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Deep Learning: Biometric Applications

Deep Learning in Biometrics

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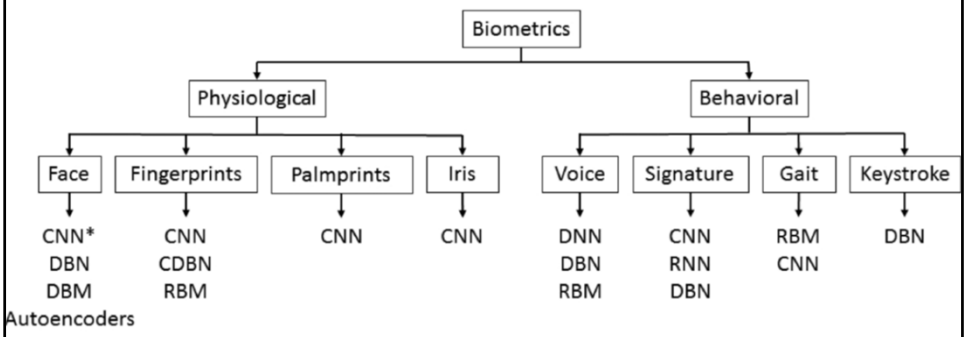
Academic year 2018/2019

Summary

- Introduction
- Face
- Fingerprint
- Iris
- Other Biometric Traits
- Discussion

Introduction

Different Deep Learning Techniques for Different Biometric Traits



Kalaivani Sundararajan,D. L. Woodard, Deep Learning for Biometrics: A Survey, ACM Comput. Surv. 51, 3, May 2018.

Identification Using Deep Learning

Deep Learning

Sample

→ Trained Classifier → Integer Identifier

Use samples of every individual during the training step

Algoritmic

```
For each template i in Gallery
        M(i) = identiry_verification(Fresh, Gallery(i))
end
ID = argmax(M)
```

Kalaivani Sundararajan,D. L. Woodard, Deep Learning for Biometrics: A Survey, ACM Comput. Surv. 51, 3, May 2018.

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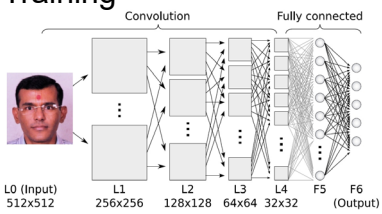
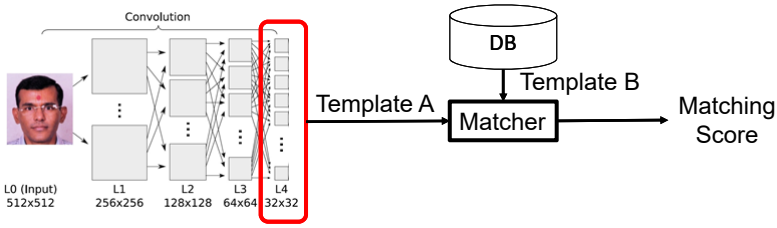
Identity Verification Using Deep Learning (1/2)

Training



Verification



Kalaivani Sundararajan,D. L. Woodard, Deep Learning for Biometrics: A Survey, ACM Comput. Surv. 51, 3, May 2018.

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Face

Some Deep Learning Appraoches for Face Recognition

Method	Recognition mode	Input	#Convolution layers	#Pooling layers	#Fully connected layers	Classification	#nets
Sun et al. [136]	Verification	60 face patches (39 × 31 and 31 × 31 patches)	4 layers (20 × 4 × 4 SW, 40 × 3 × 3 SW, 60 × 3 × 3 LS, 80 × 2 × 2 US)	3 (max pooling with 2 × 2 filters)	1 (160-dim DeepID features)	Joint Bayesian	60
Sun et al. [135]	Verification	25 face patches	4 layers (20 × 4 × 4 SW, 40 × 3 × 3 SW, 60 × 3 × 3 LS, 80 × 2 × 2 LS)	3 (max pooling with 2 × 2 filters)	1 (160-dim DeepID2 features)	Joint Bayesian	25
Sun et al. [137]	Verification	25 face patches	4 layers (128 × 4 × 4 SW, 128 × 3 × 3 SW, 128 × 3 × 3 LS, 128 × 2 × 2 LS)	3 (max pooling with 2 × 2 filters)	4 (512-dim DeepID2+ features)	Joint Bayesian	25
Hu et al. [59]	Verification - Medium	58 × 58 faces	3 layers (16 × 5 × 5, 32 × 4 × 4, 48 × 3 × 3)	3 layers (2 × 2 filters)	1 (160-dim)	Joint Bayesian	1
Taigman et al. [142]	Verification	152 × 152 RGB faces	5 layers (32 × 11 × 11 SW, 16 × 9 × 9 SW, 16 × 9 × 9 LS, 16 × 7 × 7 LS, 16 × 5 × 5 LS)	1 layer (3 × 3 filters)	1 (4096-dim)	Weighted χ^2 similarity	1
Zhu et al. [176]	Identification	96 × 96 grayscale faces	3 layers (32 × 5 × 5 LS, 32 × 5 × 5 LS, 32 × 5 × 5 LS)	2 layers (2 × 2 filters)	1 (96 × 96 reconstruction layer)	LDA	1
Pattabhi et al. [108]	Identification	28 × 32 faces	2 layers (6 × 5 × 5, 12 × 5 × 5)	2 layers (2 × 2 filters)		Neural network	1
Liu et al. [84]	Verification & Identification	7 face patches	9 layers	Yes	1 layer	softmax layer & triplet loss	7
Zhou et al. [174]	Verification	4 face patches	10 layers	Yes	1 layer	softmax layer	4
Chen et al. [18]	Verification & Identification	100 × 100 faces	10 layers (32 × 3 × 3, 64 × 3 × 3 (2), 128 × 3 × 3, 96 × 3 × 3, 192 × 3 × 3, 128 × 3 × 3, 256 × 3 × 3, 160 × 3 × 3, 320 × 3 × 3)	5 layers (2 × 2 (4), 7 × 7 mean)	1 (10548-dim)	Joint Bayesian	1
Parkhi et al. [107]	Verification	224 × 224 face patches	13 layers (64 × 3 × 3 (2), 128 × 3 × 3 (2), 256 × 3 × 3 (3), 512 × 3 × 3 (3))	5 layers (2 × 2 max-pooling)	3 (4096, 4096, 2622)	triplet loss metric learning	1
Schroff et al. [128]	Verification, identification & clustering	224 × 224 face patches	11 layers (64 × 7 × 7, 64 × 1 × 1, 64 × 3 × 3, 192 × 1 × 1, 192 × 3 × 3, 384 × 1 × 1, 384 × 3 × 3, 256 × 1 × 1, 256 × 3 × 3, 256 × 1 × 1, 256 × 3 × 3)	4 layers (3 × 3 filters)	3 (32 × 128, 32 × 128, 128)	triplet loss embedding	1
Wen et al. [153]	Verification	-	6 layers (128 × 3 × 3, 128 × 3 × 3 (2), 128 × 3 × 3, 256 × 3 × 3LS, 256 × 3 × 3LS, 256 × 3 × 3LS)	4 layers (2 × 2)	1 (512-dim)	softmax & center loss	1
Sun et al. [138]	Verification	25 face patches	10 layers (64 × 3 × 3, 64 × 3 × 3, 96 × 3 × 3, 96 × 3 × 3, 192 × 3 × 3, 192 × 3 × 3, 256 × 3 × 3, 256 × 3 × 3, 256 × 3 × 3, 256 × 3 × 3LS)	4 (max pooling with 2 × 2 filters)	1 (512-dim)	Joint Bayesian	25

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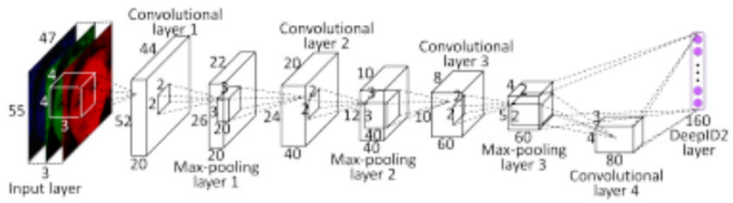
Examples of Face recognition methods (1/2)

Feature extraction



Matching
- PCA for dimensionality reduction
- Log likelyhood ratio

Yi Sun, Yuheng Chen, Xiaogang Wang, and Xiaoou Tang,Deep learning face representation by joint identification-verification, in Proc. of the 27th Int. Conf. on Neural Informatio Processing Systems, 2014.

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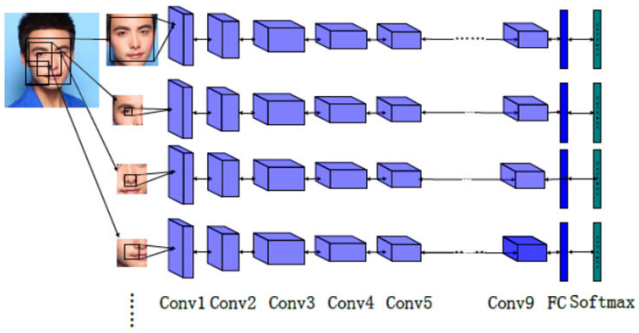
Examples of Face recognition methods (1/2)



Jinguo Liu, Yafeng Deng, and Chang Huang, Targeting ultimate accuracy: Face recognition via deep embedding, 2015.

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Some Results for Face Recognition

Table 2. Face Recognition Results: LFW (13,323 Images, 5,749 Celebrities)

Methods	Arch.	Training Dataset	Training #img	Training #subj	Protocol	Verification acc (%)	Open set acc (%)	Closed acc (%)
Cao et al. [14]	Joint Bayesian	-	-	-	unrestricted	96.33 ± 1.08	-	-
Chen et al. [17]	LBP	-	-	-	unrestricted	95.17 ± 1.13	-	-
Lu et al. [89]	Gaussian Face	-	-	-	unrestricted	98.52 ± 0.66	-	-
Best et al. [11]	COTS-s1+s4	-	-	-	unrestricted	-	66.5	35
Sun et al. [136]	CNN*	CelebFaces+	202,599	10,177	unrestricted	97.45 ± 0.26	-	-
Sun et al. [135]	CNN*	CelebFaces+	202,599	10,177	unrestricted	96.39 ± 0.13	-	-
Sun et al. [137]	CNN*	CelebFaces+, WDRef	290,000	12,000	Jain	99.47 ± 0.12	80.7	95.0
Taigman et al. [142]	CNN*	SFC	4,000,000	4,000	unrestricted	97.35 ± 0.25	-	-
Liu et al. [84]	CNN*	Private	1,200,000	18,000	unrestricted	99.41	**95.80**	**98.03**
Chen et al. [18]	CNN*	CASIA-WebFace	490,356	10,548	unrestricted	97.45 ± 0.70	-	-
Parkhi et al. [107]	CNN*	Private	2,600,000	2,622	unrestricted	98.95	-	-
Schroff et al. [128]	CNN*	Private	100M-200M	8M	unrestricted	**99.63 ± 0.09**	-	-
Zhou et al. [174]	CNN*	Megvii	5,000,000	20,000	-	99.5	-	-
Taigman et al. [143]	CNN*	SFC	4,500,000	55,000	unrestricted	97.17	46.3	72.3
Wen et al. [153]	CNN*	private dataset	700,000	-	-	99.28	-	-
Sun et al. [138]	CNN*	CelebFaces+, WDRef	290,000	12,000	-	99.30	-	-
Peng et al. [109]	CNN*	CASIA WebFace	494,414	10,575	-	96.60	-	-

*Deep learning approach.

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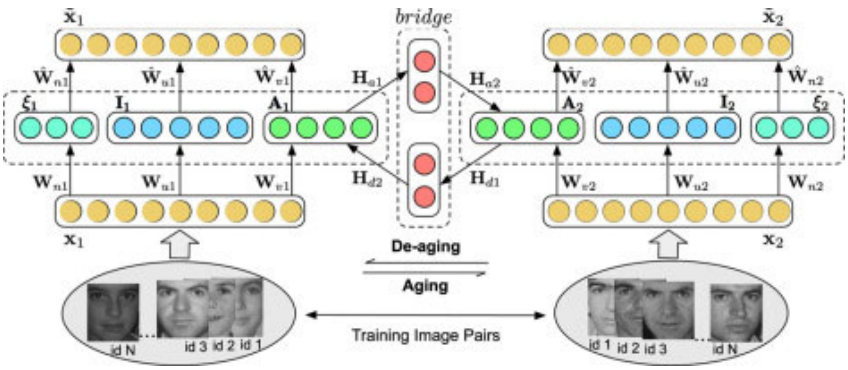
Age Invariant Face Recognition



Chenfei Xu, Qihe Liu, Mao Ye, Age invariant face recognition and retrieval by coupled auto-encoder networks, Neurocomputing, vol. 222, 2017, pp. 62-71.

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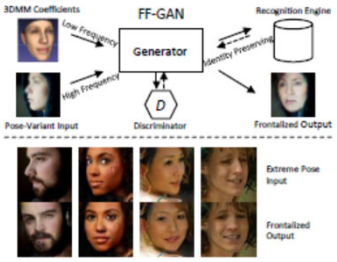
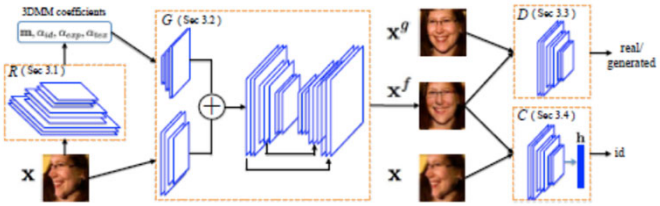
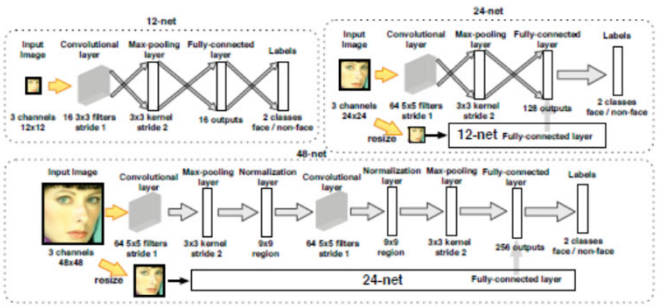
Rotation Invariant Face Recognition

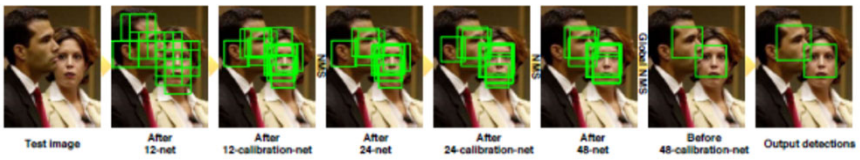




Chenfei Xu, Qihe Liu, Mao Ye, Age invariant face recognition and retrieval by coupled auto-encoder networks, Neurocomputing, vol. 222, 2017, pp. 62-71.

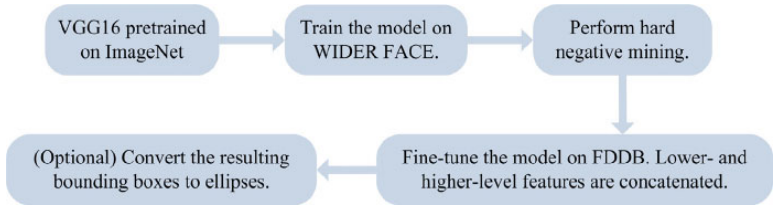
Face Detection (1/2)

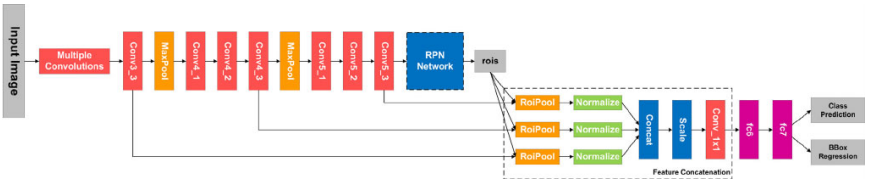




H. Li, Z. Lin, X. Shen, J. Brandt and G. Hua, A convolutional neural network cascade for face detection, in Proc. of the IEEE Conf. on Computer Vision and Pattern Recognition (CVPR), 2015, pp. 5325-5334.

Face Detection (2/2)





X. Sun, P. Wu, S.C.H. Hoi, Face detection using deep learning: An improved faster RCNN approach, Neurocomputing, volume 299, 2018, pp. 42-50.

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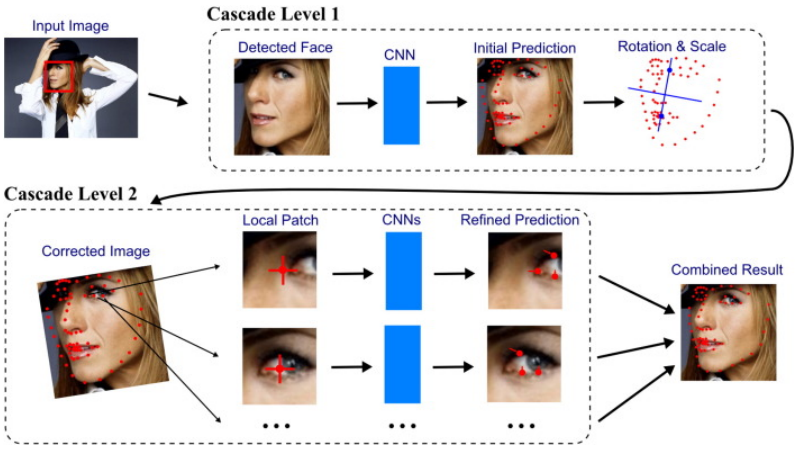
Estimation of Fiducial Points



H. Fan, E. Zhou, Approaching human level facial landmark localization by deep learning, Image and Vision Computing, vol. 47, 2016, pp. 27-35.

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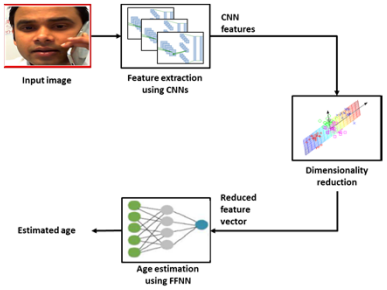
Age Estimation



A. Anand, R. Donida Labati, A. Genovese, E. Muñoz, V. Piuri and F. Scotti, Age estimation based on face images and pre-trained Convolutional Neural Networks, in Proc. of the IEEE Symp. on Computational Intelligence for Security and Defense, pp. 1-7, November 27-30, 2017.

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Some Results for Age Estimation

Attribute	Testing		Methods	Arch.	Training		#classes	MAE	Acc (%)
	Dataset	#img			Dataset	#img			
Age		-	Guo et al. [49]	BIF + KCCA	-	-	-	3.98	-
		-	Guo et al. [48]	BIF + KPLS	-	-	-	4.04	-
	MORPH-II	5-fold CV	Huerta et al. [62]	CNN*	MORPH-II	55,134	Regr.	3.88	-
		42,635	Yi et al. [162]	CNN*	MORPH-II	10,634	Regr.	3.63	-
		5,670	Qiu et al. [111]	CNN*	MORPH-II	47,582	Regr.	3.41	-
		44,634	Li et al. [81]	CNN*	MORPH-II	10,500	Regr.	3.61	-
		1,095	Wang et al. [151]	CNN*	MORPH-II	4,380	Regr.	4.77	-
		5-fold CV	Liu et al. [83]	CNN*	MORPH-II	-	Regr.	2.89	-
			Rothe et al. [121]	CNN*	IMDB-Wiki	523,051	101	**2.68**	-
			Han et al. [52]	CNN*	IMDB-Wiki	523,051	Regr	3.0	85.3
	Adience	5-fold CV	Levi et al. [79]	CNN*	Adience	26,000	8	-	84.70 ± 2.2
			Liu et al. [83]	CNN*	Adience, MORPH-II, ChaLearn	-	-	-	**98.2 ± 0.7**
			Rothe et al. [121]	CNN*	IMDB-Wiki	523,051	20	-	96.6 ± 0.9
	ChaLearn	1136	Liu et al. [83]	CNN*	MORPH-II, FG-Net	-	-	0.315	-
			Ranjan et al. [116]	CNN*	ChaLearn, Adience, MORPH	7,000	Regr	0.359	-
			Rothe et al. [121]	CNN*	IMDB-Wiki	523,051	101	**0.282**	-
			Liu et al. [87]	CNN*	CASIA WebFace, MORPH-II	1,315,000	-	0.287	-
			Ranjan et al. [115]	CNN*	IMDB-Wiki, Adience, MORPH	299,818	Regr	0.293	-
			Han et al. [52]	CNN*	IMDB-Wiki	523,051	3	0.289	-

CV, cross-validation; LOPO, leave one person out.
*Deep learning approach.

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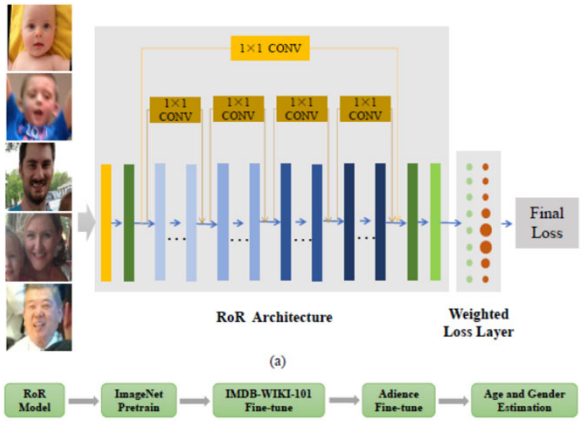
Gender and Ethnicity Estimation



K .Zhang, C. Gao, L. Guo. M. Sun, X. Yuan, T.X. Han, Z. Zhao, B. Li, Age Group and Gender Estimation in the Wild With Deep RoR Architecture, IEEE Access, vol. 5 , 2017.

Some Results for Gender and Ethnicity Estimation

Attribute	Testing		Methods	Arch.	Training		#classes	MAE	Acc (%)
	Dataset	#img			Dataset	#img			
Gender	MORPH-II	-	Guo et al. [49]	BIF + KCCA	-	-	-	-	98.45
		-	Guo et al. [48]	BIF + KPLS	-	-	-	-	98.35
		42,635	Yi et al. [162]	CNN*	MORPH-II	10,634	2	-	97.90
		44,634	Li et al. [81]	CNN*	MORPH-II	10,500	2	-	**98.48**
			Han et al. [52]	CNN*	IMDB-Wiki	523,051	2	-	98.0
	AR	1,275	Jiang et al. [67]	CNN*	FERET, CAS-PEAL	10,800	2	-	70.50
		3,288	Juefei et al. [69]	CNN*	MugshotDB, Pinellas	89,003	2	-	**85.62**
	Adience	5-fold CV	Levi et al. [79]	CNN*	Adience	26,000	2	-	86.80 ± 1.4
Ethnicity	MORPH-II	-	Guo et al. [49]	BIF + KCCA	-	-	-	-	98.95
		-	Guo et al. [48]	BIF + KPLS	MORPH-II	10,634	2	-	**99.0**
		42,635	Yi et al. [162]	CNN*	MORPH-II	10,634	2	-	98.60
			Han et al. [52]	CNN*	IMDB-Wiki	523,051	3	-	98.6

CV, cross-validation; LOPO, leave one person out.
*Deep learning approach.

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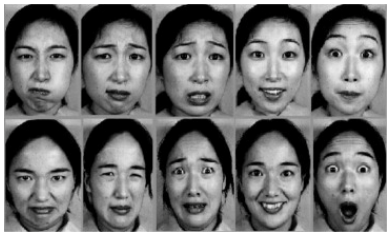
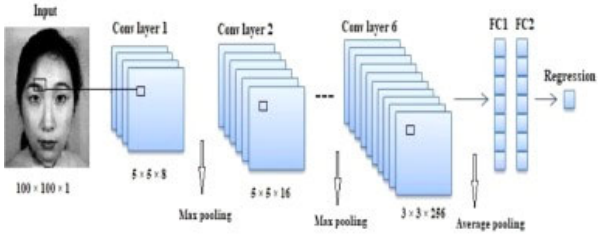
Emotion Estimation





N. Jain, S. Kumar, A. Kumar, P. Shamsolmoali, M. Zareapoor, Hybrid deep neural networks for face emotion recognition, Pattern Recognition Letters, 2018.

Fingerprint

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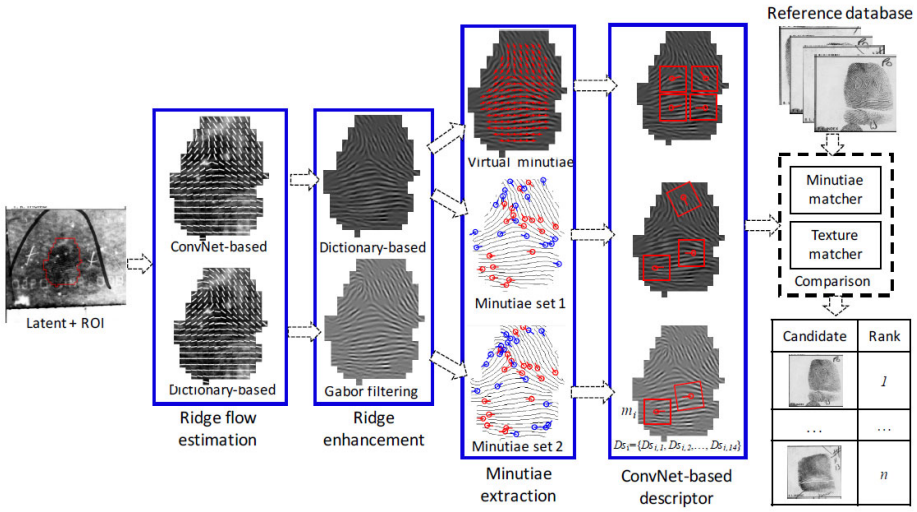
Latent Fingerprint



K. Cao and A. K. Jain, Automated Latent Fingerprint Recognition, in IEEE Trans. on Pattern Analysis and Machine Intelligence, 2017.

Some Results for Fingerprint Recognition

Dataset	Methods	Representation	EER(%)	Rank1 (%)
FVC 2002	Hong et al. [57]	Gabor	24.34	-
	Chikkerur et al. [22]	STFT	**21.99**	-
	Sahasrabudhe et al. [122]	cRBM*	22.65	-
	Sahasrabudhe et al. [123]	cDBN*	23.95	-
NIST SD27	COTS latent AFIS	COTS	-	**67.0**
	CAO et al. [13]	CNN*	-	65.0
WVU DB	COTS latent AFIS	COTS	-	71.0
	CAO et al. [13]	CNN*	-	**75.0**

*Deep learning approach.

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Live fingerprint acquisitions?

- Local features
- Repetitive pattern
- Rotations
- Non-linear distortions

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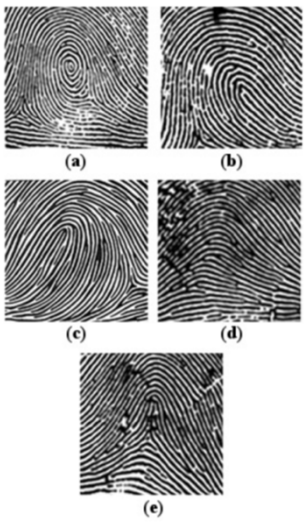
Fingerprint Classification



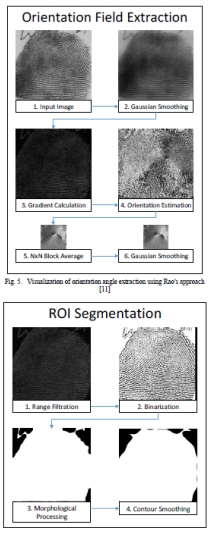
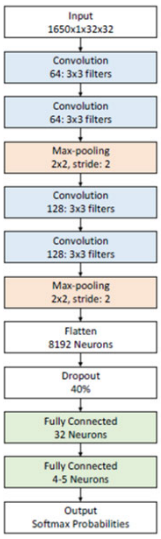


Fig. 5. Visualization of orientation angle extraction using Rao's approach [11]



J. M. Shrein, Fingerprint classification using convolutional neural networks and ridge orientation images, 2017 IEEE Symposium Series on Computational Intelligence (SSCI), 2017, pp. 1-8.

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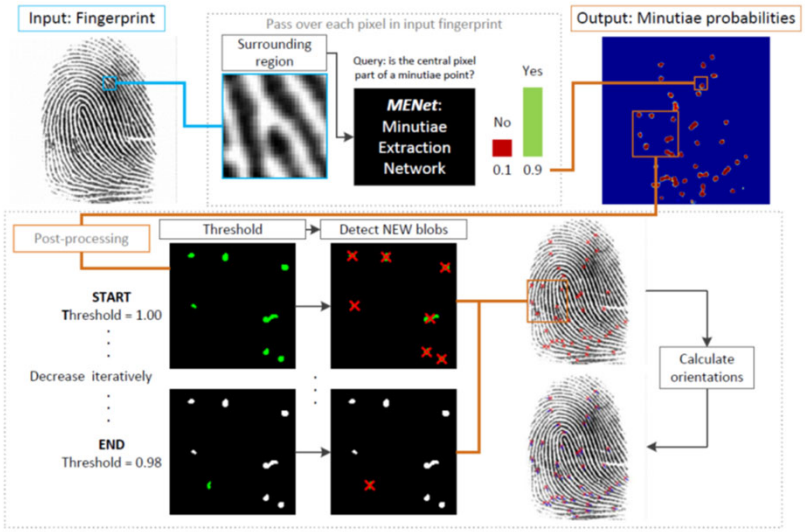
Minutiae Extraction



L. N. Darlow and B. Rosman, Fingerprint minutiae extraction using deep learning, IEEE International Joint Conference on Biometrics (IJCB), 2017, pp. 22-30

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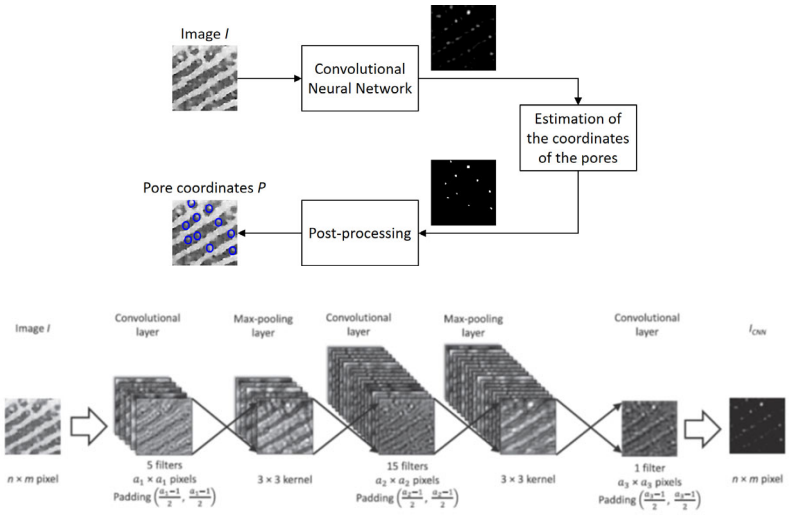
Pore Extraction (1/2)



R. Donida Labati, A. Genovese, E. Muñoz, V. Piuri, F. Scotti, A novel pore extraction method for heterogeneous fingerprint images using Convolutional Neural Networks, Pattern Recognition Letters, Vol. 113, 2018, pp. 58-66.

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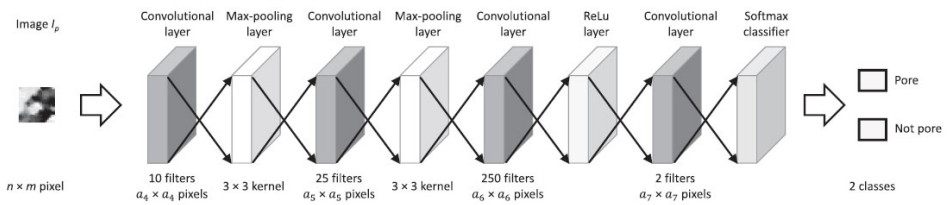
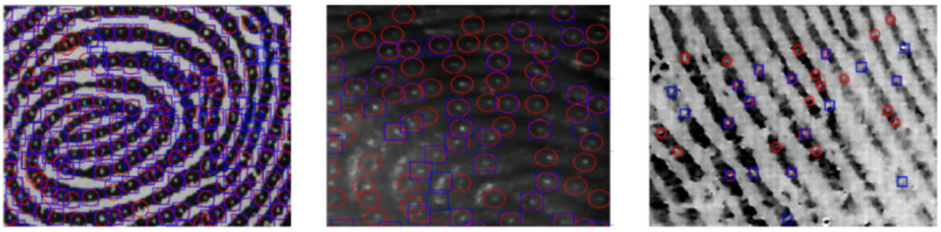
Quality Estimation

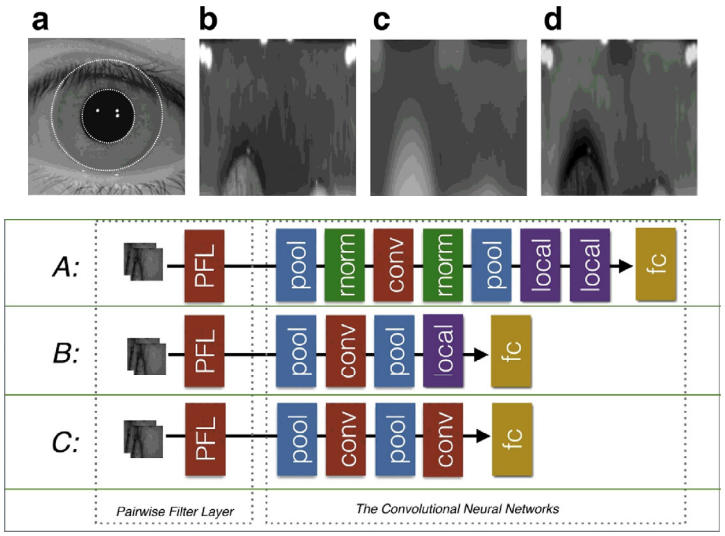




R. Donida Labati, A. Genovese, E. Muñoz, V. Piuri, F. Scotti, A novel pore extraction method for heterogeneous fingerprint images using Convolutional Neural Networks, Pattern Recognition Letters, Vol. 113, 2018, pp. 58-66.

Iris

Iris Recognition



N. Liu, M. Zhang, H. Li, Z. Sun, T. Tan, DeepIris: Learning pairwise filter bank for heterogeneous iris verification, Pattern Recognition Letters, vol. 82, 2016, pp. 154-161.

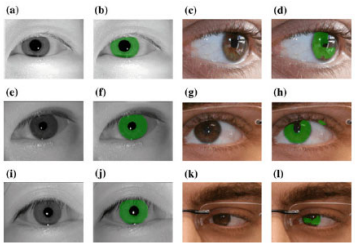
Some Results for Iris Recognition

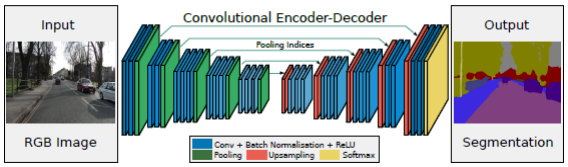
Dataset	Methods	Representation	EER(%)
MICHE-I	Daugman et al. [24]	Gabor	8.35
	Raghavendra et al. [113]	LBP	5.22
	Raja et al. [114]	SAE*	**3.93**
VSSIRIS	Daugman et al. [24]	Gabor	3.57
	Raghavendra et al. [113]	LBP	9.45
	Raja et al. [114]	SAE*	**1.70**
Q-FIRE	Weinberger et al. [152]	LMNN	1.73
	Liu et al. [85]	MDML	1.67
	Liu et al. [86]	CNN*	**0.15**
LG2200	Daugman et al. [24]	Gabor	7.12
	Gangwar et al. [41]	CNN*	**2.40**
LG4000	Daugman et al. [24]	Gabor	5.30
	Gangwar et al. [41]	CNN*	**1.82**

*Deep learning approach.

Kalaivani Sundararajan,D. L. Woodard, Deep Learning for Biometrics: A Survey, ACM Comput. Surv. 51, 3, May 2018.

Iris Segmentation

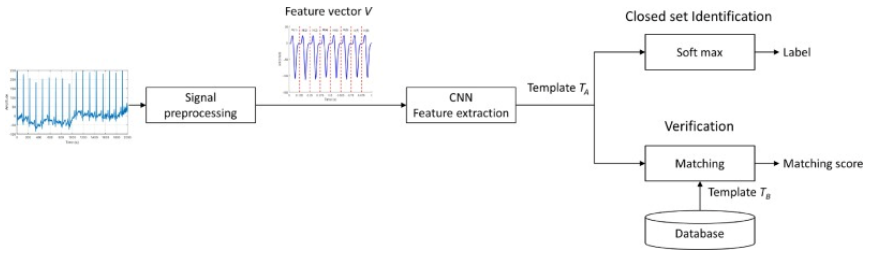


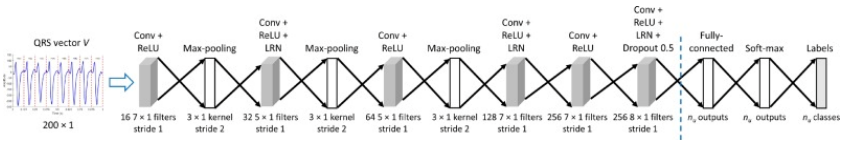


E. Jalilian, A. Uhl, Iris Segmentation Using Fully Convolutional Encoder–Decoder Networks. In Deep Learning for Biometrics, Springer, Cham, 2017.

Other Biometric Traits

Electrocardiographic Signals (ECG)



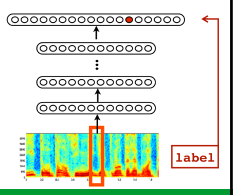


R. Donida Labati, E. Muñoz, V. Piuri, R. Sassi, F. Scotti, Deep-ECG: Convolutional Neural Networks for ECG biometric recognition, Pattern Recognition Letters, 2018.

Some Results for Speaker Recognition

Testing					Training			
Dataset	**#trials**	**#subj**	**Methods**	**Arch.**	**Dataset**	**#trials**	**#subj**	**EER(%)**
SRE 2012	C2,C5	-	Li et al. [78]	UBM-EM (4096)	SRE 2012	-	1,918	2.18
				DNN*				**1.66**
	C2	1,040	Kenny et al. [70]	DNN*	SRE 2012	4,432	1,040	2.16
SRE 2012 training data	male	1,000	Vasilakakis et al. [148]	GMM	SRE 2012 training data	28,920	1,818	**0.45**
				DBN*				0.58
SRE 2010 telephone	-	7,196	Garcia et al. [42]	GMM	Switchboard I & II	33,039	3,114	6.92
				DNN*				4.20
			Saleem et al. [125]	DNN*	SRE 2004 & 2005 & 2006			**2.18**
SRE 2006	51,068	816	Ghahabi et al. [44]	i-vector	SRE 2004 & 2005	6,000	-	7.18
				DBN*				6.44
			Ghahabi et al. [46]	RBM*	SRE 2004 & 2005	6,125	-	7.58
			Ghahabi et al. [47]	DBN & DNN*	SRE 2004 & 2005 & 2006	-	-	**4.76**

*Deep learning approach.



Kalaivani Sundararajan,D. L. Woodard, Deep Learning for Biometrics: A Survey, ACM Comput. Surv. 51, 3, May 2018.

Some Results for Signature Verification

Datasets	Methods	Representation	EER(%)	FAR(%)	FRR(%)	Acc(%)
SVS 2004	Fallah et al. [36]	Mellin transform, MFCC, etc.	3.0	-	-	-
	Ansari et al. [6]	Fuzzy modeling	2.46	-	-	-
	Fayyaz et al. [38]	SAE*	**2.15**	-	-	-
	Lai et al. [75]	RNN*	2.37	-	-	-
GPDS-300	Ferrer et al. [39]	Geometric features	-	13.12	15.41	86.65
	Vargas et al. [145]	High-pressure pts	-	14.66	10.01	**87.67**
	Ribeiro et al. [118]	DBN*	-	14.67	20.25	82.85
	Hafemann et al. [51]	CNN*	10.70	9.08	20.60	-
	Haemann et al. [50]	CNN*	**3.47**	**5.13**	**6.55**	-
	Dey et al. [29]	CNN*	-	23.17	23.17	76.83

*Deep learning approach.

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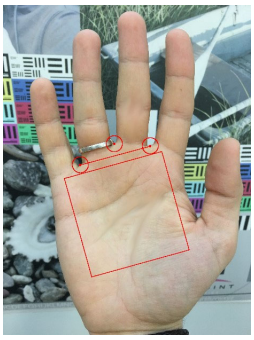
Some Results for Palmprint Verification

Datasets	Methods	Representation	Recognition Accuracy(%)	EER(%)
PolyU	Lu et al. [90]	Enhanced GRCM	98.0	-
	Xu et al. [157]	Quaternion PCA+Quaternion DWT	98.83	-
	Jia et al. [65]	KPCA on HOL	99.73	-
	Jalali et al. [64]	CNN*	99.98	-
	Minaee et al. [102]	Scattering networks*	**100.0**	-
	Dian et al. [30]	CNN*	-	0.0443

*Deep learning approach.



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Some Results for Gait Recognition

Datasets	Methods	Representation	Accuracy(%)
	Different views		
CASIA-B	Kusakunniran et al. [74]	CCA	68.5
	Yu et al. [164]	GEI+NN	23.76
	Wu et al. [156]	CNN*	84.67
	Yan et al. [159]	CNN*	30.55
	Alotaibi et al. [5]	CNN*	85.51
	Hossain et al. [58]	RBM*	92.50
	Wolf et al. [155]	3D-CNN*	**97.35**
	Different scenes		
	Hu et al. [60]	LF+iHMM	71.76
	Kusakunniran et al. [73]	STIP	79.66
	Yan et al. [159]	CNN*	**95.0**
	Alotaibi et al. [5]	CNN*	86.70
OU-ISIR	Muramatsu et al. [103]	TCM+	72.80
	Muramatsu et al. [104]	wQVTM	70.51
	Wu et al. [156]	CNN*	94.8
	Zhang et al. [166]	CNN*	80.50
	Shiraga et al. [129]	CNN*	90.45
	Li et al. [80]	CNN*	**95.04**

*Deep learning approach.

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Discussion

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Impact of Deep Learning in Biometrics

- Feature learning
- Invariant representations
- Generalization capability
- Beyond bag of words features

Real-World Applicability

- Beyond face and voice recognition
- Scaling up in terms of identification
- Large-scale datasets
- Dataset quality
- Computing resources
- Training speed-up
- Behavioral biometrics