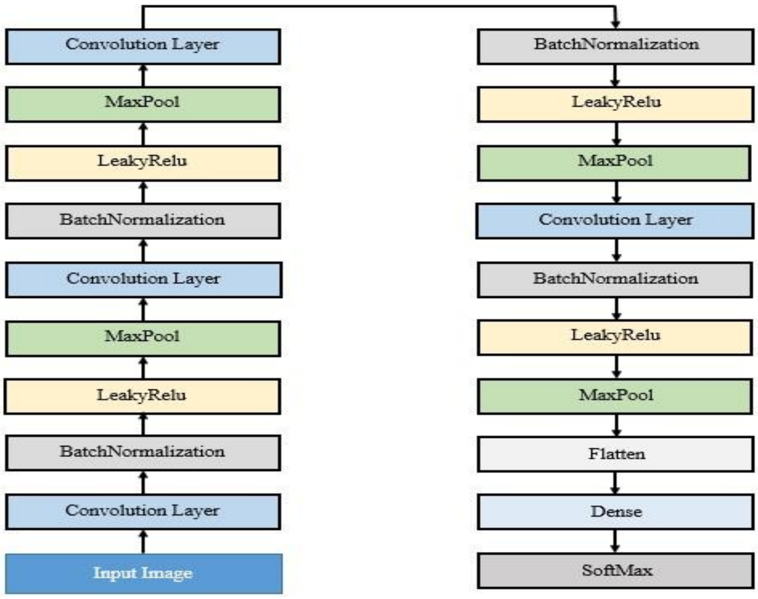


Fig 8. Sequential CNN architecture of proposed model.

IV. Results

Since most of the review works use using rank one accuracy to measure the performance of model, we also adopted the same metrics for testing the performance of the model.

Rank-one Accuracy

Rank one accuracy is used to check the percentage of how many times the ground label is same as predicted label. We divided the dataset into train and test data of varying sizes. By dividing the data into 20% of test data and 80% of train data, we were able to achieve 88.53% rank one accuracy.

$$\text{Rank one accuracy} = \frac{\text{Number of times predicted label is same as the ground label}}{\text{Length of the ground label .}} \quad \text{Eq.1}$$

Table no 1 Comparisons of state of art of Methods

Literature	Method	Rank-one accuracy
Lin and Kumar [1] 2018	Robust TPS deformation correction model	60.39%
Lin and Kumar[2] 2019	Multi Siamese CNN model	64.59%
Dabouei et al.[3] 2019	Binary ridge map extraction network	61.01%
Proposed Method	**Sequential CNN**	**88.53%**

V. Conclusion and Future Work

In this paper, we used sequential CNN model to match contact and contactless fingerprint. Data augmentation is performed on the given dataset to improve the rank one accuracy. We are considering the Publicaly available dataset. Fingerprint contact and contactless images are initially pre-processed using adaptive histogram equalization. The output obtained by the proposed model is 88.53% rank-one accuracy, when compared to other state of art methods. Since the model is more generalized it can be worked for different datasets and using different augmentation techniques to improve the performance.

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