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Fingerprint Feature Extraction and Matching using Convolutional Neural Networks(CNNs): A Review

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***Abstract*—Convolutional Neural Network (CNN) has achieved colossal success in the fingerprint recognition domain as we are seeing increasing interest in applying CNN to solve the problems of recognition systems in their various stages. The two most fundamental stages of these systems are feature extraction and matching which are still the most critical challenging of them. In recent years, a significant amount of researches and approaches for fingerprint recognition based on CNN have been carried out to give better solutions to fingerprint recognition issues. Nevertheless, we still need to conduct numerous review studies, to evaluate this method's efficacy. The major goal of this review study is to present the most recent studies and current strategies in fingerprint feature extraction and matching based on CNN to determine the effective contributions of CNN in this area. The reviewed literature have demonstrated that CNN has shown exceptional performance compared to the traditional methods and even outperformed them in many different aspects, including high accuracy, the discarding of pre-processing in many instances, the automatic extraction of features from raw data without human supervision, and others. Although, we still need to highlight CNN which will play an important role in future research directions for fingerprint recognition systems.**

Keywords*—Fingerprint, Fingerprint, recognition, CNN, Convolutional Neural Network

I. INTRODUCTION

Fingerprint consists of ridges and valleys, which form unique patterns [1]. In general, those details are split into three categories: local features known as minutiae points, global features known as singular points, and fine details [2]. The scientific foundation for using fingerprints as a technique of personal identification was developed by Henry Faulds, Francis Galton, and Edward Henry among others in the late 19th century [3]. Since then, it has been considered to be the best and fastest method for biometric identification [4]. When compared to other biometrics, fingerprints have the following advantages: it is the cost-effective, quick, reliable, and most convenient way to identify a person fingerprint recognition putting into consideration that it is widely accepted as a highly accurate method of authentication since the chance of two people with identical fingerprints is infrequent [5].

Although a lot of innovations have been developed for creating new fingerprint recognition systems, feature extraction and matching remain their most complex issues. It is still a challenging task to provide algorithms that gives better solutions to fingerprint recognition systems [6]. Very recently, several theoretical studies have demonstrated that a convolutional neural network (CNN) is a very effective recognition method compared to traditional methods where it automatically identifies the relevant features without any human supervision and the ability to scale for image data efficiently without increasing the complexity [7]. Additionally, it is robust and trainable from examples [8].

Numerous studies over the years have evinced that CNN has been effectively implemented in fingerprint recognition systems for a variety of tasks, including fingerprint image classification [9], fingerprint image segmentation [10], fingerprint pre-processing[11], fingerprint image denoising [12], and fingerprints quality enhancement [13]. Further, they are gaining momentum starting in the last decade in the area of fingerprint feature extraction and matching.

To determine the effective CNN contributions in this field, the major goal of this review study is to present the most recent studies and current strategies in fingerprint feature extraction and matching based on CNN. For this purpose, the next section will provide an introduction to CNN while the related work will be presented in section III.

II. OVERVIEW OF CONVOLUTIONAL NEURAL NETWORK

A Convolutional Neural Network known as CNN or ConvNet is a specific type of artificial neural network that has one or more convolution layers [7]. Similar to other neural networks, CNN has multiple hidden layers as well as input and output layers. The convolution layer, pooling layer, and fully connected layer are three distinct layers that make up a CNN's hidden layers and are what set it apart from the original ANN. It is successfully employed in a variety of fields including natural language processing, image recognition, sentence classification, and text categorization, and it is featured in various architectures such as LeNet, AlexNet, GoogleNet, ZFNet, and so on[14]. The fundamental CNN architecture is explained in detail in the following sub-section:

A. The architecture of CNN

The CNN architecture is composed of three basic layers:

1) Convolution Layer: This layer is the most significant layer of CNN. In this layer, the

mathematical operation of convolution is performed between the input image and a set of filters to extract the characteristics of a given image which is the output of this layer and termed the feature map [8].

2) Pool Layer: The primary aim of this layer is to reduce the size of the resulting images obtained from the previous layer. It summarizes the features generated by the prior layer and lessens the number of computations required. Depending on the method used, max pooling and average pooling are the two common types of pooling operations [15].

3) Fully Connected Layer: it's the ending layer in CNN, and it receives data from the previous layer, computes the class scores, and outputs the 1-D array whose size is equal to the number of classes [8].

III. Related Work

In this section, the significant research papers in the field published in the last five years from 2017 up until 2022, were selected, summarized, and presented in two sub-sections as follows:

A. Fingerprint Image Feature Extraction using CNN

Important related works of fingerprint image feature extraction using CNN are listed in Table I and are explained as follows:

Recently, in 2021 Pelin, and Abduls proposed a fingerprint identification system based on CNN and Gabor Wavelet Transform (GWT) to extract the minutiae of a fingerprint. Three crucial steps were taken to construct the system: ridge enhancement, ridge thinning, and minutiae extraction. The proposed CNN architecture consists of three convolution layers with filters of sizes 16, 32, and 64 sequentially. Preprocessing was implemented using dilation morphological operation and thinning. Using the FVC2006 dataset, experiments were conducted, and an accuracy of 91.50% was attained.

While in 2021 researchers in [17] applied deep-CNN to extract minutiae directly from raw contactless fingerprints image without preprocessing. The best performance was obtained during tests on the three datasets: PolyU Cross, Benchmark 2D/3D, and their dataset.

Recently researchers in [18] employed morphological operation to enhance and segment the input image and Convolutional Neural Network with Gabor filters to extract features from the enhanced image.

Authors in [19] designed a CNN Auto-encoder model where the CNN was utilized to extract the fingerprint features from the given images. The architecture of CNN has the 11-layer with a 3×3 filter size while the filter size of Max pooling layers is set to 2×2.

While authors in [20] proposed a contactless, fingerprint recognition system, where local features and global features were extracted and matched, first they employed adaptive mean thresholding (AMT) on a grayscale image before extracting local features extraction using the standard NBIS minutiae detector MINDTCT. A siamese-CNN was created to extract global features from an input fingerprint image. On the IITI-CFD dataset, experimental results were performed, and equal-error-rate of 2.19% was achieved.

Another research conducted in 2020 by the authors in [21] where used CNN to directly extract minutiae from raw fingerprint images. The proposed algorithm was developed using two networks in two main phases, the first network was used in the first stage to create minutiae patches, while another network was used in the second stage to extract minutiae from each patch. Both networks share a common aspect of the system. For their investigation, they employed the FVC2002 and 2004 datasets, and they achieved 87.90% accuracy.

The CNN and spectral minutiae representation were combined in a work by Shu Yu to improve the direct matching of the spectral minutiae representation in fingerprint recognition. This work applied the Darknet-19 network structure, which constant 19 convolutional layers with one fully connected layer and it produced a 128-dimensional feature vector. The similarity score of feature vectors extracted by the CNN is used as the decision criterion of fingerprint recognition.

While authors in [23] employed CNN to extract fingerprint features from texture, minutiae, and frequency spectrum. The best performance was obtained during tests on the FVC2004 DB1 and DB2 databases.

In 2020 F-Net network by Nguyen was proposed for fingerprint minutiae extraction. The proposed network structure was derived by modifying the structure of U-Net. The architecture of the proposed network was built up with three important differences namely: the 3 × 3 convolutional filters are revised to the padding version, a batch normalization layer was added after each ReLU layer and the pooling layer has one fewer. The experimental results reveal that the proposed network was successful in achieving high accuracy and robustness in extractor minutiae regardless of image quality or type of sensor.

While authors in [25] presented a fully automatic minutiae extraction method based on deep-CNN and the fingerprint domain knowledge known as MinutiaeNet. The proposed method comprises two networks, known as CoarseNet and FineNet. The CoarseNet used both CNN and fingerprint domain knowledge to find out minutiae in the whole fingerprint image while FineNet was used to estimate the existence probability of minutiae and get final results. Good results were obtained from experiments using the NIST SD27 and FVC 2004 datasets.

Darlow and Benjamin also adopted a deep-CNN to address the issue of extracting minutiae from the raw fingerprint images. The architecture of the neural network in this work was built with five convolutional layers and each one involves 32 5×5 filters and pooling is employed on the first two of them. It also has two fully connected layers. On the FVC 2002 and 2004 datasets, experiments were conducted, and good results were obtained.

Soure/ Year	Gap filled	Methods	Dataset	Results
[16] 2021	Fingerprint minutiae extraction by combining CNN and Gabor Wavelets	CNN and GWT while dilation morphological operation and thinning for the Pre-processing	FVC2006 databases	91.5 % accuracy
[17] 2021	A multi-task fully deep-CNN for contactless fingerprint minutiae extraction	deep-CNN	PolyU Cross, Benchmark 2D/3D, and their dataset	It gives the best performs
[18] 2021	Combining gabor filter and CNN for an automatic fingerprint identification	CNN and Gabor filters	FVC 2000, 2002, and 2004 databases	99.8 % accuracy
[20] 2021	A contactless fingerprint recognition system	A siamese-CNN to extract global features	the IITI-CFD dataset	equal-error-rate of 2.19%
[21] 2020	Fingerprint minutiae extraction	CNN	FVC2002 and 2004 databases	87.9 % accuracy
[23] 2020	An extracting fingerprint feature Fingerprint feature extraction by combining texture, minutiae, and frequency spectrum using multi-task CNN	CNN	FVC2004 databases	It gives the best performance
[25] 2017	Robust minutiae extractor by combining deep-CNN and fingerprint domain Knowledge	deep-CNN	NIST SD27 and FVC 2004 database	It gives good results
[28] 2017	Fingerprint recognition with fast match speed	VGGNet CNN	FVC 2000, 2002, and2004 databases	98.3% accuracy
[29] 2017	Fingerprint pore extraction for recognition	CNN	High-resolution fingerprint database (HRF)	93.0 % performance

While authors in [27] introduced an algorithm to directly extract raw latent fingerprints using a fully convolutional network (FCN). In this algorithm, FCN was applied to directly extract raw latent fingerprints then CNN was used to classify the regions centering at proposed minutiae and computing their orientations.

Another study by Wang and Sang adopted VGGNet convolutional neural network for fingerprint classification and feature extraction. Results from the experiment using the FVC 2000, 2002, and 2004 databases showed a maximum accuracy of 98.3%.

A study by [29] focused on fingerprint pore extraction based on CNN. They conducted research using a high-resolution-fingerprint (HRF) database and achieved a performance of 93.09%.

TABLE I. IMPORTANT WORKS ON FINGERPRINT FEATURE EXTRACTION USING CNN

B. *Fingerprint Image matching using CNN*

In this section, important related works of fingerprint image matching using CNN are presented below. A summary of these studies is shown in Table II.

In 2022 authors in [30] introduced fingerprint recognition based on the Siamese-CNN to address the issues of the complexity of the fingerprint recognition algorithm and the compatibility of the fingerprint database with multiple fingerprint systems. The structure of Siamese networks consists of three networks, two networks which were a pair of convolutional neural networks with share weight, to generate pair of minutia vectors and they achieve the final output after the vectors went through the fully connected third network. Pre-processing was skipped in this approach, and it can be performed from any source (databases, pictures, and photographs). The proposed algorithm provided up to 92% accuracy.

Ibrahim first unveiled the FIGO model in 2022, which combines two models: a Pix2Pix model to enhance pattern legibility, and a fingerprint identification model that uses two twin CNNs with shared parameters and weights to generate feature vectors. The SOCOFing dataset was used to evaluate this model, and promising results were obtained.

While authors in [32] presented a contact and contactless fingerprint matching model using CNN in 2022, they pre-processed the given image using adaptive histogram equalization, and the model outperformed other approaches by 88.53% rank-one accuracy.

In a work by the authors in [33], a deep-CNN was used for parallel fingerprint minutiae matching to address the issues of low throughput and long time-consuming in traditional methods. Four procedures make up the preprocessing: normalization, image enhancement, parallel thinning, and image segmentation. While the matching outcomes were achieved by first feature minutiae matching, then local minutiae matching, and then global minutiae matching. The experiment performed on the NIST DB4 demonstrates that deep-CNN fingerprint matching throughput is boosted by 25% and matching time is reduced by around 8 seconds.

While Preetha and Sheela used CNN in 2021 to address the performance matching issue. The system is put into two primary phases that are implemented in succession: enhanced and matching stages. The skeletonization method was used for preprocessing to thin the ridgeline, and CNN was used for fingerprint matching. Using the Sokoto Coventry Fingerprint Dataset (SOCOFing), the performance of the proposed CNN method was assessed, and the successful system performance was obtained.

Source / Year	Methods	Gap filled	Dataset	Results
[30] 2022	Siamese-CNN	The complexity of the fingerprint recognition algorithm and the compatibility of the fingerprint database with multiple fingerprint systems	Any sources of databases	Up to 92% accuracy
[32] 2022	Sequential CNN	Matching of contactless and contact fingerprints	Public dataset	88.53% rank one accuracy
[33] 2021	deep-CNN	Problems of low throughput and time-consuming	The NIST DB4	Fingerprint matching increased by 25%
[34] 2021	CNN	The performance matching problem	Sokoto Coventry Fingerprint Dataset(SOCOFing)	Good performance
[34] 2020	**CNN**	Stained fingerprint recognition problem	The NISTDB4F database	A greater recognition rate
[36] 2019	Siamese-CNN	Fingerprint cross- matching problem	Public dataset	It gives the best performance
[38] 2018	CNN	Fingerprint matching problem	FVC2002 database	High performance was attained

While the research was done by Hongbin to address the issue of stained fingerprint recognition. The damaged fingerprint identification method based on CNN was presented, simulated, and compared with the traditional point matching recognition method proposed and the traditional CNN recognition method to tackle the issue. The NISTDB4F database findings showed that the traditional point matching recognition method took an average of 1.87 seconds to recognize a single unknown fingerprint, the traditional CNN recognition method took an average of 0.62 second, and the improved CNN recognition method took an average of 0.12 second. The improved CNN recognition method exhibited a greater recognition rate and a lower false acceptance and rejection rate.

While the fingerprint cross-matching problem was the topic of prior study by the authors in [36], CNN was utilized in this work to tackle the problem and it contains three subnets with Siamese-CNN. Pre-processing was done on the provided image using down sampling, ROI calculation, and Gabor filtering as the first step in this work. Then, minutia features and ridge features were separately extracted from the preprocessed fingerprint image and given to a CNN model along with the original fingerprint image. The average accuracy of three CNN models was calculated to arrive at the final score. When applied to the publicly available dataset of fingerprint cross matching, the proposed model exhibits the best performance.

Sunil and Kinage used a CNN technique to create a contactless fingerprint recognition system. This method uses histogram equalization to enhance a given image before applying the CANNY algorithm to detect edges. CNN is used for fingerprint feature extraction and matching process.

While the authors in [38] also used CNN to present a novel fingerprint matching technique. This approach uses CNN to classify fingerprint pairings as matching or not matching. After experimental results were applied to the FVC2002 database, high performance was attained.

In a study by Chenhao and Ajay, a multi-Siamese CNN that had been trained and used for feature extraction and contactless fingerprint image matching was deployed. Using a public database, the proposed architecture was assessed, and the results were favorable.

TABLE II. IMPORTANT WORKS ON FINGERPRINT IMAGE MATCHING USING CNN

IV. DISCUSSION AND CONCLUSIONS

This paper provided a summary of recent studies on fingerprint feature extraction and matching using CNN. This review offers a useful tool to explore the actuality of the employment of CNN to address fingerprint recognition systems issues and it also highlights new research directions in this area of research. The studied literature revealed that CNN is a successful method that can be used to solve a variety of fingerprint recognition challenges, including fingerprint image enhancement, fingerprint image denoising, fingerprint feature extraction, and matching, fingerprint image classification, fingerprint image segmentation, and so on. In the fingerprint feature extraction and matching domain, the reviewed study confirms that CNN has been successfully applied in various categories of fingerprint databases and various types of sensors with dissimilar architecture for different purposes. As a result, CNN is well suited for applications that demand high performance in fingerprint recognition systems. In some instances, this method has demonstrated outstanding performance when compared to the traditional methods, sometimes even outperforming them in a variety of areas, including the ability to automatically feature an extract from raw fingerprints image and the often-dropped pre-processing, the high accuracy of matching fingerprints from various types of sensors, and the ability to increase recognition rates, particularly in low or poor quality. Additionally, it contributed to solving some problems like low throughput, fingerprint database compatibility, and other issues. Although CNN has obtained promising results, there are still a lot of difficulties and issues that need to be addressed and further researched to make these systems secure, accurate, and resilient.

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