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الباحث

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Chapter One

Introduction

1.1 Overview

A major security problem in worldwide is the capacity of recognize individual features in the area of smart recognition. The term biometrics refers to measures relating to human traits. The unique, quantifiable traits that are used to identify and categorize people are called biometric identifiers. Biometric are often put into two groups: (a) behavioral characteristics, such as typing rhythm, gait and voice (b) physiological characteristics, such as fingerprints, faces, iris, and finger veins [1][2].

A biometric pattern is effective in identity authentication after it meets seven criteria: universality, uniqueness, permanence, measurability, performance, acceptability, and circumvention [3]. The majority of scientists conducting research in the field of fingerprints and veins are interested in them because they have unique biometric properties [2][4].

Fingerprints are very important for forensic analysis, law enforcement, tax obtaining, public security, and criminal investigation. For its simplicity, uniqueness and durability [5].

The utilization of finger vein biometric modality in biometric recognition is common due to its numerous advantages compared to other modalities. These advantages include its user-friendliness, as it can be easily captured using a sensor that detects Near-Infrared light. Additionally, the high level of security it offers is attributed to the fact that the vein structure is concealed beneath the skin, making it challenging to deceive the human recognition system. Furthermore, each individual possesses unique and distinct veins [6].

1.2 Literal Review

The application of convolutional neural network (CNN) methods has been widely explored and utilized in various research studies related to fingerprint and vein identification, determining region of interest (ROI), and feature extraction. In the subsequent section, the specifics of both fingerprint and vein biometric systems will be delved into, examining their individual characteristics and functionalities.

❖ Finger Print Biometric System

1. B.Pandya et al. The proposed architecture introduces a unique deep learning framework for fingerprint recognition and includes a pretreatment stage for the extraction of texture data from fingerprints. This step comprises methods like fingerprint thinning, Gabor augmentation, and histogram equalization. The Deep -Convolutional -Neural -Network (DCNNC), a classifier, is then fed the pre-processed fingerprints. A dataset made up of data from 56 participants was developed in the lab using a Futronics FS88 scanner device to assess the performance of the suggested approach. Interestingly, the suggested method produced a remarkable classification accuracy of 98.21% [7].
2. B. Bakhshi and H. Veisi Using the FVC2002 dataset from the Fingerprint Verification Competition 2002, a CNN-based fingerprint matching method has been developed. The suggested method, in contrast to conventional approaches, eliminates the need for preprocessing because the model derives fingerprint patterns straight from the images' raw pixel data. Two CNN modules, CNN-1 and a trained version of AlexNet, were tested as part of an end-to-end CNN verification workflow. The speed of the training phase was greatly increased by using the trained AlexNet. The model beat the

MinutiaSC and A-KAZE techniques with an Equal Error Rate (EER) of 17.5%, proving its usefulness for fingerprint matching [8].

3. W. Jian et al. ssuggests a thin CNN structure built on a ROI pattern for singularities. First, a number of preprocessing steps are applied to all raw photos to create unique ROI (Region of Interest) patterns. Second, NN (neural network) classifiers use ROI patterns as their input data. Three sets of control trials are used to demonstrate the higher classification performance and computation efficiency of the proposed model based on NIST SB4 (National Institute of Standards and Technology Special Database). The experimental results of the proposed technique show that the accuracy of 93% obtained is much greater than that of conventional non-NN (neural network) classifiers [9].
4. A.Takahashi et al. Developed a unique CNN architecture that combines texture, minutiae, and frequency spectrum to extract characteristics from fingerprint photos. It was suggested to use a minutia attention module to focus on the location of the minutiae. Authors also presented unique data augmentation techniques tailored to fingerprint photos for effective training with a limited set of training data classes. The EERs of the suggested technique achieve 1.10 percent in the FVC2004 DB2 dataset and 1.41 percent in the FVC2004 DB1 dataset [10].
5. Provides a smart computational method for automatically verifying and authenticating fingerprints for personal identity. Gabor filtering method and "Convolutional Neural Network" (CNN) features are used to create the feature vector. The feature vectors underwent Principal Component Analysis (PCA) to decrease overfitting issues and improve the accuracy and dependability of the classification outcomes. Studies using 9000 finger print images from public

databases showed that the proposed approach performed better in terms of accuracy (99.87%) than more recent classification techniques like SVM “Support Vector Machine” (97.86%) or RF “Random Forest” (95.47%). But the suggested strategy also shown more accuracy in comparison to other validation strategies like K-fold (98.89%) and accuracy (97.75%)[5].

6. M. Ahsan et al. to detect specific fingerprint information, a deep learning classification technique was proposed. It differentiated between classes for the left and right hands, sweat pores, scratches, and fingers. To solve the issues of personalization and security, a private collection of fingerprint images was produced. Five deep learning models—CNN, “Alexnet”, “VGG-16”, “Yolo-v2”, and “Resent”—were trained entirely from scratch for the categories. For the categorization of left-right hands, scratches, and fingers, the “Yolo-v2 “model performed with accuracy of 90.98%, 78.68%, and 66.55% in experiments. In terms of classifying sweat pores, the “Resnet-50” model had 91.29% accuracy [11].

The table (1.1) shows a summary of the previous work presented above. This summary is based on the dataset, feature extraction and recognition methods, and the recognition metrics' accuracy (Acc.) and Error Rate (EER) values.

Table (1.1) Summary of the Previous Works for Fingerprint Recognition.

Ref.	Year	Dataset			Metrics
		Name	Image size	No. of users or images	
[7]	2018	New dataset was collect by authors	350x233	56	Acc.= 98.21%
[8]	2019	FVC2004 DB1	300×300	110	EER= 17.5%
		FVC2004 DB2	256×364		
		FVC2004 DB3	448×478		
		FVC2004 DB4	240×320		
[9]	2020	NIST SD4	512×512	4000 image	Acc.= 93%
[10]	2020	FVC2004 DB1	640x480	800	EER= 1.41%
		FVC2004 DB2	328x364		EER= 1.10%.
[5]	2021	standard public databases	227×227	9000 images	Acc. =99.87%
[11]	2021	New dataset was collect by authors	800 × 750	10,690 images	Acc= 95.80% with Yolo-V2

❖ Finger Vein Biometric System

1. S.A. Radzi, et al. Suggested a new model for finger-vein biometric identification using a “convolutional neural network” (CNN). A four-layer CNN with fused “convolutional-subsampling” architecture and decreased complexity is suggested in this study for the identification of finger veins. Stochastic diagonal Levenberg-Marquardt method has been altered and implemented by the authors for network training, yielding a quicker convergence time. VeCAD Laboratory at University Technology Malaysia created the database

that was utilized in this study, which includes 50 participants and 10 samples from each finger. With an 80/20 ratio for separating the training and test samples, a 100.00% identification rate is attained [12].

2. G. Meng et al. implemented a finger vein detection technique using a CNN. In order for the authors to perform authentication through determining the Euclidean distance between these feature vectors, the picture samples are immediately entered into the CNN model in order to extract its feature vector. The Deep Learning Framework Caffe is then used to validate this approach. The finger vein picture database from DataTang, which consists of 64 participants with 15 samples per finger and was collected during three months at a rate of 5 images each month, was employed in the suggested technique. The findings have a 99.4% accuracy rate and an extremely low 0.21 error rate [13].
3. R. Das et al. A CNN-based finger-vein identification system is suggested. Four publically accessible datasets are used to analyses the constructed network's capabilities. The major goal of this research is to provide a deep-learning technique for finger-vein recognition that can perform consistently and very well while dealing with photos of varying quality. The broad set of tests that have been published demonstrate that the accuracy that can be achieved using the suggested technique may exceed 95% accurate identification rate for each of the four databases that have been taken into consideration [14].
4. K.J. Noh et al. Offered rough finger-vein regions in an image are detected to reduce the effect of mis-segmented regions, to complement the drawbacks of shape image-based finger-vein recognition. Furthermore, score-level fusion is performed for two output scores of deep convolutional neural networks extracted from the texture and shape images, which can reduce the sensitivity to

noise, while diverse features provided in the texture image are used efficiently. Two open databases, SDUMLA-HMT and HKPU, are used for experiments. The proposed method shows better recognition performance with error rate = 0.05 [15].

5. S.M.M. Najeeb et al. Proposes the Re-enforced Deep Learning (RDL), a novel Deep Learning (DL) paradigm. Use of finger veins (FVs) in this method offers an additional method of personal verification. RDL is made up of several levels and feedback. For each individual, two FV fingers are used: the index finger for the first personal verification and the middle finger for the second confirmation. Hong Kong Polytechnic University Finger Image (PolyUFI) database (Version 1.0) is the source of the utilized database. The result shows a good performance of 91.19% for the suggested RDL [16].

6. I.Boucherit et al. Merge Convolutional Neural Network (Merge CNN), a better deep network that makes use of many CNNs with short routes, is presented. method is based on combining the outputs of numerous identical CNNs with various input picture quality into a single layer. With various network configurations and layers, the authors ran several tests. The contrast limited adaptive histogram (CLAH) approach was used to improve both the original and enhanced pictures in the best model. Using the datasets FV-USM, SDUMLA-HMT, and THU-FVFDT2, the model was trained, and it successfully obtained recognition rates of 96.75%, 99.48%, and 99.56%, respectively [17].

7. L.D.Tamang and B.W.Kim Convolutional layer, hybrid pooling layer, and concatenated activation map blocks were combined to create a feature extraction network. Maxpooling and average pooling are both used in the hybrid pooling layer, with the former placing more emphasis on discrete features and the latter taking the full input volume into account for greater feature localization. Three fully connected layers (FCLs) are then used to classify the retrieved features. Performance of the proposed model was assessed using publically accessible datasets, HKPU and FVUSM. It's impressive that the model was able to recognize objects with a high degree of accuracy, up to 97.84% for excellent photographs and 97.22% for subpar photos [18].

Table (1.2) shows a summary of the previous work presented in this section. This summary is based on the dataset, feature extraction and recognition methods, and the recognition metrics' accuracy (Acc.) and Error Rate (EER) values.

Table (1.2) Summary of the Previous Works for Finger Vein Recognition.

Ref.	Year	Dataset			Metrics
		Name	**Image size**	**No. of users or images**	
[12]	2016	New dataset was collect by authors	55 × 67	50	100%
[13]	2017	DataTang	256×256	64	99.4%
[14]	2018	HKPU	513×256	156	71.11%
		FV-USM	640×480	123	72.97%
		SDUMLA	320×240	106	98.90%
		UTFVP	672×380	60	95.56%
[15]	2020	HKPU	513×256	156	EER= 0.05
		SDUMLA-HMT	320×240	106	
[16]	2021	PolyUFI	513×256	156	91.19 %
[17]	2022	FV-USM	300×100	6	96.75 %

		SDUMLA-HMT	320×240	3816	99.48 %
		THU-FVFDT2	200×100	610	99.56 %
[18]	2022	HKPU	513×256	156	97.84 %
		FVUSM	640×300	494	97.22 %

1.3 Problem Statements

Fingerprints and finger vein features are prominent modalities in biometric authentication systems, enabling robust and secure identification based on distinctive characteristics.

Despite the valuable utility of fingerprints and veins as biometric tools, there remains a lack of comprehensive studies that effectively compare and analyze these modalities in terms of crucial aspects such as preprocessing techniques, determine region of interest techniques, feature extraction methods, accuracy of personal identification, and resilience against potential attacks. The need for in-depth investigation and evaluation of these biometric modalities is essential to gain a deeper understanding of their individual strengths, weaknesses, and overall suitability for various authentication scenarios.

This thesis investigates a comparative analysis of fingerprints and finger-veins from the same individual using the convolutional neural network (CNN) and accuracy metrics.

1.4 Objective of Thesis

The primary goal of this study is to introduce a Biometric Comparison Identification System, referred to as "BCIS-FPV," that utilizes the version of the CNN classification method to compare and identify fingerprints and finger-veins. This comparison encompasses various aspects such as:

1- The proposed system employs innovative techniques to improve the quality of input finger images and accurately determine the ROI. Presents an investigation into the impact of defining the important region (ROI) on system performance, highlighting its significance in enhancing accuracy.

2- This thesis conducts an extensive examination, analysis, and comparison of fingerprint and vein biometrics to determine their relative effectiveness in verifying the identification of a specific user. The comparison encompasses several factors, such as the feature extraction algorithms utilized in the proposed system, specifically VGG16, VGG19, and ResNet-50. Additionally, the study evaluates the accuracy of individual identification through the implementation of CNN. The proposed system leverages the publicly available the Nanjing University of Posts and Telecommunications (NUPT-FPV) dataset, ensuring a reliable and comprehensive evaluation of the biometric modalities.

1.5 Plan of the Thesis

The remaining chapters of the thesis are explained as follows:

Chapter two: the work's theoretical foundation;

Chapter Three: the model's components and architecture;

Chapter Four: The results and Evaluation of the Experimental;

Chapter Five: The conclusions and future work.

الخلاصة

في الوقت الحاضر ، ظهرت أنظمة القياسات الحيوية التي تستخدم أنماط الوريد الإصبعي وبصمات الأصابع كتقنيات ذات ميزات فريدة ومميزة يمكن استخدامها لتحديد الهوية الشخصية بدقة وأمان. تقترح هذه الأطروحة نظام تحديد المقارنة البيومترية ، المشار إليه باسم BCIS-FPV ، والذي يستخدم طرق التصنيف العميق لمقارنة بصمات الأصابع وأوردة الأصابع. أهداف النظام المقترح هي المساعدة في تحديد أقوى طريقة بيومترية لتحديد هوية الأفراد بدقة. يتكون BCIS-FPVمن نظامين فرعيين لتحديد الهوية: الوريد الإصبعي (FV) وبصمة الإصبع (FP). يستخدم النظام المقترح مجموعة بيانات NUPT-FPV والتي تتضمن 33,600 صورة لكل من بصمات الأصابع وأوردة الأصابع التي تنتمي إلى نفس الشخص .

يقوم النظام الفرعي FV بمعالجة الصورة الرمادية المدخلة مسبقا باستخدام مرشح التمويه الغاوسي. نستخدم تقنيات مثل K-Mean و Flood Fill واكتشاف منطقة الإصبع لتحديد المنطقة المهمة في صورة الوريد الإصبعي. تستخدم أنظمة السحب الفرعية FV و FP خوارزميات تعلم النقل VGG16 و VGG19 و ResNet-50 لاستخراج الميزات. ثم تنفيذ هذا الناتج في بنية CNNجديدة مع 20 طبقة عصبية مقترحة للتصنيف والاعتراف. استنادا إلى تدريب واختبار CNN-20الجديد ، أظهرت قيم النتيجة (الدقة ، TPR، PPV، و F1-Score) أن أداء VGG16و VGG19 بشكل عام كان أفضل عبر الأنظمة الفرعية لتحديد FV و FP .
تتضمن الأنظمة الفرعية المقترحة لتحديد FV و FP حالتين بحثيتين متميزتين: تحديد صورة بمنطقة اهتمام محددة (ROI) والتعرف على الصورة الأصلية. يظهر FP-ORIGINAL دقة فائقة (0.999982405) مقارنة ب FV-ORIGINAL معVGG19 ، مما يدل على متانته ودقته في تحديد الهوية الشخصية. وبالمثل ، يحقق FP-ROI دقة أعلى (0.99998425) من FV-ROIمعVGG16 ، مما يشير إلى طريقة أكثر قوة ودقة لتحديد الهوية الشخصية.
يتفوق نظام BCIS-FPV المقترح على الأعمال ذات الصلة بقيم الدقة المثلى في نظامين فرعيين. تظهر هذه النتائج الأداء الاستثنائي للنظام المقترح مقارنة بالنهج الحالية.