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A Survey of Biometric Recognition Using Deep Learning

Haider Mehraj[1,*] and Ajaz Hussain Mir[1]

[1] Department of Electronics and Communication Engineering, National Institute of Technology Srinagar, Srinagar, J&K, India-19006.

Abstract

Biometrics is a technique used to define, assess, and quantify a person's physical and behavioral property. In recent history, deep learning has shown impressive progress in several places, including computer vision and natural language processing for supervised learning. Since biometrics deals with a person's traits, it mainly involves supervised learning and may exploit deep learning effectiveness in other similar fields. In this article, a survey of more than 60 promising biometric works using deep learning is provided, illustrating their strengths and potential in various applications. The paper starts with biometric basics, transfer learning in deep biometrics, an overview of convolutional neural networks, and then survey work. We address all the strategies and datasets used along with their accuracy. Further, some of the main challenges when utilizing these biometric recognition models and potential future avenues for research into this field are also addressed.

Keywords: Intelligent Systems, Unimodal Biometrics, Multimodal Biometrics, Deep Learning, and Transfer Learning.

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1. Introduction

The advancement of information technology and cyber challenges is rapidly undermining conventional access mechanisms focused on IDs and passwords to protect digital identities. This encourages the world to implement innovative techniques and processes for safety and reliability. In this case, technical advances have led to the introduction of new, highly sophisticated detection and authentication technologies, including biometrics, a process focused on the identification of unique biological traits known as biological identifiers. These biological identifiers compromise two factors, i.e., the physical descriptors based on the shape of the body such as fingerprint, palmprint, iris, face, and Ear, and the behavioral attributes are linked to the attitudes and behaviors of the person, such as gait, signature, keystroke, and voice. Biometric recognition is carried out by obtaining the person's biometric data, retrieving its attributes, and comparing this against the reference model in the database to decide similarities. The characteristics extracted from the biometric data can be divided into the unimodal and multimodal systems. Unimodal schemes utilized a single biometric attribute of the person for biometric authentication. Unimodal authentication technical sounds very capable, but in practice, when dealing with a large population, unimodal has several limitations. Such drawbacks include the vulnerability of the biometric sensor to distortion or inadequate data, inter, and intraclass comparison (1). Unimodal biometric devices are also prone to fake attacks in which the data can be replicated or fabricated (1). Therefore, the multimodal systems are designed to account for the shortcomings of the unimodal system. Multimodal biometrics are devices proficient in using more than one physical or attitudinal unimodal biometric attribute for authentication, confirmation, and recognition. Multimodal solutions utilized data from single or multiple biometric sensors to calculate more than one distinct biometric feature as it uses fusion techniques so that merging can take place at attributes or comparison or decision level (1-3).

*Corresponding author. Email: haider_50phd2015@nitsri.net

A neural network is a set of algorithms in which a computer learns to execute specific functions by evaluating some training models. It is closely related to the human brain's neural network in which neurons are called nodes to gather and classify data by architecture. These nodes are densely interconnected to receive data from the previous layer and send data to the next. Each node is associated with an adjustable weight (just a number reflects the intensity of the relation between the components) for the desired output.

Neural networks are basically of two types: shallow and deep networks. Shallow networks, also known as conventional networks, consist of only a few hidden layers. They rely on good handcrafted features for performing suitable classification. Feature extraction is a difficult task in image recognition and needs a knowledge expert to perform it adequately. Features that are extracted from each of the samples is provided to shallow networks for classification. The deep network was developed to avoid the complicated method of extraction of features. It strives to automatically learn the hierarchy of features from low to high stages, providing an end to end network. It pushes machine learning forward closer to the target of artificial intelligence, that is, a machine that can think as a person does.

Deep learning methods learn distinct characteristics from the data, and they can learn subtle characteristics that can differentiate between large numbers of people when trained discriminatively. Besides, if adequate samples represent various variables that affect identification, deep learning techniques may learn to disengage these factors while studying discriminating representations. This will result in managing differences in the intraclass and noisy biometric data. However, one of the main disadvantages is that the model must be sufficiently complex to capture all these variations, requiring vast training data quantities. It may take immense efforts to gather data that would eventually alter over time. In such conditions, to synthesize such variants, generative deep learning methods may be used. Generative Adversarial Network (GAN) is part of generative models, which means they can produce and generate new materials similar to training data (4). It compromises of two neural networks, generator and discriminator. A generator learns to create misleading information that tries to fool the discriminator while the discriminator classifies the data by predicting the category under which it belongs. Another technique often used in deep learning to deal with the curse of less information is image augmentation. Image Augmentation is a technique in which artificially new images are created using the existing trained images to train our model. In this way, we do not need to gather pictures manually. In recent times, deep learning techniques such as convolutional neural networks and transfer learning and image augmentation have been used extensively for biometric recognition.

Deep network training from the start is computationally extensive and requires a significant amount of labeled data. Transfer learning is a deep learning method used when training data or resources are less. Transfer learning is a technique in which a model trained on a specific project such as VGGNet, Inception, SqueezeNet and ResNet, etc. has been previously trained on a huge dataset ImageNet, is re-used on a different similar project. ImageNet is a dataset designed for image recognition applications and has more than million images and thousands of different classes (5). Transfer learning considers the trained model's pre-trained weights and used these features to predict or classify classes, which reduced the computational cost of the model. There are two methods of using a pre-trained network: fixed feature extraction and fine-tuning (6).

The last fully connected layers are removed from the pre-trained network in the feature extraction method while keeping the system's rest. This network segment comprises a series of convolutional/pooling layers called a network base (6). Any machine learning classifier or new CNN layers can be added on the top of the network base to solve the classification problem for a given dataset. The central concept here is to use the pre-trained model's weighted layers to extract features but not alter the model's layer weights during training with new data for the current task.

A fine-tuning method replaces the pre-trained model's last few layers with a new set layers to retrain on a given dataset and fine-tune selectively or all-layers of convolution base via backpropagation. The initial layers are left frozen in selective methodology while the remainder of the deeper layers are finely tuned (6). This is because the initial layer features like edges, corners, or lines for several datasets and tasks are more general. In contrast, the latter features are gradually more specific to a single database or task. Overall, this approach is not always as practical as it first seems like time spent doing a detailed introspection of the model, and attempting to decide where to cut-off the unfreeze is very difficult. Rather than freezing specific layers, the usage of differential learning rates, where the learning rate is calculated on a layer basis, is usually a smart option. The initial layers will then have a minimal learning rate as they generalize very well, most of them responding to corners, blobs, and other superficial geometries. In contrast, the layers corresponding to more complex features would have a higher learning rate.

In view of these prospects, this paper aims to enable new researchers with this niche to steer on the growth of a deep learning-based biometric recognition system. The significant contributions of this paper are as follows:

(i) We examine how biometric recognition approaches have leveraged deep learning advantages and ways where deep learning can further enhance biometric recognition systems.
(ii) We provide a comprehensive overview of crucial unimodal biometrics involving the face, Ear, ECG, fingerprint, finger-vein, gait, iris, palmprint, and signature using deep learning.
(iii) We provide a detailed summary of recent deep learning-based multimodal biometric approaches.
(iv) We discuss the advantages and limitations of existing deep learning-based unimodal and multimodal

biometrics and the way forward for further utilizing deep learning in biometrics.

The rest of the article is divided as follows: Section 2 provides an insight into convolutional neural networks, which are extensively used in biometric identification. In section 3, identification using a single biometric trait, i.e., unimodal biometrics, are discussed. Identification using deep learning for nine important traits is discussed. In section 4, identification using multimodal biometrics are discussed. At the end of sections 3 and 4, overviews of work done in biometrics using deep learning discussed are summarised in tabular form. In section 5, the use of Generative Adversarial Network in biometric recognition is provided. In the end, challenges faced in biometric identification and conclusions drawn are discussed in section 6.

2. Convolutional Neural Networks

Convolutional Neural Networks (CNN) are amongst the deep learning community's most popular and commonly used architectures, especially for computer vision tasks. CNN's was influenced by the human visual system suggested by Fukushima (7). These are state-of-the-art solutions to pattern analysis, shape identification, and several other image applications. In particular, the 2012 ImageNet Large Scale Visual Recognition Challenge champion was a deep CNN approach, Alexnet by Krizhevsky et al. (5), which illustrated the substantial strength of deep CNNs.

CNN's are relatively distinct from other pattern recognition algorithms, where CNN's incorporate both attribute extraction and classification. Underlying CNN architecture is shown in figure 1. CNN's consist mostly of four types of layers: convolution layers where a sliding kernel is added to the picture in order to remove features as in image convolution operation; non-linear layers, usually implemented in an element-wise fashion that add the activation function to the features to allow the simulation of non-linear tasks by the network; pooling layers which take up a small feature map neighborhood and substitute it with some statistical details; and output layer, there exists one output neuron for each object category(8). The output of the classification layer or output layer is the classification result. Nodes are connected locally in the CNN layers; that is, every unit in a layer receives feedback from a specific neighborhood of the previous layer (known as the receptive field). CNN's main advantage is the weight-sharing mechanism by using the sliding kernel that passes through the images and aggregates local information to extract the features. Because the kernel weights are shared across the entire image, CNNs have a significantly smaller number of parameters than a similar neural network with the full connection. The higher-level layers also learn features from ever wider receptive fields by stacking multiple layers of convolution.

CNN's are applied to numerous computer vision activities, such as textual segmentation, medical image segmentation, entity detection, super-resolution, picture enhancement, image, and video caption generation, among many others. Some of CNN's most popular architectures include AlexNet, ZFNet, VGGNet, ResNet, GoogLenet, MobileNet, and DenseNet, among many others (5, 6, 9-13).

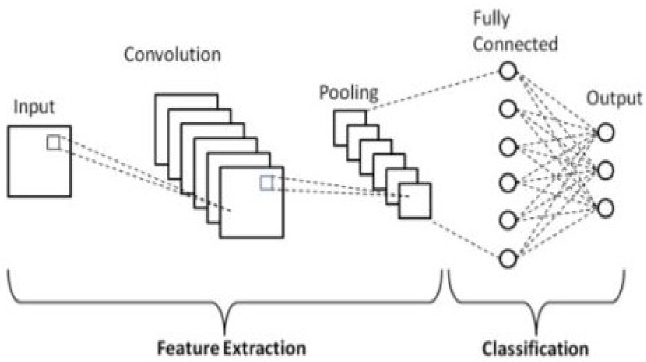

Figure 1. Underlying convolutional neural network (CNN) architecture (8).

3. Unimodal Biometrics

In unimodal techniques, identification is made by using a single unique trait of the human body like Ear, face, gait, etc. The various Unimodal techniques employing deep learning are discussed as under:

3.1. Face recognition

Face recognition is the identification of a person from the image or frame of a video on the basis of facial structure. Work on face recognition started in the 1960s by the US government. They build a semi-supervised system that locates the key features on the face and calculates the ratio between them for identification (14). Now the work of facial recognition has come a long way and has overcome several hurdles. Now some models can provide high accuracy for identification only based on face recognition. With the advancements in processing power and deep learning, identification accuracy has also increased by a huge factor. Khiyari and Wechsler (15) carried a study to recognize face over different age groups. They used VGG-Face CNN for feature extraction; they found that VGG-Face CNN can extract features that do not change over the years and show a small error variation with change in age. In another study, Khiyari and Wechsler (16) took demographics like race, gender, and age into account for face recognition. They used VGG-Face CNN for feature extraction and found that it is possible to better accuracy when considering proposed demographics for face recognition. In another study, Khiyari and Wechsler (17) carried out face recognition, which was invariant to factors like pose, illumination, expression, and aging using VGG-Face CNN. Lee et al. (18) worked on face identification using RGB-depth images for more accurate identification. They also used deep learning for feature extraction. They first trained a neural network for RGB images and then fine-tuned it through transfer learning for depth face images. Kamencay et al. (19) carried out a comparative study between PCA, LBPH, KNN, and CNN for face recognition on the ORL database. They found that PCA worked better for face recognition in their study environment. Hu et al. (20) did both 2D and 3D face recognition through two CNNs proposed by them CNN-1 with two convolutional layers and CNN-2 with one convolutional layer. They used the FRGCv2.0 dataset for depth images and ATT dataset for raw 2D images. Wang et al. (21) worked on facial recognition under variation of illumination and pose using Deep reinforcement learning (DRL) and CNN. Datasets from ImageNet 2012 and LFW were used for the study, and they got an accuracy of 100% using the InceptionV3 model, which was pretrained for ImageNet. Pai et al. (22) extracted features through haar-cascade and makes comparisons through the InceptionV3 CNN model. They used the LWF dataset for their implementation. Lin and Chin (23) worked on thermal face recognition, which is illumination invariant. They used CNN for feature extraction; the dataset used by them was Yale facial image dataset. They achieved a maximum of 99.65% accuracy. Phillips et al. (24) used facial recognition in the bio-capsule technique, using deep learning to enhance the existing system's security. They used Multi-Task (Cascaded) Convolutional Neural Network (MTCNN) for their implementation. They chose Caltech Faces 1999 dataset and the Georgia Tech Face Database dataset for their experimentation. Their model performed better than the existing techniques. Khan et al. (25) worked on facial recognition and their implementation in glasses. They used haar cascade for face detection and AlexNet for face recognition. They achieved 98.5% accuracy. Perdana and Prahara (26) worked on face recognition using a modified VGG16 convolution model. They used ROSE-Youtu Face Liveness Detection Database for their implementation. They achieved 94.4% accuracy. Duan et al. (27) worked on face recognition, and for feature comparison, they used ResNet architecture. They used MegaFace Challenge I, IARPA Janus Benchmark A (IJB-A), YouTube Faces (YTF), and Labelled Faces in the Wild (LFW) datasets for their training. They achieved 99.8% accuracy on the LWF dataset. Zhu et al. (28) combined neural architecture search (NAS) and reinforcement learning to give a new recognition pipeline for face recognition. The dataset used for experiments was large-scale face dataset and MS-Celeb-1M; they achieved 98.77% and 99.89% accuracy on them, respectively. Liu et al. (29) worked on face recognition through different angles and different image quality. Each image is weighted according to how good it is. They used CNN for feature extraction. They used various datasets like IJB-A, YTF, and celebrity-1000 dataset and used different assemblies to get results. The maximum accuracy they got was 99.9%. Sen et al. (30) worked on face recognition and used Siamese Network for feature extraction purposes. They used the Happy house dataset for training purposes along with transfer learning to compensate for fewer data. They got 56% accuracy for testing. Heidari and Ghaleh(31) worked on face recognition for small datasets through transfer learning using Siamese networks. They got 95.62% accuracy on the LFW dataset. Zhao et al. (32) worked on multi-view face recognition. They used a convolutional neural network for feature extraction, PCA for feature dimensionality reduction, and used a Bayesian framework for feature identification. They used CAS-PEAL dataset that they compiled on which they got 98.52% accuracy. Kute et al. (33) worked on face recognition for forensic applications. They used pretrained traditional CNN for feature extraction and reduced the dimensionality of features through FLDA and classified through KNN. They collected datasets on their own and achieved a maximum accuracy of 93.8%. Mehraj and Mir (34) proposed the use of Alexnet and VGG-16 for feature extraction and traditional classifier SVM for classification. They got an accuracy of 96.75% over the VIDTIMIT database.

Table 1. Important works on face-based identification using deep learning.

Author	Gap filled	Deep Learning Architecture	Dataset	Results
Khiyari and Wechsler (15)	Face recognition over time lapse	VGG-Face CNN Deep feature extraction	FG-NET, MORPH	Max 92.2% test accuracy
Khiyari and Wechsler (16)	Face recognition using demographics	VGG-Face CNN Deep feature extraction	MORPH and datasets from previous studies	Different for different demographics (see original paper)
Khiyari and Wechsler (17)	Age invariant face recognition	VGG-Face CNN Deep feature extraction	FG-NET dataset	

				Different for different demographics (see original paper).
Lee et al (18).	Face identification through RGB-D images	CNN	CASIA-WebFace, IIR3D, GavabDB, Texas 3D for training. EurocomKinect Face Dataset (EKFD) and SuperFaces for testing	Max 99.7% test accuracy
Kamencay et al. (19)	Comparison between PCA, LBPH, KNN, and CNN for face recognition	PCA, LBPH, KNN, and CNN	ORL database	PCA gives better accuracy.
Hu et al. (20)	2D and 3D face recognition	Two CNN models designed by them	FRGCv2.0 and AT&T dataset	85.15% accuracy for FRGCv2.0 and 95% for AT&T dataset with CNN-2
Wang et al. (21)	Face recognition for varying poses and illumination	DRL and CNN (Pre-trained InceptionV3)	Imagenet 2012 and LFW	100%
Pai et al. (22)	Face recognition through deep learning	InceptionV3 CNN	LFW	Max. 86.2% accuracy
Lin and Chin (23)	Thermal face recognition	CNN	Yale facial image dataset	Max. 99.65% accuracy
Phillips et al. (24)	Bi-capsule deep face recognition	Multi-Task (Cascaded) Convolutional Neural Network (MTCNN)	Caltech Faces 1999 dataset and the Georgia Tech Face Database dataset	Max. 99.85% accuracy
Khan et al. (25)	Face recognition and glass implementation	AlexNet	-	Max. 98.5% accuracy
Perdana and Prahara (26)	Face recognition through deep learning	Modified VGG-16 CNN	ROSE-Youtu Face Liveness Detection Database	Max. 94.4% accuracy
Duan et al. (27)	Face recognition with equidistributed representations	RASNet for feature comparison	MegaFace Challenge IIJB-A, YTF, and LFW Datasets	99.8% accuracy on LWF
Zhu et al. (28)	Face recognition with an enhanced loss function	NAS and reinforcement learning	Large-scale face dataset and MS-Celeb-1M	98.77% and 99.89% accuracy on both datasets, respectively.
Liu et al. (29)	Multi-view face recognition	CNN feature extraction	IJB-A, YTF, and celebrity-1000 dataset	Max. 99.9% accuracy
Sen et al. (30)	Face recognition with one-shot learning	Siamese Network (Transfer learning)	Happy house dataset	56% test accuracy
Heidari and Ghaleh(31)	Face recognition over a small dataset	MSiamese Network	LWF Dataset	95.62% accuracy
Zhao et al. (32)	Multi-view Face recognition	CNN feature extraction	CAS-PEAL dataset	98.52% accuracy

3.2. Ear Recognition

The Ear can be said as an essential feature for biometric identification as it carries out the minimal change over the years despite all the other biometric features. Cintas et al. (35) also highlighted these ear features and worked on feature extraction of the Ear through CNN. Dataset they took was from the CANDELA initiative, and they got 98.8% accuracy from it. Dodge et al. (36) worked on-ear recognition, and for feature extraction, they used five deep neural networks AlexNet, VGG16, VGG19, ResNet18, and ResNet50. They used a very small dataset, and to compensate for this, they used data augmentation and a pretrained model. They used AWE and CVLE datasets for training and testing purposes. They got a maximum of 99.69% accuracy in CVLE dataset through VGG19 and ResNet50. Chowdhury et al. (37) worked on ear recognition. They first detected the Ear, then extracted edge features, and then used a modular neural network (MNN) for ear recognition. They used different datasets composed by the University of Notre Dame (UND), the

University of Science and technology in Beijing (USTB), and the Indian Institute of Technology, Delhi (IITD). They achieved 93.5% accuracy. Eyiokur et al. (38) studied the effect of domain adaptation on ear recognition accuracy. They used models like VGG-19, AlexNet, Google net, and SqueezeNet, and implemented fine-tuning and augmentation to check the effects. Datasets used by them include AWE, AMI, WPUT, IITD, CP, UERC train, multi-PIE Ear. The authors compiled the Multi-PIE Ear by using the Multi-PIE face dataset. They achieved a maximum of 67.53% accuracy. Tian and Mu (39) worked on ear recognition based on CNN. They used the USTB ear database for experimentation. They got a maximum of 99.24% accuracy. Almisreb et al. (40) used transfer learning on AlexNet CNN and fine-tunned it to classify ten classes. They collected the data themselves and achieved 100% validation accuracy.

3.3. ECG Recognition

ECG of a healthy person can also be used for biometric recognition. Although it is a bit of an unstable means of identification, there is still work done in this filed. Gawande and Ladhake (41) worked on ECG recognition through Multi-Layer Perceptron (MLP). They collected the data of 12 people over 36 months and got 99.76% accuracy. Eduardo et al. (42) worked on ECG recognition through deep auto-encoders. They collected data from a local hospital and reached a 99% confidence level of recognition.

3.4. Fingerprint Recognition

Human fingerprints have been used in biometric verification in almost all security systems as fingerprints do not vary with age and have no effect due to illumination or other environmental factors. Khetri et al. (43) worked on fingerprint recognition through a feedforward backpropagation neural network. They used the CASIA and FVC2002 fingerprint database for training and testing purposes. They found out that the CASIA database shows better performance than the FVC2002 database. Abdullah (44) worked on fingerprint recognition through ANN, and they proposed a supervised recurrent neural network (RNN). They checked for the same features from different images of the same finger to check which features to keep and which to omit. Thus, they provide a solution that uses fewer data storage. They used FVC2002 databases for experimentation. Jang et al. (45) worked on fingerprint pore extraction for fingerprint recognition through CNN. They used a high-resolution-fingerprint (HRF) database for investigation and got 93.09% performance. Jeon and Rhee (46) proposed fingerprint classification through VGGNet convolutional neural network for feature extraction and classification. They got a maximum of 98.3% accuracy. Minaee et al. (47) worked on fingerprint recognition through neural networks. They used ResNet50 neural network for feature extraction and recognition. They used pre-trained CNN and fine-tuned it according to their dataset. They achieved an accuracy of 95.7% through this experiment model. Goel et al. (48) worked on double identity fingerprint detection through neural networks. They used traditional feature extractors like SIFT and deep learning models like AlexNet and DCNN for feature extraction. They found out that deep learning models can detect the cutline with an equal error rate.

3.5. Finger-vein Recognition

Conventional biometric identification methods have several drawbacks and can be forged. So, there was a need to introduce new ways of identity recognition. Finger-vein recognition is one of those ways. Radzi et al. (49) worked on finger vein recognition through LeNet-5 CNN as they can extract features, reduce their dimensionality, and classifying simultaneously. They formulated their database and got a maximum accuracy of 100%. Das et al. (50) also used traditional CNN with five convolutional layers, three max-pooling, 1 ReLU, and a softmax loss layer for classification. They used four publicly available datasets HKPU, FV-USM, SDUMLA, and UTFVP. They got 95% accuracy. Swetha et al. (51) also worked on finger-vein identification through CNN with fused convolution/subsampling, and their work was mostly based on previous methods by (49). Fairuz et al. (52) used transfer learning on AlexNet to classify finger vein images. They collected the dataset on their own and achieved a 95% accuracy.

3.6. Gait Recognition

Gait is another potential candidate for biometric recognition and has also been used in various identification models. It has also shown promising results in the neural network domain. Dehzangi et al. (53) worked on human gait recognition. They got 2d gait pattern through time-frequency expansion and used deep convolutional neural network (DCNN) for feature extraction. They collected their dataset using five sensors on ten individuals. They got 97.06% accuracy with the proposed approach. Xu et al. (54) worked on gait recognition through a capsule network to tackle environmental and clothing factors' challenges. They used the CASIA-B dataset and OU-ISIR Treadmill dataset B for experimentation purposes. They achieved an accuracy of 74.44%. Su et al. (55) worked on gait recognition through CNN based on a new loss function called Center- ranked. Dataset used by them was CASIA-B and OU-MVLP dataset. They worked on different datasets and different deep learning models and got a maximum of 100% accuracy. Wu et al. (56) worked on gait recognition. They used different pretrained DenseNet for feature extraction and KNN for classification. They used the CASIA-B dataset and achieved an accuracy of 98.87%. Min et al. (57) worked on gait recognition using different versions of activation functions. They used the Rectifier Linear Unit (ReLU), Leaky ReLU, and parametric ReLU with the same CNN network. A 10-layer CNN architecture using four layers of convolutional and sampling layers, one SoftMax, and one classification layer was employed. They used Gait Energy Images (GEI) of the CASIA-B gait dataset and obtained 98.8% accuracy with the Leaky ReLU activation function. Wang and Yan (58) proposed a CNN Ensemble (GCF-CNN) based gait classification architecture using a three-step strategy. To build subtly different training sets, they first use a Bagging-like technique to preprocess the generic GEIs. Then, with numerous hyper-parameters and training sets, diverse CNN primary learners are separately trained. Finally, they use them as inputs to prepare a secondary learner to merge the main learners after receiving every CNN's output. The proposed framework is evaluated on the CASIA Dataset B and OU-ISIR LP Dataset, and an accuracy of 86.04% is obtained. Huynh-The et al. (59) proposed the use of geometric and orientation features with CNN. First, a gait sequence's descriptive statistical characteristics are calculated across several frames by aggregating geometric distance and orientation characteristics. The recognition learning is achieved by a DCNN designed from multiple stacks of asymmetric deep convolutional filter, capable of simultaneously extracting intra-class links, inter-class relations, and cross-class connections from the representation of multi-scale feature maps. The experimentation was carried on three datasets: UPCV Gait, UPCV Gait K2, and KS20 VisLab Multi-View Kinect Skeleton and obtained 99.65% accuracy on UPCV Gait K2 dataset. Arshad et al. (60) proposed an interconnected system using deep neural network and fuzzy entropy-controlled skewness (FEcS). The proposed technique operates in two stages: in the first stage, VGG19 and AlexNet, pre-trained CNN architectures are used to obtain CNN features and then by parallel fusion deep net features are combined. Entropy and skewness vectors are determined from the fused function vector (FV) in the second stage to pick the best subsets of characteristics using the FEcS method. They validated their experiments on AVAMVG and CASIA (A-C) gait datasets and got 99.8% accuracy on the AVAMVG gait dataset.

Table 2. Important works on Ear based identification using deep learning.

Author/s	**Gap filled**	**Deep Learning Architecture**	**Dataset**	**Results**
Cintas et al. (35)	Ear recognition using morphometric landmarks	CNN feature extraction	CANDELA initiative dataset	Max 98.8% test accuracy
Dodge et al. (36)	Ear recognition over small dataset	AlexNet, VGG16, VGG19, ResNet18 2015 and ResNet50	AWE and CVLE datasets	Max 99.69% accuracy in CVLE dataset
Chowdhury et al. (37)	Ear recognition invariant to changes in illumination and occlusion	MNN features	Datasets are composed of UND, USTB, and IITD.	Max 93.5% test accuracy
Eyiokur et al. (38)	Domain adaptation on ear recognition	VGG-19, AlexNet, GoogleNet and SqueezeNet.	AWE, AMI, WPUT, IITD, CP, UERC train, multi-PIE Ear	Max 67.53% test accuracy
Tian and Mu(39)	Ear recognition with partial occlusion	CNN	USTB ear database	Max 99.24% test accuracy
Almisreb et al. (40)	Ear recognition with data augmentation	Pre-trained and fine-tuned AlexNet CNN	Self-collected	100% validation accuracy

Table 3. Important works on ECG based identification using deep learning.

Author/s	**Gap filled**	**Deep Learning Architecture**	**Dataset**	**Results**
Gawande and Ladhake (41)	ECG recognition with statistical and morphological features	Multi-Layer Perceptron (MLP)	Self-collected	99.76% test accuracy

Eduardo et al. (42)	ECG recognition with lower-dimensional heartbeat representations.	Deep auto-encoders	Self-collected	99% confidence level

Table 4. Important works on fingerprint-based identification using deep learning.

Author/s	**Gap filled**	**Deep Learning Architecture**	**Dataset**	**Results**
Khetri et al. (43)	Fingerprint recognition with error optimization	Feedforward backpropagation network	CASIA and FVC2002 fingerprint database	CASIA database gives better performance than FVC2002
Abdullah (44)	Fingerprint recognition with a 1D representation	ANN and RNN	FVC2002 databases	Reduced data storage for fingerprints
Jang et al. (45)	Fingerprint pore extraction for recognition	CNN	High-resolution fingerprint database (HRF)	93.09% performance
Jeon and Rhee (46)	Fingerprint recognition with fast match speed	VGGNet CNN	Fingerprint verification Competition (FVC) 2000, 2002, 2004 databases	98.3% accuracy
Minaee et al. (47)	Scalable Fingerprint recognition	ResNet50	Self-Collected	95.7% accuracy

Table 5. Important works on Finger-vein based identification using deep learning.

Author/s	**Gap filled**	**Deep Learning Architecture**	**Dataset**	**Results**
Radzi et al. (49)	Finger-vein recognition robust to noise and misalignment	LeNet-5 CNN	Self-collected	100% test accuracy
Das et al. (50)	Finger-vein recognition under different imaging quality	Ten layer CNN	HKPU, FV-USM, SDUMLA and UTFVP	95% accuracy
Swetha et al. (51)	Finger-vein recognition	CNN	----	100% test accuracy

Table 6. Important works on Gait based identification using deep learning.

Author/s	**Gap filled**	**Deep Learning Architecture**	**Dataset**	**Results**
Dehzangi et al. (53)	Human gait recognition using 2D spectral and temporal patterns	DCNN for feature extraction	Self-collected	Max. 97.06% accuracy
Xu et al. (54)	Multi-view and clothing invariant Gait recognition	Capsule network	CASIA-B dataset and OU-ISIR Treadmill dataset	Max. 74.44% accuracy
Su et al. (55)	Gait recognition with an optimized loss function	CNN	CASIA-B and OU-MVLP dataset	Max. 100% test accuracy
Wu et al. (56)	Multi-view Gait recognition	Pretrained DenseNet	CASIA-B dataset	98.87% accuracy
Min et al. (57)	Gait recognition with reduced training time	10 Layer CNN with different activation functions	CASIA-B dataset	Max of 98.8% accuracy
Wang and Yan (58)	Gait recognition	CNN Ensemble (GCF-CNN)	CASIA-B dataset and	86.04%

			OU-ISIR LP	
Huynh-The et al. (59)	Gait recognition with invariance to background motion	Geometric and orientation features with CNN	UPCV Gait, UPCV Gait K2, and KS20 VisLab Multi-View Kinect Skeleton	Max of 99.65% accuracy
Arshad et al. (60)	Multi-view Gait recognition	VGG19 and AlexNet	AVAMVG gait and CASIA (A-C) gait datasets	Max of 99.8% accuracy

3.7. Iris Recognition

Iris is also one of the biometric traits that do not change over the years of life, but there is one disadvantage: retrieving the iris in surveillance. However, much work has been done on it, as it is still an excellent recognition method. Abiyev and Altunkaya(61) worked on Iris retrieval and making a dataset after preprocessing, plus they used a neural network defined by them for the classification of iris for recognition. They achieved a recognition accuracy of 99.25%. Sarhan(62) proposed an efficient way of iris recognition. He used a discrete cosine transform for feature extraction and ANN for classification. Dataset used by him was from the CASIA database. He achieved 96% accuracy. Sibai et al. (63) worked on iris recognition through feedforward ANN for iris recognition. They reached an accuracy of 99.33%. Nguyen et al. (64) worked on Iris feature extraction through CNN and then classifying them. They used VGG, GoogleNet, ResNet, and AlexNet. Dataset they used were ND-CrossSensor-2013 and CASIA-Iris-Thousand dataset. With their experiments, they achieved an accuracy of 98.5%. Zhao and Kumar(65) worked on Iris recognition through FeatureNet and MaskNet. For non-iris masking, they used the Extended Triplet Loss function. They used ND-IRIS-0405 Iris Image Dataset (ICE 2006), CASIA Iris Image Database V4 – distance, IITD Iris Database, and WVU Non-ideal Iris Database – Release 1. They got a maximum equal error rate of 3.85%. Tien et al. (66) worked on Iris recognition through modified CNN and Softmax classifier. Dataset they used was from the CASIA eye image database (320x280 pixel). CNN they used was Resnet50. The maximum accuracy they achieved was 96.67%. Jayanthi et al. (67) worked on iris detection, segmentation, and recognition. Neural Network used by them was Inception V2, dataset they used was CASIA-Iris Thousand dataset, and the accuracy that they achieved was 99.14%.

3.8. Palm Recognition

Just like fingerprints, palmprints are also unique for every person and can be used for biometric recognition. Minaee and Wang(68) worked on palmprint recognition through defining a deep scattering network that extracts features through SIFT, reduces their dimensionality through PCA, and classifies them using SVM. Dataset they collected was from the PolyU palmprint database, and the maximum accuracy they got was 100% through the SVM classifier. Shao and Zhong (69) worked on cross dataset palm print recognition as a model trained on a dataset from one database might not work well on a different database. To tackle this, they proposed a system to align pixels and features. They used CNN for feature extraction. The datasets they used were obtained from XJTU-UP (Xi'an Jiaotong University Unconstrained Palmprint) database, PolyU multispectral palmprint database, and Mobile Palmprint Database (MPD). They increased palmprint recognition in cross-dataset recognition by 28.10% and reduced the equal error rate by 4.69%. Izadpanahkakhk et al. (70) worked on palmprint verification and used Chatfield's fast convolutional neural network (CNN) architecture(71), which is inspired by AlexNet for feature extraction. They used Kong Polytechnic University Palmprint (HKPU) database and achieved an IoU score of 93%.

3.9. Signature Recognition

Signature has been a means of personal verification, and people are working on it for decades. Karouni et al. (72) worked on offline signature verification through scanned images. They used ANN for classification and validation. They collected the data by themselves and got a 93% accuracy. Tolosana et al. (73) worked on online signature recognition through their proposed Long Short-Term Memory (LSTM) RNN architecture. They got 17.76% to 28.00% performance improvement for the BiosecurID database. Alajrami et al. (74) worked on offline signature verification using traditional CNN. They collected the dataset themselves and got a training accuracy of 99.9% and testing accuracy of 99.7%. Mersa et al. (75) worked on offline signature verification from Persian writing through Residual CNN transfer learning. They used MCYT (a Spanish signature dataset), UTSig (a Persian one), and GPDS- Synthetic (an artificial dataset) for testing and achieved EER od 3.98% on the MCYT dataset.

Table 7. Important works on Iris based identification using deep learning.

Author/s	Gap filled	Deep Learning Architecture	Dataset	Results
Abiyev and Altunkaya (61)	Iris recognition with fast localization and segmentation	Self-defined NN	Real-time collection	99.25% accuracy
Sarhan(62)	Iris recognition with optimized error rates	Discrete cosine transform for feature extraction and ANN for classification	CASIA database	96% accuracy
Sibai et al. (63)	Noise invariant iris recognition	Feedforward ANN	---	99.33% accuracy
Nguyen et al. (64)	Iris recognition	VGG, GoogleNet, ResNet and AlexNet	ND-CrossSensor-2013 and CASIA-Iris-Thousand dataset	98.5% accuracy
Zhao and Kumar(65)	Iris recognition with superior generalization	FeatureNet and MaskNet	ND-IRIS-0405, CASIA, IITD, and WVU Iris Database	Equal error rate of 3.85%
Tien et al. (66)	Iris recognition with improved computational time	Modified CNN and Soft-max classifier	CASIA database	96.67% accuracy
Jayanthi et al. (67)	Noise invariant iris recognition	Inception V2	CASIA-Iris Thousand Dataset	99.14% accuracy

Table 8. Important works on palmprint based identification using deep learning.

Author/s	Gap filled	Deep Learning Architecture	Dataset	Results
Minaee and Wang(68)	Palm print recognition with reduced computational complexity	A self-defined deep model with SIFT, PCA, and SVM	PolyU palmprint database	Max. 100% accuracy through SVM classifier
Shao and Zhong(69)	Cross dataset palm print recognition	CNN for feature extraction	XJTU-UP, PolyU, and MPD	Max. 74.44% accuracy

Table 9. Important works on signature based identification using deep learning.

Author/s	Gap filled	Deep Learning Architecture	Dataset	Results
Karouni et al. (72)	Offline signature recognition	ANN	Self-defined	93% accuracy
Tolosana et al. (73)	Online signature recognition	LSTM RNN architecture	BiosecurID database	17.76% to 28.00% performance improvement
Alajrami et al. (74)	Offline signature recognition	CNN	Self-defined	Training accuracy of 99.9% and testing accuracy of 99.7%

4. Multimodal Biometrics

Multimodal techniques use more than one biometric trait for classification, i.e., iris and face, Ear and gait, iris and face, etc. Unimodal approaches have many flaws in it as only one trait is responsible for recognition. In this aspect, multimodal methods are way better because more than one attribute is being used for classification. In this case, there is a higher chance of recognition if one trait fails to do so.

Multimodal biometrics have focussed on using transfer learning for leveraging the power of deep learning. Further, some researchers have tried to work on deep networks from scratch for multimodal biometrics, but such research has been confined to shallow CNNs. The primary reason for the same is the lack of databases in biometrics; having a significant number of labeled data for training a network from scratch. Another reason is that if the network is extensive, it will be challenging to reach a reliable local minimum. In these cases, it becomes imperative to use the transfer learning method to better deal with labeled data limitations and the local-minimum issue.

Tiong et al. (76) worked on a facial multimodal; they used the face and periocular region for recognition. They proposed using CNN with seven convolutional layers for each trait separately and then combining the feature vectors at the end. Dataset used by them was Multi-PIE dataset on which they achieved 98.35% accuracy. Geng et al. (77) worked on recognition through video and audio. They used CNN with six convolutional layers, one fully connected layer, and at the end SoftMax for output. In the end, they combined the features collected from both traits for recognition. They raised their data from a Tv series naming "Friends." With this, they got an accuracy of 97.85%. Navdeep and Surinder(78) worked on using palm-pint and face for biometric recognition. They combined NN and SVM to increase efficiency. They got a cumulative match score of 101.0414%. Priya and Mukesh(79) worked on biometric identification through human skeletal and facial features. They preprocessed images, extracted features, and classified them through ANNs. They achieved an accuracy of 98.34%. Silva et al. (80) worked on recognition through eye and iris. They used modified VGG for iris and eye feature extraction. They used NICE.II competition database for experimentation and achieved 5.55% EER. Singh and Kant(81) worked on recognition through finger-knuckle print (FKP) and iris using PCA for feature extraction and Neuro-Fuzzy Neural Networks (NFNN) for matching. The datasets used by them were PolyU FKP and CASIA Iris database. They achieved an EER of 0.23% with their model. Cherrat et al. (82) worked on finger vein and face recognition. For finger veins, they extracted features through CNN with three convolutional layers and one fully connected layer; then, features were classified through Random Forest. For the face, they obtained features using the same CNN architecture and classified through SVM and calculated fusion score based on both predictions. They used VERA Fingervein, Color Feret, and AR face database for experimentation and achieved 99.89% accuracy. Salem et al. (83) worked on securing the personal biometric details of iris and fingerprint. By using transfer learning, training on users' data is reduced hence making the system more secure. They used AlexNet and DenseNet for training. With their architecture, they achieved an F1 score of 95.47%. Kumari and Seeja (84) worked on face and iris recognition using non-clear images. They used seven types of CNN (Alex net, Googlenet, Resnet18, Resnet50, Resnet101, VGG16, and VGG19) on the UBIPr database. They achieved validation accuracy of 100%, and the maximum testing accuracy of 96% with VGG19. Wang et al. (85) worked on face and vein recognition through pretrained and fine-tuned VGG, VIM, and VGM. They used the PolyU NIR-face and lab-made hand-dorsal vein database for experimentation and obtained 91.60% accuracy.

Table 10. Important works on Multimodal Biometrics identification using deep learning.

Author/s	Gap filled	Deep Learning Architecture	Dataset	Results
Tiong et al. (76)	Face and periocular region recognition invariant to illumination and appearance.	Self-designed CNN	Multi-PIE	98.35% accuracy
Geng et al. (77)	Video and audio recognition	Self-designed CNN	Videos from Tv series naming "Friends."	97.85% accuracy
Navdeep and Surinder(78)	Palm-pint and face recognition	NN and SVM	-	Cumulative match score of 101.0414%
Priya and Mukesh(79)	Human skeletal and facial features recognition	ANN classification	-	98.34% accuracy
Silva et al. (80)	Eye and iris recognition	Modified VGG	NICE.II database Competition	5.55% EER
Singh and Kant(81)	FKP and iris recognition	Neuro-Fuzzy Neural Networks (NFNN)	PolyU FKP and CASIA Iris database	EER of 0.23%

Cherrat et al. (82)	Finger vein and face	Traditional CNN feature extraction	VERA Fingervein, Color Feret and AR face database	99.89% accuracy
Salem et al. (83)	Securing biometric details of iris and fingerprint	Pre-trained AlexNet and DenseNet	-	F1 score of 95.47%
Kumari and Seeja (84)	Face and iris recognition	Pre-trained Alex net, Googlenet, Resnet18, Resnet50, Resnet101, VGG16 and VGG19	UBIPr database	Max. testing accuracy of 96% with VGG19
Wang et al. (85)	Face and vein recognition	Pretrained and fine-tuned VGG, VIM and VGM	PolyU NIR-face and lab-made hand-dorsal vein database	91.60% accuracy

5. Generative Adversarial Network

Generative Adversarial Network (GAN) is a network that is used to generate new images. It was first proposed by Ian Goodfellow(4). It consists of two parts a generator and a discriminator. The generator generates new images using noise signals, and the discriminator takes original images and generated images to compare and calculates error value. This error value is then passed to the generator, which tries to reduce the error value. Hence the network learns and generates new images. A simple architecture of GAN is shown in fig. 2.

GANs have proved their worth when it comes to image generation as in biometric identification, datasets with a sufficient number of images are very low. Many researchers have used GANs for dataset generation, image enhancement, and image reconstruction. In biometric recognition, GANs are used for generating new data and for image quality enhancement for recognition. Huang et al. (86) used GANs for fingerprint image enhancement from crime scenes. They used standard GAN architecture, but for the recognition, they used PatchGAN for identification. For evaluating their mode, they used the NISTSD27 latent fingerprint dataset. Zou et al. (87) worked on fake iris recognition and used 4DCycle-GAN to generate fake iris images. Minaee and Abdolrashidi(88) worked on developing realistic iris images through DC-GAN. They used CASIA Iris Dataset and IIT Delhi Iris Database for generating images. Minaee and Abdolrashidi(89) also worked on generating fingerprint images through the same DC-GAN architecture. They used FVC 2006 Fingerprint and PolyU Fingerprint Databases for generating images. Wang et al. (90) worked on image enhancement for person identification when a person is far in camera. They used Cascaded SR-GAN for enhancement purposes. For training the GAN, they used SALR-VIPeR, SALR-PRID, and CAVIAR databases. Hu et al. (91) worked on generating a gait template through GiGGAN, which they proposed from any viewpoint. This helped with changing factors like illumination, clothing etc. that might affect the recognition process. They used OU-ISIR, Multi-View Large Population Dataset (OU-MVLP) for training their GAN. Wu et al. (92) worked on face de-identification. They proposed Privacy-Protective-GAN (PP-GAN), which generates de-identified images. Takahashi et al. (93) worked on image normalization using CycleGAN so that they can be used for the recognition process. Wang et al. (94) worked with invariant gait feature learning through two stream-GAN. They used CASIA-B and OU-ISIR datasets for training their model. Joshi et al. (95) also worked on latent image enhancement using GANs. They used IIITD-MOLF and IIITD-MSLFD dataset for training their architecture. Kashihara(96) worked on classifying iris, but he used Super-resolution GAN (SRGAN) to enhance the images before doing that. Minaee et al. (97) worked on generating realistic palm images using DC-GANs. They used the PolyU Plamprint Database for training the GAN. Xue et al. (98) worked on increasing the frame rate of gait videos. They proposed Frame-GAN for this purpose and used CASIA-B and OU-ISIR gait databases for training their model.

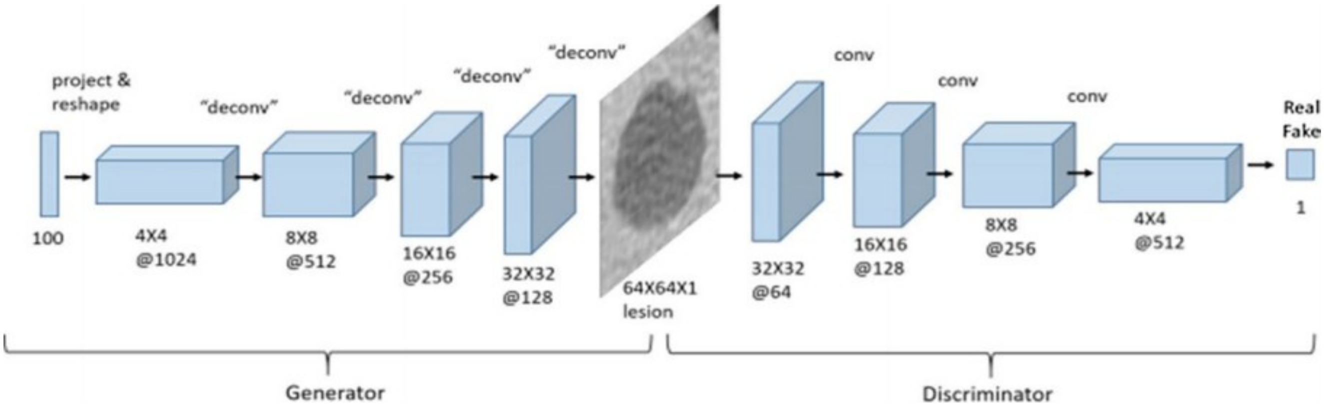

Figure 2. Generative Adversarial Network (GAN) (4).

6. Conclusion

In this article, an overview of recent work done in the field of biometric recognition through deep learning has been provided. A comprehensive overview of the use of deep learning in unimodal and multimodal biometrics has been provided. Deep learning has shown great potential over conventional ways of feature extraction and recognition. Although some biometric techniques such as face have been more popular, other biometric traits are also picking up rapidly.

Though deep learning models have obtained promising results, there are still some challenges faced by biometric recognition systems. First among them is real-time implementation as deep nets are slow and require more resources and power to implement. Second is the lack of memory-efficient networks. Many deep learning-based models need substantial memory even during inference. To date, much of the attention has concentrated on increasing the performance of these models, but to incorporate deep learning into real-world biometric applications, networks must be optimized. This can be done either using a simpler model and model compression techniques or by training a complex model and then using knowledge distillation techniques to compress it into a smaller network imitating the initial complex model. A memory-efficient model opens the door to these models, which can be used even on consumer devices. Thirdly, biometric recognition systems protection is of great importance. The presentation attack and adversarial attack endanger deep biometric recognition systems' reliability and question the current antispoofing methods. While there have been some attempts to detect adversarial cases, there is still a long way toward robust/reliable antispoofing capabilities. Fourthly, deep networks are data-hungry networks and require a large amount of data for training. However, except for the face, datasets with a substantial number of images are not available. However, GAN and image augmentation for preprocessing images have been a great help for the recognition system as it helps in data enhancement and generation.

The limiting factor for leveraging the full power of deep learning CNN architecture in biometrics is the lack of labeled data. Further, the labeled data available as been obtained under standard conditions, and few databases have been acquired in outdoor conditions. In the future, if sufficient labeled data is made available, then deep networks may be developed from scratch for a given biometric problem. Also, the development of databases in the wild is the need of the hour to test deep learning efficacy in real-world applications. Despite this, biometric identification using deep learning has made rapid progress in a decade of research. However, there is still a long way to go as there are challenges that need to be overcome to get a secure, accurate, and robust identification system using deep nets.

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