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Fingerprint classification based on deep convolutional neural networks: a survey

Sajidah Jaber Habib
Mustansiriyah University – Baghdad

Dr.Abdul-Wahab Sami Ibrahim
Mustansiriyah University - Baghdad

Abstract
The use of Automated Fingerprint Identification Systems (AFIS) for person identity based totally on fingerprints is giant in many countries. However, when dealing with large databases, the sheer variety of fingerprint comparisons required may be overwhelming. To cope with this mission, fingerprint class is hired to reduce the range of necessary comparisons, consequently enhancing the efficiency of database searches. Deep knowledge of strategies, in particular in the field of laptop imagination and prescient, have made large advancements. This paper conducts a comprehensive survey of studies related to fingerprint type the use of deep convolutional mastering. The survey affords an overview of convolutional deep neural networks (CNNs) and highlights various varieties of CNN fashions utilized in fingerprint class tasks. Furthermore, it affords a radical contrast and evaluation of ten study projects in this area, deliberating the CNN models hired, the datasets used, and the carried out accuracy along with the associated hyperparameters. Among the findings, the most general CNN architectures hired in fingerprint category show off high-quality accuracy quotes of 98.9%, 99.2%, or even a 100%. This underscores the effectiveness of deep studying strategies in improving fingerprint-type structures.
Keywords: CNN, Deep Learning, Fingerprint Classification

الملخص:
استخدام نظم التعرف الآلي على البصمات (AFIS) لتحديد هوية الشخص بناءً على البصمات مُنتشر في العديد من الدول. ومع ذلك، عند التعامل مع قواعد البيانات الكبيرة، قد تكون كمية المقارنات المطلوبة ضخمة. لمواجهة هذا التحدي، يتم استخدام تصنيف البصمات لتقليل عدد المقارنات اللازمة، مما يعزز فعالية البحث ضمن القواعد. وقد شهدت الأساليب المتقدمة، خصوصًا في مجال رؤية الحاسوب، تقدمًا كبيرًا. يقدم هذا البحث نظرة شاملة على الأبحاث المتعلقة بتصنيف البصمات باستخدام التعلم المتعمق. البحث يوضح مفهوم الشبكات العصبية العميقة ويبرز أنواعًا مختلفة من نماذجها المستخدمة في مهام تصنيف البصمات. بالإضافة إلى ذلك، يقدم مقارنة دقيقة لعشرة مشاريع بحثية في هذا المجال، مع الأخذ في الاعتبار النماذج وقواعد البيانات والدقة المحققة والمعلمات المرتبطة. من النتائج، أظهرت أكثر الهياكل الشائعة للشبكات العصبية العميقة أداءً متميزًا بدقة تصل إلى 98.9%، 99.2%، وحتى 100%. وهذا يؤكد فعالية التقنيات المتقدمة في تعزيز أنظمة تصنيف البصمات.
الكلمات المفتاحية: CNN ، التعلم العميق، تصنيف بصمات الأصابع

1. Introduction

Biometrics is a discipline of take a look at employed for each identity and authentication purposes, encompassing two foremost categories: behavioral and physiological biometrics, which are inherent and particular to individuals [1]. Biometric identification systems are complex, incorporating diverse components, and integrating biometrics with different authentication methods can decorate protection, finding packages in surveillance, safety investigations, fraud detection, and get admission to manipulate. Machine mastering-based biometric identity usually entails preprocessing, characteristic extraction, feature selection, category, and assessment levels, and may rely upon single or multiple biometrics [2.[

Biometric systems determine people' identities primarily based on their unique biometric attributes, falling into behavioral and physiological categories [3, 4]. Various biometric modalities had been explored, including facial, iris, retinal, palm vein, fingerprint, and ear biometrics, addressing the need for robust and correct identification strategies in evolving generation landscapes [5, 6, 7, 8]. Ear biometrics has emerged as a novel modality, with significance in system vision and sample reputation [9].

Traditional or conventional methods of human recognition, relying on possession of items like keys or ID cards or knowledge of information like passwords or PINs, have inherent limitations. These methods do not provide a guarantee that unauthorized individuals won't gain access to the protected system. For instance, ID cards can be stolen or misplaced,and passwords can be forgotten, which can hinder authorized individuals from accessing the system. In contrast, person recognition based on their biometric characteristics offers both enhanced security and convenience compared to traditional methods. This is because biometrics cannot be lost or forgotten,making it a more reliable means of authentication[10-11].

However, it's worth noting that implementing a person recognition system based on biometric traits presents its own set of challenges. These challenges include the presence of noise in biometric data, variations in lighting conditions during image capture, and the overall accuracy of the biometric images. These factors collectively impact the process of person recognition, making it challenging to extract the essential features needed for effective utilization in the classification system [10-11].

Deep learning plays a crucial role in pattern recognition, owing to its capacity to handle vast datasets and achieve accurate recognition and detection. In this paper, the focus lies on human recognition using fingerprint images, one of the most well-known biometric identifiers. Deep Convolutional Neural Networks (CNNs), a prominent and powerful machine learning algorithm, will be employed to verify individuals' identities based on their fingerprint images.

This paper aims to review and evaluate the performance of different CNN networks for fingerprint classification, and to provide guidance to new researchers on how to select the best CNN network for their specific needs.

2. Human Biometric Overview

In today’s world with the rise, in identity theft and global security threats there are a growing demand for systems to manage identities. To address this challenge biometrics has emerged as an alternative to methods like using ID cards or passwords [12]. Biometrics involves using automated measurement and statistical analysis of individuals physical characteristics (such as face, fingerprint, iris) or behavioral traits (like voice, gait, signature) to recognize or identify them [13]. It's worth noting that biometrics has gained acceptance as a security tool supported by governments, industries and individuals alike. Some notable examples include the 'US VISIT' program where visitors entering the United States must provide fingerprints and facial images for identification purposes; HSBCs 'Voice Fingerprint ID' that combines fingerprint and voice recognition, for online and phone account access [14];. Touch ID,' allowing users to unlock iPhone 5s devices using their fingerprints.

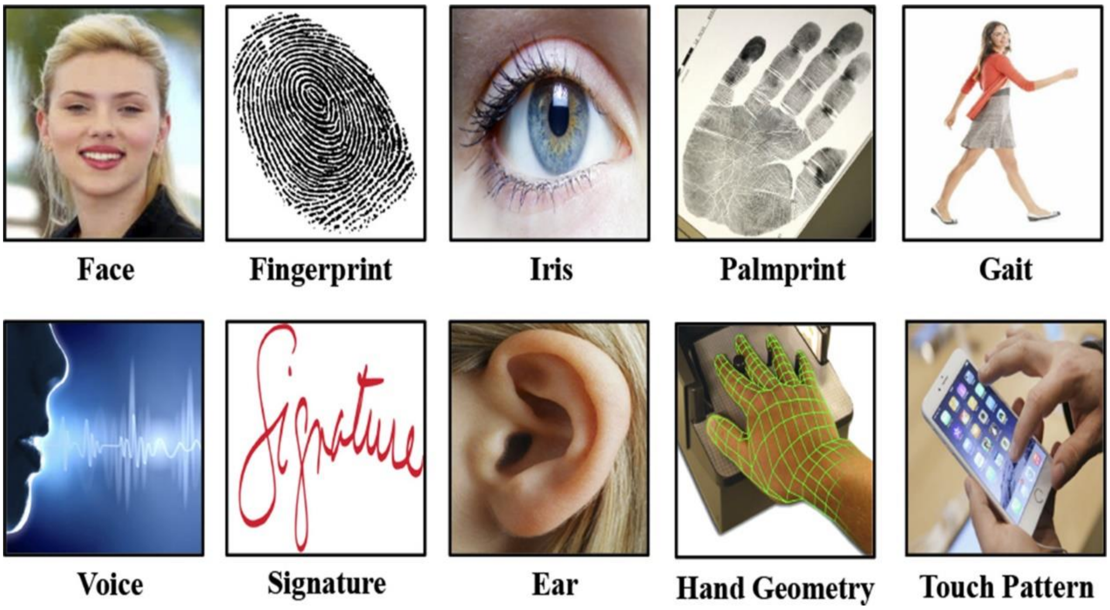

Figure 1 : Examples of attributes that have been proposed and utilized for biometric person recognition [15]

2.1. A simple biometric system consists of four basic components:

1.The sensor module is responsible for collecting biometric data.
2. Within the feature extraction module,the collected data undergoes processing to derive feature vectors.
3. In the matching module, these feature vectors are compared with those stored in the template.
4. The decision-making module plays a critical role in determining the user's identity or determining whether a claimed identity should be accepted or rejected.

2.2.Any human behavioral or physiological trait can serve as a biometric characteristic so long as it satisfies the following requirements [16]:

1. Universality: Each individual should have the feature.
2. Distinctiveness: Any two individuals should be different.
3. Permanence: The feature should be sufficiently invariant.
4. Collectability: The feature should be quantitatively measurable.

3. Convolutional Neural Networks (CNN)

Convolutional Neural Networks (CNNs) have revolutionized the sphere of computer imaginative and prescient and photo processing in current years. They are a class of deep gaining knowledge of models specifically designed for processing structured grid records, including snapshots and video frames. CNNs have demonstrated great overall performance in a wide variety of programs, together with photo type, item detection, facial popularity, and medical image evaluation CNNs are inspired by way of the human visible device and have the capability to routinely learn hierarchical features from raw pixel data, making them tremendously powerful for duties that contain know-how visible content material. They have end up a cornerstone technology inside the discipline of artificial intelligence, enabling machines to understand and interpret visual facts with first rate accuracy [17-18].

3.1. CNN Layers

The conventional layers commonly encountered in a CNN

1. **Convolutional Layer**: the convolutional layer serves because of the fundamental issue of a CNN by way of employing convolution operations rather than traditional matrix multiplication. Its parameters include a group of adaptable filters or kernels. The primary function of the convolution layer is to extract features found in localized portions of the input statistics (image) in order to produce a function map [19].
2. **Activation Layer**: The subsequent layer employs a non-linear activation function to process the output of the convolutional layer. The primary objective of incorporating this layer is to add non-linearity within the network, hence enhancing its ability to acquire and comprehend intricate features. The user's text does not contain any information to rewrite in an academic manner [20].
3. **Pooling Layer**: The purpose of this layer is to decrease the spatial dimensions of the feature maps by the implementation of a down sampling operation. One of the most often used pooling operations in computer vision is max pooling, which involves retaining the maximum value within each pooling window while discarding the other values [20].
4. **Dropout Layer**: During the training process, a specific proportion of neurons in the network are randomly deactivated by this layer. The implementation of this technique aids in mitigating overfitting and enhancing the network's ability to generalize [20].
5. **Flatten Layer**: The output of the preceding layer is compressed into a single-dimensional vector in order to facilitate its input into a fully connected layer [20].
6. **Fully Connected Layer**: The present layer accepts the flattened vector as an input and does a matrix multiplication operation using a collection of adjustable weights. The resulting output of this layer is a probability distribution that assigns probabilities to each class in a set of classes [19].
7. **Softmax Layer**: The function of this layer is to standardize the output of the fully linked layer, resulting in a probability distribution across the various classes. The prediction of the network is determined by identifying the class with the highest probability [20].

The figure 2 show example of CNN

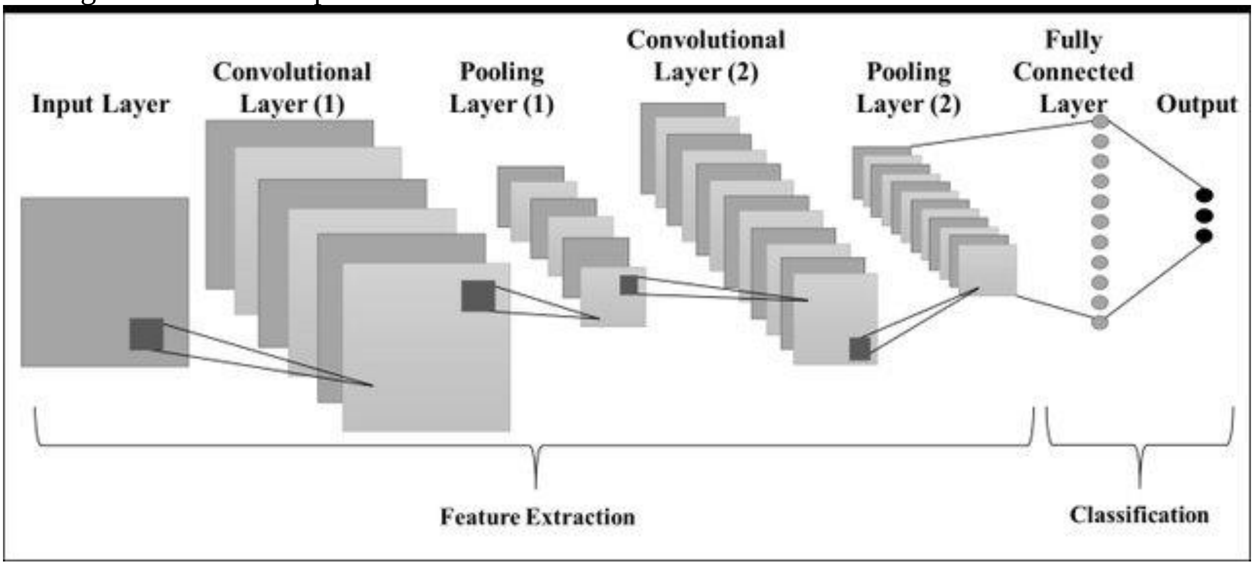

Figure 2: Show example of CNN [21].

4. Related work

This section reviews ten research papers that have been published in the last five years on the use of deep convolutional neural networks (CNNs) for fingerprint classification.

The paper [21] introduces a deep getting method designed for the difficult category of fingerprint snap shots into 4 wonderful categories, along with left-right hand, sweat-pore, scratch, and finger kind. This take a look at explores the usage of 5 deep gaining knowledge of models, specifically Classic CNN, AlexNet, VGG-16, YOLO-v2, and ResNet-50, whilst also curating a unique dataset of fingerprint pics for experimentation. Notably, YOLO-v2 demonstrates the very best accuracy costs, accomplishing 90.98% for left-proper hand, 78.68% for scratch, and 66.55% for finger type. In comparison, ResNet-50 excels with a 91.29% accuracy in sweat-pore category. Moreover, the efficient processing times exhibited through both YOLO-v2 and ResNet-50, averaging about 250.37 milliseconds consistent with picture, role them as promising alternatives for actual-time fingerprint photo classification. The experimentation extends to embody Cambodian and Korean fingerprint datasets, asserting the robustness and generalization abilties of the proposed technique.

In the paper [22], the authors delve into the realm of fingerprint classification using Convolutional Neural Networks (CNNs) with the primary objective of exploring the critical factors influencing this classification process. Their work revolves around the design, training, and testing of a novel deep CNN model specifically tailored for fingerprint recognition. This model comprises two sequential stages, a preprocessing phase to enhance fingerprint image quality, and a post-processing phase for classification model training. Leveraging the NIST DB4 dataset, which initially consists of 4,000 fingerprint images, each with five distinct labels and dimensions of 512 x 512 pixels, the study reduces image dimensions to 200 x 200 pixels to expedite training. Remarkably, the results showcase an exceptional classification accuracy of 99.2% with a zero rejection rate, underscoring the effectiveness of the newly devised deep CNN model in the realm of fingerprint classification.

In the paper [23], the author presents an innovative approach by combining the Gabor Filter and Convolutional Neural Network (CNN) for enhanced fingerprint feature extraction. The model is structured with two distinct channels: a Deep Convolutional Neural Network (DCNN), featuring eight layers designed to capture deep fingerprint features, and a Shallow Convolutional Neural Network (SCNN), which integrates Gabor Filters and a two-layer neural network to extract features from clear fingerprint images. The experimentation employs the NIST Special Database 4, and the compelling results reveal an outstanding accuracy of 91.4% in fingerprint classification. Notably, this accuracy outperforms other existing algorithms, showcasing the efficacy of the Gabor Filter and CNN fusion in extracting vital ridge features from fingerprint images.

In the paper [24], the author presents an innovative methodology for fingerprint liveness detection, leveraging an attention model and ResNet convolutions. This approach incorporates both spatial attention (SA) and channel attention (CA) models in sequence to enhance feature learning. The method involves a three-fold sequential attention model combined with five convolutional learning layers. Performance evaluations are conducted using various pooling strategies, including Max, Average, and Stochastic, on the LivDet-2021 dataset. Comparative analyses against state-of-the-art Convolutional Neural Networks (CNNs) like DenseNet121, VGG19, InceptionV3, and conventional ResNet50 are performed. Notably, ResNet34 and ResNet50 models are assessed for feature extraction alongside the sequential attention model. A Multilayer Perceptron (MLP) classifier, in conjunction with a fully connected layer, provides the final prediction. This attention-based technique demonstrates remarkable success in detecting fingerprint liveness, achieving an impressive accuracy of 97.78% on the LivDet fingerprint dataset, showcasing its potential in distinguishing real from fake fingerprint images.

In the paper [25], the authors employ deep transfer learning and data augmentation to create a robust fingerprint pattern classifier capable of distinguishing six different fingerprint patterns. They leverage pre-trained models, specifically VGG16, VGG19, and DenseNet121, after conducting preliminary experiments. The study utilizes datasets from LivDet Competition and NIST. The effects reveal enormous improvements in classification accuracy, with figures attaining 98.2%, ninety seven%, and 97.Eight% for VGG16, VGG19, and DenseNet121 fashions, respectively, while information augmentation is applied. In contrast, the same fashions without information augmentation attain decrease accuracies of 93.Nine%, 93.7%, and ninety two%. This highlights the significance of statistics augmentation in improving the effectiveness of fingerprint sample classifiers.

In the paper [26], the proposed technique addresses the challenge of effectively identifying latent fingerprints and increasing identification rates. Instead of counting on traditional strategies like weighted sums or likelihood ratios, the observe employs a stacking approach that combines more than one base algorithms, which include Convolutional Neural Networks (CNNs) and Backpropagation Neural Networks (BPNNs). This hybrid deep mastering method, concerning the fusion of CNN and BPNN fashions, is incorporated right into a semi-supervised classifier for fingerprint identification. The aim is to enhance the Fingerprint Identification System the use of improved deep getting to know strategies, leveraging the complementary strengths of different algorithms to acquire higher identity consequences. The study emphasizes the benefits of this approach for addressing latent fingerprint reputation demanding situations, in the end main to advanced identity accuracy. A category accuracy fee of ninety eight.32% was completed for four training, and the identical accuracy charge of 98.32% was received for eight instructions. All three Convolutional Neural Networks (CNNs) exhibited comparable patterns, making it clean that the outcomes were consistent throughout specific lessons

In their paper [27], the authors introduce an innovative method for the automated design of Convolutional Neural Network (CNN) architectures customized for fingerprint classification. This technique automates the configuration of the CNN's architecture, encompassing the determination of filter numbers and layers, through the application of the Fukunaga-Koontz transform and the assessment of the between-class scatter to within-class scatter ratio. The primary goal is to craft efficient and lightweight CNN models that significantly enhance the speed and efficiency of fingerprint recognition. To validate this approach, the authors conducted evaluations using two publicly available benchmark datasets, FingerPass and FVC2004, both featuring noisy and low-quality fingerprint samples, including cross-sensor fingerprints from live scan devices. Remarkably, the results demonstrate the superiority of the designed CNN models over well-established pre-trained models and state-of-the-art fingerprint classification techniques, achieving an impressive accuracy rate of 98.9%.

In the paper [28], the authors introduce an efficient fingerprint authentication model based on deep learning, specifically a deep CNN. This deep CNN comprises fifteen layers and is organized into two distinct stages. The first stage involves preparatory steps such as collecting fingerprint images, performing data augmentation, and preprocessing. The second stage focuses on feature extraction and matching. The proposed system demonstrated outstanding matching performance for the provided fingerprint features, and it utilized a fingerprint sensor named ZKT ZK4500. Notably, the implemented model achieved remarkable results with a training accuracy of 100% for both the training and validation datasets, highlighting its capability for accurate fingerprint authentication.
In their paper [29], the authors introduce an algorithm designed for fingerprint classification, employing a Convolutional Neural Network (CNN) model, with a particular emphasis on overcoming the challenges associated with low-quality fingerprint images that can impede the identification process. The proposed model encompasses multiple stages, including preprocessing, data resizing, data augmentation, and post-processing, all dedicated to the task of classification. In the preprocessing phase, fingerprint images are subject to enhancement through the application of Prewitt and Laplacian of Gaussian filters. The study draws upon fingerprint data originating from four digital databases, encompassing a total of 240 real fingerprint images and 80 synthetic fingerprint images captured by diverse sensors. Notably, their innovative approach revolves around the meticulous selection of the number of epochs, serving as a critical hyperparameter influencing the performance of deep learning models, achieving a balance between training time and effectiveness. The results reveal varying accuracy rates ranging from 67.6% to 98.7% for the validation set and between 70.2% and 75.6% for the test set. Impressively, the proposed method exhibits outstanding performance, even without the need for handcrafted feature extraction operations, outperforming traditional hand-crafted features in the context of fingerprint classification tasks.
In the paper [30], the authors present an innovative approach to enhancing fingerprints in the presence of substantial background noise. Their method comprises a two-step process, beginning with frequency domain enhancement of the fingerprint image, followed by the generation of a binary fingerprint. However, in cases where the second step inadvertently boosts undesired regions, a deep Convolutional Neural Network (CNN) with orientation selection is employed for reassembling the fingerprint. Notably, this paper also explores the synergy between traditional frequency domain enhancement techniques and deep learning methods within their proposed framework. The experimental results demonstrate that their suggested approach outperforms other existing methods in terms of enhanced fingerprint identification, showcasing its potential for addressing challenges posed by noisy backgrounds.

Table 1 : Papers Information

Authors name	Aim of Paper	CNN Models	Dataset	Result
Beanbonyka Rim et al, [21]	Detailed classification of fingerprint information using deep learning.	Classic CNN, Alexnet, VGG-16, YOLO-v2, Resnet-50	Privately constructed dataset of fingerprint images	YOLO-v2: 90.98% accuracy for left-right hand classification, 78.68% for scratch

				classification, and 66.55% for fingers classification. Resnet-50: 91.29% accuracy for sweat-pore classification. YOLO-v2 and Resnet-50 took at most 250.37 ms per image.
Mohamed Hirsi [22]	Explore factors affecting fingerprint classification and design a deep CNN model.	Custom deep CNN model	NIST DB4 dataset with 4,000 fingerprint images	Impressive 99.2% classification accuracy with zero rejection rate for fingerprint recognition.
Zhengfang He et al, [23]	Fingerprint classification	DCNN and SCNN	NIST Special Database 4	Impressive 91.4% accuracy in fingerprint classification, surpassing other algorithms.
D. Kothadiya et al,[24]	Propose a methodology for fingerprint liveness detection	Dual attention-based ResNet34 and ResNet50 models	LivDet DB and ATVS DB	Achieved an impressive accuracy of 97.78% on the LivDet fingerprint dataset
D. S. Ametefe et al, [25]	Develop a fingerprint pattern classifier f	VGG16, VGG19, DenseNet121	LivDet Competition and NIST datasets	Significant improvement in accuracy, with 98.2%, 97%, and 97.8% achieved for VGG16, VGG19, and DenseNet121, respectively, compared to 93.9%, 93.7%, and 92% without data augmentation.
R. Kumar et al, [26]	The aim is to evaluate various CNN architectures for fingerprint	AlexNet, GoogleNet, ResNet.	The PolyU database	he classification accuracy rate is 98.32% for both

	classification and their impact on recognition efficiency.			four and eight classes
F. Saeed et al.[27]	To automate the design of CNN architectures for fingerprint classification and enhance efficiency.	DeepFKTNet Architecture	FingerPass and FVC2004 benchmark datasets	The proposed models achieved an accuracy rate of 98.9%, outperforming existing methods and pre-trained models
A. F. Yaseen Althabhawee et al, [28]	To propose an efficient fingerprint authentication model using a deep CNN	A deep Convolutional Neural Network with fifteen layers	ZK4500	the proposed model achieved 100% accuracy on both the training and validation datasets, showcasing its effectiveness in fingerprint authentication.
Andreea Monica et al,[29]	Fingerprint classification using a Convolutional Neural Network (CNN)	Proposed CNN model	FVC2004, DB1, DB2, DB3, and DB4	the proposed method achieved varying levels of accuracy, ranging from 67.6% to 98.7% for the validation set and between 70.2% and 75.6% for the test set
Ram Kumar et al,[30]	fingerprint enhancement and identification	deep Convolutional Neural Network	-	The results of the paper indicate that the proposed method outperforms other methods in terms of enhanced fingerprint identification. Unfortunately, specific numerical results or performance metrics

				are not provided in the text.

Table 2 : Hyper Parameters

Authors name	**Learning rate**	**Number of epochs**	**Batch size**	**Optimizer**
Beanbonyka Rim et al, [21]	0.0001	250, 500 and 1000	16	SGD with momentum to 0.9, weight decay to 0.0005
Mohamed Hirsi [22]	-	10	-	-
Zhengfang He [23]	0.0001	3000	128	Adam optimizer
D. Kothadiya et al,[24]	0.001	20	16	Adam optimizer
D. S. Ametefe et al, [25]	0.00001	50	32	SGD optimizer
R. Kumar et al, [26]	-	-	-	-
F. Saeed et al.[27]	0.0005 and 0.0008	10	16	RMSprop
A. F. Yaseen Althabhawee et al, [28]	0.0001	300	128	SGD with momentum to 0.9
Andreea Monica et al,[29]	0.01	10, 20, 30, 50	20	-
Ram Kumar et al,[30]	-	-	-	-

5. Conclusion

the survey on fingerprint classification utilizing deep convolutional learning has revealed significant advancements and achievements in this domain. The use of Automated Fingerprint Identification Systems (AFIS) is widespread in many countries, and the need to efficiently process and identify individuals from large fingerprint databases has led to the development of fingerprint classification techniques. Deep mastering techniques, mainly Convolutional Neural Networks (CNNs), have played a pivotal role in improving the accuracy and efficiency of fingerprint classification structures. Through an evaluation of ten research projects, it became obvious that CNN-based fashions have always carried out splendid accuracy quotes, often exceeding 98.9%, 99.2%, or even accomplishing 100%. These consequences underscore the efficacy of deep getting to know in enhancing fingerprint classification, even in hard eventualities with noisy or low-satisfactory fingerprints. Furthermore, the survey highlighted the significance of dataset choice and the first-class-tuning of hyperparameters in achieving top-quality consequences with CNN fashions. Researchers have leveraged diverse datasets and tailored hyperparameters to inshape precise fingerprint type duties, similarly demonstrating the adaptability and versatility of deep getting-to-know tactics. Overall, the survey reflects the growing importance of deep convolutional learning in fingerprint classification and its potential to significantly improve the accuracy and efficiency of Automated Fingerprint Identification Systems (AFIS). As technology continues to advance, it is likely that deep learning techniques will continue to play a vital role in the field of fingerprint recognition and biometrics.

References

[1] Rahim, M. (2017) "Ear biometrics for human classification based on region features mining," Biomedical Research, 28(10), pp. 4660–4664.

[2] Jabeen, S. et al. (2018) "An effective content-based image retrieval technique for image visuals representation based on the bag-of-visual-words model," PloS one, 13(4), p. e0194526. doi: 10.1371/journal.pone.0194526.

[3] Abbas, N. et al. (2018) "Machine aided malaria parasitemia detection in Giemsa-stained thin blood smears," Neural computing & applications, 29(3), pp. 803–818. doi: 10.1007/s00521-016-2474-6.

[4] Rehman, A. et al. (2022) "Microscopic retinal blood vessels detection and segmentation using support vector machine and K-nearest neighbors," Microscopy research and technique, 85(5), pp. 1899–1914. doi: 10.1002/jemt.24051.

[5] Harouni, M. and Mohamad, D. (2010) "): Deductive method for recognition of on-line handwritten Persian/Arabic characters," in 2010 the 2nd International Conference on Computer and Automation Engineering (ICCAE), A. Rasouli. IEEE.

[6] Harouni, M. et al. (2014) "Online Persian/Arabic script classification without contextual information," The imaging science journal, 62(8), pp. 437–448. doi: 10.1179/1743131x14y.0000000083.

[7] Dashti, M. M. and Harouni, M. (2021) "Smile and laugh expressions detection based on local minimum key points," arXiv [cs.CV]. Available at: http://arxiv.org/abs/2101.01874.

[8] Rehman, A., Harouni, M., Karchegani, N. H. S., et al. (2022) "Identity verification using palm print microscopic images based on median robust extended local binary pattern features and k-nearest neighbor classifier," Microscopy research and technique, 85(4), pp. 1224–1237. doi: 10.1002/jemt.23989.

[9] Khan, M. Z. et al. (2021) "A realistic image generation of face from text description using the fully trained generative adversarial networks," IEEE access: practical innovations, open solutions, 9, pp. 1250–1260. doi: 10.1109/access.2020.3015656.

[10] *Biometric Recognition: Challenges and Opportunities by the National Academies Press (2010).*

[11] Maltoni, D. et al. (2009) Challenges in Biometric Recognition: A Review.

[12] Bhanu, B. and Govindaraju, V. (2011) Multibiometrics for human identification. USA: Cambridge University Press.

[13] Jain, A. K., Ross, A. A. and Nandakumar, K. (2011) Introduction to Biometrics. 2011th ed. New York, NY: Springer.

[14] Akhtar, Z. et al. (2018) "Biometrics: In search of identity and security (Q & A)," IEEE multimedia, 25(3), pp. 22–35. doi: 10.1109/mmul.2018.2873494.

[15] Abderrahmane, H. et al. (2020) "Weighted quasi-arithmetic mean based score level fusion for multi-biometric systems," IET biometrics, 9(3), pp. 91–99. doi: 10.1049/iet-bmt.2018.5265.

[16] Tuama, S. A., Jamila, H. and Saud, Z. A. (2022) "Using an Accurate Multimodal Biometric for Human Identification System via Deep Learning," Al-Mansour Journal, 37, pp. 69–90.

[17] Goodfellow, I., Bengio, Y. and Courville, A. (2016) Deep Learning. London, England: MIT Press.

[18] Weidman, S. (2019) Deep learning from scratch: Building with python from first principles. Sebastopol, CA: O'Reilly Media.

[19] Tasci, T. and Kim, K. (2015) Imagenet classification with deep convolutional neural networks.

[20] He, K. et al. (2016) "Deep residual learning for image recognition," in 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). IEEE.

[21] Rim, B., Kim, J. and Hong, M. (2021) "Fingerprint classification using deep learning approach," Multimedia tools and applications, 80(28–29), pp. 35809–35825. doi: 10.1007/s11042-020-09314-6.

[22] Mohamed, M. (2021) "Fingerprint classification using deep convolutional neural network," J. Electr. Electron. Eng, 9, pp. 147–152.

[23] He, Z. et al. (2023) "Fingerprint classification combined with Gabor filter and convolutional neural network," International journal of advanced and applied sciences, 10(1), pp. 69–76. doi: 10.21833/ijaas.2023.01.010.

[24] Kothadiya, D. et al. (2023) "Enhancing fingerprint liveness detection accuracy using deep learning: A comprehensive study and novel approach," Journal of imaging, 9(8). doi: 10.3390/jimaging9080158.

[25] Ametefe, D. S. et al. (2022) "Fingerprint pattern classification using deep transfer learning and data augmentation," The visual computer. doi: 10.1007/s00371-022-02437-x.

[26] Kumar, R. and Patil, M. E. (2022) "Improved Fingerprint Identification System Using Hybrid Deep Learning," Industrial Engineering Journal, 15(11).

[27] Saeed, F., Hussain, M. and Aboalsamh, H. A. (2022) "Automatic fingerprint classification using deep learning technology (DeepFKTNet)," Mathematics, 10(8), p. 1285. doi: 10.3390/math10081285.

[28] Yaseen Althabhawee, A. F. and Chabor Alwawi, B. K. O. (2022) “Fingerprint recognition based on collected images using deep learning technology,” IAES International Journal of Artificial Intelligence (IJ-AI), 11(1), p. 81. doi: 10.11591/ijai.v11.i1.pp81-88.

[29] Dincă Lăzărescu, Andreea-Monica, Simona Moldovanu, and Luminita Moraru. 2022. "A Fingerprint Matching Algorithm Using the Combination of Edge Features and Convolution Neural Networks" Inventions 7, no. 2: 39. https://doi.org/10.3390/inventions7020039

[30] Kumar, R. and Patil, M. (2022) “DESIGN A DEEP LEARNING MODEL FOR AN ENHANCED FINGERPRINT IDENTIFICATION SCHEME. Dongbei Daxue Xuebao,” Journal of Northeastern University, 25, pp. 549–556.