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CONTACTLESS FINGERPRINT RECOGNITION SYSTEM BASED ON CNN

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ABSTRACT Fingerprint recognition is a popular problem in the field of pattern recognition. It is majorly used in modern authentication technology like in access devices in mobile phones. The goal of this project is to investigate the applicability of convolutional neural networks for fingerprint recognition. This paper builds a CNN-based framework to precisely match contactless and contact-based fingerprint images. This framework initially trains a multi-Siamese CNN using fingerprint details, respective ridge map and specific area of ridge map. A distance-aware loss function is generated using deep fingerprint representation. For more accurate cross comparison deep fingerprint representations generated in such multi- Siamese network are concatenated. The proposed methodology for cross-fingerprint comparison is calculated on two publicly available data. The available database contains contactless 2D fingerprints and respective contact-based fingerprints.

KEYWORDS- CNN, Neural network, SVM, Dataset, RELU, Convolution, GPU

INTRODUCTION

These days fingerprint verification systems are popularly used in personal identification and verification systems. Nowadays, fingerprint recognition has been accepted officially for personal identification. The security departments identify the criminals by using the fingerprints left on the suitable surfaces. There are several methods introduced for fingerprint recognition in the literatures. The first paradigm of the Cellular Neural Networks (CNN) is introduced by Chua and Yang. The structure of CNN is simple and parallel that makes it suitable for image processing. The CNN architecture contains many processing cells. The cells operate in parallel in a 2D grid. Each cell is connected to the cells in its local neighborhood only. The CNN cells are really simple circuit nodes. Hence many of them can easily be integrated into a single chip. Consider an image of 64x64 pixels to be processed. Then a 64x64 CNN cells can be used to process the image by using a series of CNN algorithms. That means each pixel corresponds to each cell in the CNN. The faster processing is provided by the built in parallelism. The structure of the CNN is simple and because of its simple structure it is suitable for VLSI implementation. Different image processing tasks, such as edge detection, noise removal, contrast stretching, dilation and erosion can be performed by changing the template coefficients of the CNN

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RELATED WORK Almost to the mark comparison of contactless 2D fingerprint images with contact-based fingerprints is difficult for the success of emerging contactless 2D fingerprint innovations, which offer more clean and deformation-less acquisition of fingerprint features. Convolutional neural networks (CNN) have proved its remarkable capabilities in biometrics recognition. However, there have been almost no attempts to match fingerprint images using CNN based reaches. Paper [1] develops a CNN-based framework to accurately match the contactless and contact-based fingerprint images. Our framework first trains a multi-Siamese CNN using fingerprint, respective ridge map and specific region of ridge map. This network is used to produce a deep fingerprint representation using a distance awareness loss function. Deep fingerprint representations generated in such multi-Siamese network are concatenated for more accurate cross comparison. The proposed approach for cross-fingerprint comparison is evaluated by two publicly available databases containing contactless 2D fingerprints and respective contactbased fingerprints. Our experiments are presented in this paper consistently achieve outstanding results, over various popular deep learning architectures and over contactless to contact-based fingerprints comparison methods in the literature. Paper [2] presents a Cellular Neural Networks (CNN) based rotating invariant fingerprint recognition system by taking in consideration the hardware implements ability in mind. Core point was used as a origin point and detection of the core point was implemented in the CNN framework. Developed system consists of four stages: pre-processing, feature extraction, false feature elimination and matching. Preprocessing enhances the input fingerprint image. Feature extraction creates rotation invariant features by using core point as a preface point. Unmatched feature elimination increases the system performance by removing the false minute points. Matching stage compares extracted features and produces a matching score. Recognition performance of the proposed system has been tested by using high resolution Poly U HRF DBII databases. The results are very helpful for implementing a CNN based fully automatic rotation invariant fingerprint recognition system. paper [3] present a fingerprint PAD scheme based on i) a newly captured device able to acquire images within the short wave infrared (SWIR) spectrum, and ii) an in-depth analysis of various state-of-the-art techniques based on both handcrafted as well as deep learning features. The approach is evaluated on a database

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comprising over 4700 samples, stemming from 562 different subjects and 35 different presentation attack instrument (PAI) species in them. The results show the soundness of the successful approach with a detection equivalent to error rate (D-EER) as low as 1.36% even in a realistic scenario where five different PAI species are considered only for testing purposes (i.e., unknown attacks). In [4], author investigated all the possibilities of incorporating artificial neural networks into the fingerprint identification process, implemented and documented our own software solution for fingerprint identification based on neural networks whose impact would mainly affect on feature extraction accuracy and overall recognition rate was highly evaluated. The result of this research is a fully functional software system for fingerprint recognition that consists of fingerprint sensing modules by using high resolution sensor, image enhancement module responsible for image quality restoration, Level-1 along with Level-2 feature extraction module based on neural networks, and finally fingerprint matching module using the industry standards BOZORTH3 matching algorithm. Aim of evaluation we used more fingerprint databases with differing image quality, and the performance of our system was evaluated using FMR/FNMR and ROC indicators.

From the obtained results, we may come to conclusions about a very significant impact of neural networks on overall recognition rate, specifically in bad quality. In paper [5], a fully Cellular Neural Networks (CNN) based fingerprint recognition system is introduced. The system includes a preprocessed phase where the input fingerprint image is developed and a recognition phase where the enhanced fingerprint image is matched with the fingerprints in the pre-defined database. Both preprocessing and recognition phases are realized by means of CNN approaches. A novel application of skeletonization method is used to perform ridgeline thinning which improves the quality of the extracted lines for other upcoming processing, and hence increases the overall system performance.

PROPOSED METHEDOLOGY

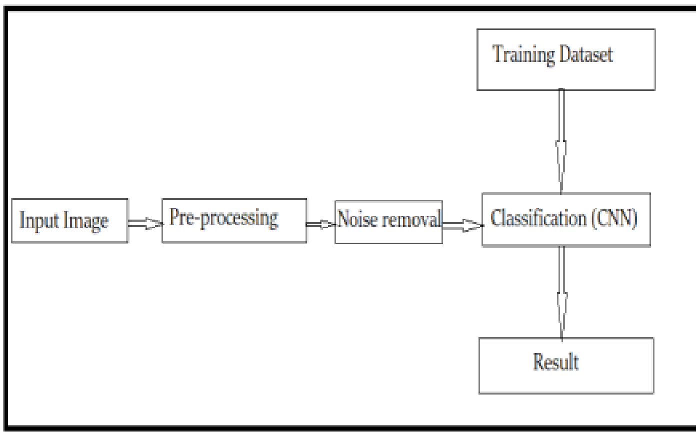

Fig: Block Diagram Of Proposed System

A. Image Enhancement: The results of pre-processed image are highly enhanced by automotive and accurate classification of the image. The image enhancement technique is divided into two parts which are spatial domain technique and frequency domain innovation. In spatial domain technique the value of the pixel is exchanged with respect to the requirement while the frequency domain technique deals with the rate of change of the image pixels which are changing due to spatial domain. It cannot be determined that what type of technique is better for image enhancement. There are various techniques are used for image enhancement. **B. De-noising Method:** A essential step in image processing is the step of removal of various kinds of noisy elements from the image. In this stage, various de-noising methods will be used to get good quality of the image by removing the unnecessary noise from the MRI image. The important property of a good image de-noising model is that it should completely remove noise as far as possible as well as preserve edges. The image de-noising technique will be mainly depending upon the type of the image and noise in cooperating with it. There have been various published algorithms and each approach has its assumptions, advantages, and limitations. Spatial filters like mean and median filter are useful to remove the noise from image.

C. Feature Extraction: The last stage includes feature extraction from the image. Image feature extraction is one of the most important techniques of image processing. It uses different techniques and algorithm to bifurcate and detect various shapes and portions of the image. There are numerously introduced techniques to apply this to the image. Wavelet transform is one of the tool for feature extraction. The wavelet transform has a characteristic of analyzation of the image with varying unit of resolution and has multi resolution analytic property. The wavelet transform is better than Fourier transform and a short time Fourier transform because preserves both time and frequency as in Fourier transform. One of the main part of neural network is convolution network(CNN). CNNS use image recognition and classification in order to detect objects, recognize faces, etc. They are made up of neurons with learnable weight. Each specific neuron receive numerous inputs and then takes a weighted sum over them, where it passes it through an activation function and respond back with an output.

CONCLUSION In this paper, we have presented a specially designed fingerprint cross comparison framework. It is used to accurately match contactless to contact-based fingerprints. This is the first such attempt to address challenging cross-fingerprint comparison problem using convolution neural network. The cross comparison using contactbased to contactless fingerprints are more challenging so it can be handled using this system very effectively. In practice, lack of sufficient training data, i.e. contact-based and respective contactless fingerprints, in proposed framework can significantly degrade the matching accuracy

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