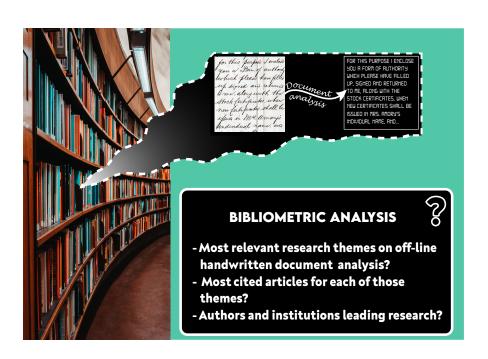
Examining the Literature from 1990 to 2020 on Off-line Handwritten Document Analysis

Victoria Ruiz, Rubén Heradio, Ernesto Aranda-Escolástico, Ángel Sánchez, and José F. Vélez

Appendix: Most Influential Papers



Abstract

This document is an appendix to the paper "Examining the Literature from 1990 to 2020 on Off-line Handwritten Document Analysis", whose abstract is the following one:

Computers with the ability to process handwriting is both important and challenging since many difficulties (e.g., different writing styles, alphabets, languages, etc.) need to be overcome for addressing a variety of problems (text recognition, signature verification, writer identification, word spotting, etc.). This paper reviews the growing literature on off-line handwritten document analysis over the last thirty years. A sample of 5,389 articles is examined using bibliometric techniques. This paper identifies (i) the most influential articles in the area, (ii) the most productive authors and their collaboration networks, (iii) the countries and institutions that have led research on the topic, (iv) the journals that have published most papers, and (v) the most relevant research topics and their evolution over the years.

This appendix summarizes the most influential papers identified in our bibliometric analysis.

Contents

Lı	st of	tables																						V1
1	Mo	st Influen	tial	Pape	\mathbf{rs}	0	f t	hε	, 1	W	ho	ole	e A	٩r	ea	ì								1
2	Mo	st Influen	tial	Pape	rs	p	er	P	er	ic	\mathbf{d}	a	nc	1 ′.	Γŀ	ıeı	\mathbf{m}	\mathbf{at}	ic	A	re	ea		9
	2.1	Period 1:	1990)-1994																				9
	2.2	Period 2:	1995	5-1999																				10
	2.3	Period 3:	2000)-2004																				11
	2.4	Period 4:	2005	5-2009																				12
	2.5	Period 5:	2010)-2014																				13
	2.6	Period 6:	2015	5-2020																			•	15
$\mathbf{R}_{\mathbf{c}}$	efere	nces																						19

List of Tables

1.1	Citation classics (the h -index is 93)	1
1.2	Hot papers: top 5 cited articles in 2020, 2019 and 2018	7
2.1	Thematic networks' performance (Period 1: 1990-1994)	9
2.2	Thematic networks' performance (Period 2: 1995-1999)	10
2.3	Thematic networks' performance (Period 3: 2000-2004)	11
2.4	Thematic networks' performance (Period 4: 2005-2009)	12
2.5	Thematic networks' performance (Period 5: 2010-2014)	13
2.6	Thematic networks' performance (Period 6: 2015-2020)	15

Most Influential Papers of the Whole Area

This chapter identifies the most relevant papers on the *Off-line Handwritten Document Analysis* research area considered as a whole. To do so, we use the concepts of citation classics. Garfield [71] coined the term *citation classics* to refer to the most impacting papers of a research area according to their number of citations. Later, Martinez et al. [157] provided the following formal definition, which will be used in this paper: "the citation classics, also called the h-core, of a research area whose h-index is h are the top h cited papers".

Table 1.1 summarizes the identified citation classics, whose h-index is 93. Table 1.2 includes the 5 most cited papers from 2018, 2019 and 2020.

Table 1.1: Citation classics (the h-index is 93).

Paper	Year	Publisher	#Cit
Plamondon and Srihari [176]. On-line and off-line	2000	IEEE T Pattern	1,749
handwriting recognition: A comprehensive survey		Anal	
Xu et al. [244]. Methods of combining multiple clas-	1992	IEEE T syst Man	1,655
sifiers and their applications to handwriting recogni-		Cyb	
tion			

Paper	Year	Publisher	#Cit
Hull [99]. A database for handwritten text recogni-	1994	IEEE T Pattern	1,029
tion research		Anal	
Graves et al. [75]. A novel connectionist system for	2009	IEEE T Pattern	982
unconstrained handwriting recognition		Anal	
Marti and Bunke [156]. The IAM-database: An En-	2003	Int J Doc Anal Recog	588
glish sentence database for offline handwriting recog-			
nition			
Graves and Schmidhuber [76]. Offline handwriting	2009	NeurIPS	522
recognition with multidimensional recurrent neural			
networks			
Huang and Suen [98]. A method of combining multi-	1995	IEEE T Pattern	418
ple experts for the recognition of unconstrained hand-		Anal	
written numerals			
Liu et al. [137]. Handwritten digit recognition:	2003	Pattern Recogn	401
Benchmarking of state-of-the-art techniques			
Lorigo and Govindaraju [147]. Offline Arabic hand-	2006	IEEE T Pattern	342
writing recognition: A survey		Anal	
Marti and Bunke [155]. Using a statistical language	2001	Int J Pattern Recogn	314
model to improve the performance of an HMM-based			
cursive handwriting recognition system			
Suen et al. [217]. Computer recognition of uncon-	1992	P IEEE	300
strained handwritten numerals			
Arica and Yarman-Vural [15]. An overview of char-	2001	IEEE T Syst Man Cy	291
acter recognition focused on off-line handwriting		С	
Said et al. [192]. Personal identification based on	2000	Pattern Recogn	246
handwriting			
Pham et al. [175]. Dropout Improves Recurrent Neu-	2014	ICFHR	239
ral Networks for Handwriting Recognition	2004	D. II. D.	224
Liu et al. [138]. Handwritten digit recognition: In-	2004	Pattern Recogn	226
vestigation of normalization and feature extraction			
techniques			
Bhattacharya and Chaudhuri [20]. Handwritten nu-	2009	IEEE T Pattern	210
meral databases of Indian scripts and multistage		Anal	
recognition of mixed numerals			
Kimura et al. [111]. Handwritten numerical recogni-	1991	Pattern Recogn	203
tion based on multiple algorithms			
Vinciarelli et al. [232]. Offline recognition of uncon-	2004	IEEE T Pattern	201
strained handwritten texts using HMMs and statisti-		Anal	
cal language models			

Paper	Year	Publisher	#Cit
Lauer et al. [124]. A trainable feature extractor for	2007	Pattern Recogn	194
handwritten digit recognition			
Kirn and Govindaraju [113]. A lexicon driven ap-	1997	IEEE T Pattern	189
proach to handwritten word recognition for real-time		Anal	
applications			
Fischer et al. [63]. Lexicon-free handwritten word	2012	Pattern Recogn Lett	186
spotting using character HMMs			
Madhvanath and Govindaraju [151]. The role of	2001	IEEE T Pattern	177
holistic paradigms in handwritten word recognition	1000	Anal	
Kato [106]. A handwritten character recognition sys-	1999	IEEE T Pattern	177
tem using directional element feature and asymmetric		Anal	
mahalanobis distance			
Manmatha et al. [153]. Word spotting: a new ap-	1996	CVPR	176
proach to indexing handwriting	1000	IEEE T Pattern	170
El-Yacoubi et al. [58]. An HMM-based approach	1999		173
for off-line unconstrained handwritten word modeling		Anal	
and recognition	1004	IEEE T Pattern	170
Chen et al. [33]. OffLine handwritten word recog-	1994		173
nition using a hidden Markov model type stochastic		Anal	
network	1000	IEEE T. D. t	170
Senior and Robinson [198]. An off-line cursive hand-	1998	IEEE T Pattern	172
writing recognition system Liu et al. [142]. Online and offline handwritten Chi-	2013	Anal Pattern Recogn	169
	2013	1 attern recogn	103
nese character recognition: Benchmarking on new			
databases España-Boquera et al. [60]. Improving offline hand-	2011	IEEE T Pattern	168
	2011		100
written text recognition with hybrid HMM/ANN		Anal	
models Oliveira et al. [166]. Automatic recognition of hand-	2002	IEEE T Pattern	165
	2002		100
written numerical strings: A Recognition and Verifi-		Anal	
cation strategy Thoma at al. [258] High performance offline	2015	ICDAR	158
Zhong et al. [258]. High performance offline	2010	IODAN	100
handwritten Chinese character recognition using			
GoogLeNet and directional feature maps Lavrenko et al. [125]. Holistic Word Recognition for	2004	DIAL	155
	2004	DIAL	100
Handwritten Historical Documents Marti and Bunke [154]. A full English sentence	1999	ICDAR	154
	1000	100/110	104
database for off-line handwriting recognition			

Paper	Year	Publisher	#Cit
Zheng and Doermann [257]. Machine printed text	2004	IEEE T Pattern	142
and handwriting identification in noisy document im-		Anal	
ages			
Plötz and Fink [177]. Markov models for offline hand-	2009	Int J Doc Anal Recog	141
writing recognition: A survey			
Adankon and Cheriet [4]. Model selection for the	2009	Pattern Recogn	140
LS-SVM. Application to handwriting recognition			
Fukushima and Wake [66]. Handwritten Alphanu-	1991	IEEE T Neural	140
meric Character Recognition by the Neocognitron		Netwo	
Louloudis et al. [148]. Text line and word segmenta-	2009	Pattern Recogn	138
tion of handwritten documents			
Rodríghez-Serrano and Perronnin [188].Handwritten	2009	Pattern Recogn	136
word-spotting using hidden Markov models and uni-			
versal vocabularies			
C.L Liu et al. [134]. Lexicon-driven segmentation	2002	IEEE T Pattern	134
and recognition of handwritten character strings for		Anal	
Japanese address reading			
Ha and Bunke [81]. Off-line, handwritten numeral	1997	IEEE T Pattern	133
recognition by perturbation method		Anal	
Zhang et al. [254]. Online and offline handwrit-	2017	Pattern Recogn	132
ten Chinese character recognition: A comprehensive			
study and new benchmark			
Li et al. [130]. Script-independent text line segmen-	2008	IEEE T Pattern	132
tation in freestyle handwritten documents		Anal	
Jain and Zongker [101]. Representation and recogni-	1997	IEEE T Pattern Ana	132
tion of handwritten digits using deformable templates			
Shi et al. [203]. Handwritten numeral recognition	2002	Pattern Recogn	130
using gradient and curvature of gray scale image			
Chacko et al. [29]. Handwritten character recogni-	2012	Int J Mach Learn	126
tion using wavelet energy and extreme learning ma-		Cyb	
chine			
Kimura et al. [112]. Improvement of handwritten	1997	Pattern Recogn	126
Japanese character recognition using weighted direc-			
tion code histogram Hildebrant and Liu [94]. Optical recognition of hand-	1993	Pattern Recogn	126
written Chinese characters: Advances since 1980	1000	1 3000111 10000811	120
Lu and Shridhar [150]. Character segmentation in	1996	Pattern Recogn	124
handwritten words - An overview			
Wunsch and Laine [242]. Wavelet descriptors for	1995	Pattern Recogn	123
		1	

Paper	Year	Publisher	#Cit
El-Hajj et al. [56]. Arabic handwriting recognition	2005	ICDAR	122
using baseline dependant features and hidden Markov			
modeling			
Lee [128]. Off-line recognition of totally uncon-	1996	IEEE T Pattern	122
strained handwritten numerals using multilayer clus-		Anal	
ter neural network			
Yamada et al. [245]. A nonlinear normalization	1990	Pattern Recogn	121
method for handprinted kanji character recognition-			
line density equalization			
Koerich et al. [115]. Large vocabulary off-line hand-	2003	Pattern Anal Appl	119
writing recognition: A survey			
Pal et al. [170]. Handwritten numeral recognition of	2007	ICDAR	118
six popular Indian scripts			
Bunke et al. [27]. Recognition of cursive roman hand-	2003	ICDAR	118
writing - past, present and future			
Chen and Wang [34]. Segmentation of single- or	2000	IEEE T Pattern	118
multiple-touching handwritten numeral string using		Anal	
background and foreground analysis			
Guerbai et al. [77]. The effective use of the one-class	2015	Pattern Recogn	117
SVM classifier for handwritten signature verification			
based on writer-independent parameters			
Mohamed and Gader [162]. Handwritten word recog-	1996	IEEE T Pattern	117
nition using segmentation-free hidden Markov mod-		Anal	
eling and segmentation-based dynamic programming			
techniques			
Liu et al. [143]. ICDAR 2011 Chinese handwriting	2011	ICDAR	113
recognition competition			
Al-HajjMohamad et al. [7]. Combining slanted-frame	2009	IEEE T Pattern	113
classifiers for improved HMM-based Arabic hand-		Anal	
writing recognition			
Liu and Nakagawa [136]. Evaluation of prototype	2001	Pattern Recogn	112
learning algorithms for nearest-neighbor classifier in			
application to handwritten character recognition			
Arica and Yarman-Vural [16]. Optical character	2002	IEEE T Pattern	111
recognition for cursive handwriting		Anal	
Knerr et al. [114]. Handwritten Digit Recognition	1992	IEEE T Neural Net-	111
by Neural Networks with Single-Layer Training		wor	
Pal and Datta [169]. Segmentation of Bangla uncon-	2003	ICDAR	109
strained handwritten text			

Paper	Year	Publisher	#Cit
Cao et al. [28]. Recognition of handwritten numerals	1995	Pattern Recogn	108
with multiple feature and multistage classifier			
Papavassiliou et al. [171]. Handwritten document	2010	Pattern Recogn	106
image segmentation into text lines and words			
Sudholt and Fink [214]. PHOCNet: A deep convolu-	2016	ICFHR	106
tional neural network for word spotting in handwrit-			
ten documents			
Yin and Liu [248]. Handwritten Chinese text	2009	Pattern Recogn	106
line segmentation by clustering with distance metric			
learning			
Liu [132]. Normalization-cooperated gradient feature	2007	IEEE T Pattern	105
extraction for handwritten character recognition		Anal	
Revow et al. [187]. Using generative models for hand-	1996	IEEE T Pattern	105
written digit recognition		Anal	
Pechwitz and Maergner [174]. HMM based approach	2003	ICDAR	104
for handwritten Arabic word recognition using the			
IFN/ENIT-database Heutte et al. [93]. HMM based approach for hand-	1998	ICDAR	104
• •	1330	IODAIL	104
written Arabic word recognition using the IFN/ENIT			
- database			
Salah et al. [193]. A selective attention-based	2002	IEEE T Pattern	102
method for visual pattern recognition with applica-		Anal	
tion to handwritten digit recognition and face recog-			
nition			
Wang et al. [236]. Handwritten Chinese text recog-	2012	IEEE T Pattern	101
nition by integrating multiple contexts		Anal	
Stamatopoulos et al. [211]. ICDAR 2013 handwriting	2013	ICDAR	100
segmentation contest			
Yin et al [249]. ICDAR 2013 Chinese handwriting	2013	ICDAR	100
recognition competition			
Su et al. [213]. Off-line recognition of realistic Chi-	2009	Pattern Recogn	100
nese handwriting using segmentation-free strategy			
He et al. [91]. Writer identification of Chinese hand-	2008	Pattern Recogn	100
writing documents using hidden Markov tree model			
Su et al. [212]. Corpus-based HIT-MW database for	2007	Int J Doc Anal Recog	100
offline recognition of general-purpose Chinese hand-			
written text			

Paper	Year	Publisher	#Cit
Seni and Cohen [197]. External word segmentation	1994	Pattern Recogn	99
of off-line handwritten text lines			
Si Wei Lu et al. [149]. Hierarchical attributed graph	1991	Pattern Recogn	99
representation and recognition of handwritten chi-			
nese characters			
Hafemann et al. [82]. Learning features for offline	2017	Pattern Recogn	98
handwritten signature verification using deep convo-			
lutional neural networks			
Toselli et al. [225]. Integrated handwriting recogni-	2003	Int J Pattern Recogn	98
tion and interpretation using finite-state models			
Oliveira et al. [167]. A methodology for feature selec-	2003	Int J Pattern Recogn	98
tion using multiobjective genetic algorithms for hand-			
written digit string recognition			
Dehghan et al. [48]. Handwritten Farsi(Arabic) word	2001	Pattern Recogn	98
recognition: A holistic approach using discrete HMM			
Gader et al. [69]. Handwritten word recognition with	1997	IEEE T syst Man	98
character and inter-character neural networks		Cyb B	
Van Breukelen et al. [230]. Handwritten digit recog-	1998	Kybernetika	96
nition by combined classifier			
Favata and Srikantan [61]. A multiple feature/res-	1996	Int J Imag syst Tech	96
olution approach to handprinted digit and character			
recognition			
Chi et al. [39]. Handwritten numeral recognition	1995	Pattern Recogn	95
using self-organizing maps and fuzzy rules			
H. Liu and Ding. [144]. Handwritten numeral recog-	2005	Pattern Recogn	94
nition using self-organizing maps and fuzzy rules			
Sako et al. [139]. Discriminative learning quadratic	2004	IEEE T Neural Net-	93
discriminant function for handwriting recognition		wor	
Al-Ohali et al. [8]. Databases for recognition of hand-	2003	Pattern Recogn	93
written Arabic cheques			

Table 1.2: Hot papers: top 5 cited articles in 2020, 2019 and 2018.

Paper	Year	Publisher	#Cit
Ghosh et al. [73]. Graphology based handwritten	2020	CAAI T Intell Tech-	35
character analysis for human behaviour identification		nol	
Ahlawat et al. [5]. Improved handwritten digit recog-	2020	Sensors	19
nition using convolutional neural networks (CNN)			

Paper	Year	Publisher	#Cit
Zhao and Liu [255]. Multiple classifiers fusion and	2020	Granul Comput	18
CNN feature extraction for handwritten digits recog-			
nition			
$\it Jiang \ and \ Zhang \ [102].$ Edge-SiamNet and Edge-	2020	IEICE T Inf Syst	18
TripleNet: New deep learning models for handwritten			
numeral recognition			
$Malakar\ et\ al.\ [152].\ A\ GA\ based\ hierarchical\ feature$	2020	Neural Comput Appl	16
selection approach for handwritten word recognition			
Diaz-Cabrera et al. [49]. A perspective analysis of	2019	ACM Comput Surv	64
handwritten signature technology			
Cilia et al. [41]. A ranking-based feature selection	2019	Pattern Recogn Lett	44
approach for handwritten character recognition			
De Stefano et al. [47] Handwriting analysis to sup-	2019	Pattern Recogn Lett	31
port neurodegenerative diseases diagnosis: A review			
Baldominos et al. [19]. A survey of handwritten	2019	Appl Sci	27
character recognition with MNIST and EMNIST			
He and Schomaker [89]. Deep adaptive learning	2019	Patter Recogn	24
for writer identification based on single handwritten			
word images			
Hafemann et al. [83]. Offline handwritten signature	2018	IPTA	65
verification - Literature review			
Baldominos et al. [18]. Evolutionary convolu-	2018	Neurocomputing	57
tional neural networks: An application to handwrit-			
ing recognition			
Pramanik and Bag [181]. Shape decomposition-	2018	J Vis Commun Im-	53
based handwritten compound character recognition		age R	
for Bangla OCR			
Kulkarni and Rajendran [119]. Spiking neural net-	2018	Neural Networks	49
works for handwritten digit recognition—Supervised			
learning and network optimization			
Sueiras et al. [215]. Offline continuous handwriting	2018	Neurocomputing	46
recognition using sequence to sequence neural net-			
works			

Most Influential Papers

per Period and Thematic Network

To analyze the temporal evolution of the area, our bibliometric analysis divides the document sample into six periods of five years. In each period, the most relevant research themes are identified.

2.1 Period 1: 1990-1994

Table 2.1 summarizes the top ten cited papers for the most relevant research themes from 1990 to 1994. The last column follows the notation [reference]_{#citations}, e.g., [217]₃₀₀ means that [217] has been cited 300 times since its publication.

Table 2.1: Thematic networks' performance (Period 1: 1990-1994).

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
Character	Character Recognition, Statistical	43	22	$[217]_{300}$ $[111]_{203}$
Recognition	Model, Graph, Decision Tree, MLP,			$[33]_{173}$ $[94]_{126}$
	NN, Numeral Recognition, Prepro-			$[245]_{121}$ $[149]_{99}$
	cessing, Arabic Text Recognition,			$[210]_{80}$ $[127]_{78}$
	Template Matching, Japanese Text			$[3]_{71}$ $[67]_{51}$
	Recognition, Ensemble Classification			
Text Recog-	Text Recognition, Segmentation,	14	11	$[99]_{1029}$ $[197]_{99}$
nition	Feature Extraction			$[210]_{80}$ $[216]_{72}$
				$[234]_{49}$ $[57]_{42}$
				$[200]_{38}$ $[239]_{34}$
				$[172]_{19} [14]_{18}$

2.2 Period 2: 1995-1999

Table 2.2 summarizes the top ten cited papers for the most relevant research themes from 1995 to 1999.

Table 2.2: Thematic networks' performance (Period 2: 1995-1999).

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
Character Recognition	Character Recognition, Structural Features, Statistical Model, MLP, Character Segmentation, Feature Ex- traction, NN, Classification, HMM, Word Recognition, Template Match-	162	37	$ \begin{bmatrix} 113]_{189} & [153]_{176} \\ [58]_{173} & [198]_{172} \\ [81]_{133} & [101]_{132} \\ [112]_{126} & [150]_{124} \\ [242]_{123} & [128]_{122} \end{bmatrix} $
	ing, Japanese Text Recognition			[]120 [-]122
Numeral Recognition	Numeral Recognition, Ensemble Classification, Structural Classifica- tion, Segmentation, GA, Clustering, Fuzzy Logic	75	29	[98] ₄₁₈ [113] ₁₈₉ [58] ₁₇₃ [81] ₁₃₃ [101] ₁₃₂ [128] ₁₂₂ [28] ₁₀₈ [39] ₉₅ [247] ₇₈ [222] ₇₇

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
Chinese	Chinese Character Recognition,	41	15	$[106]_{177}$ $[58]_{173}$
Character	Directional Feature, Preprocessing,			$[198]_{172}$ $[101]_{132}$
Recognition	Graph			$[112]_{126}$ $[222]_{77}$
				$[12]_{66}$ $[227]_{63}$
				$[145]_{49} [30]_{48}$
Word Spot-	Word Spotting, Information Re-	27	14	$[98]_{418}$ $[153]_{176}$
ting	trieval, Text Recognition			$[154]_{154}$ $[165]_{69}$
				$[109]_{46}$ $[36]_{43}$
				$[2]_{35}$ $[108]_{32}$ $[85]_{31}$
				[40] ₂₉
Digit Recog-	Digit Recognition, KNN, Feature Se-	16	8	$[81]_{133}$ $[101]_{132}$
nition	lection			$[88]_{69}$ $[68]_{45}$
				$[204]_{38}$ $[35]_{22}$
				$[159]_{17}$ $[116]_{14}$
				$[110]_7$ $[158]_5$

2.3 Period 3: 2000-2004

Table 2.3 summarizes the top ten cited papers for the most relevant research themes from 2000 to 2004.

Table 2.3: Thematic networks' performance (Period 3: 2000-2004).

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
HMM	HMM, Sentence Recognition, Dictio-	122	29	$[176]_{1749}$ $[156]_{588}$
	nary, Large Vocabulary, Text Recog-			$[155]_{314}$ $[15]_{291}$
	nition, Feature Selection, Preprocess-			$[138]_{226}$ $[232]_{201}$
	ing, Word Recognition, Arabic Text			$[151]_{177}$ $[257]_{142}$
	Recognition, Language Model, En-			$[134]_{134} [115]_{119}$
	semble Classification, Synthetic Data			

Thematic network	Network's keywords	#Papers	h-index	Top 10 papers	
Character	Character Recognition, Statistical	164	35	[137] ₄₀₁ [15] ₂₉₁	
Recognition	Model, Graph, SOM, Character Seg-			[166] ₁₆₅ [134] ₁₃₄	
	mentation, Feature Extraction, Seg-			$[203]_{130}$ $[34]_{118}$	
	mentation, NN, Classification, Tem-			$[136]_{112}$ $[16]_{111}$	
	plate Matching, Fuzzy Logic, Struc-			[48] ₉₈ [139] ₉₃	
	tural Features				
Chinese	Chinese Character Recognition,	59	19	$[137]_{401}$ $[257]_{142}$	
Character	PCA, Active Shape Model, SVM,			$[203]_{130}$ $[136]_{112}$	
Recognition	GA, Wavelet, Supervised Learning,			$[133]_{85}$ $[140]_{74}$	
	Postprocessing			$[209]_{59}$ $[256]_{52}$	
				$[202]_{50}$ $[31]_{38}$	
Writer Identi-	Writer Identification, Signature Ver-	23	10	$[176]_{1749}$ $[192]_{246}$	
fication	ification, Mathematical Transform,			$[257]_{142}$ $[196]_{56}$	
	Texture Features			$[231]_{45}$ $[92]_{29}$	
				$[251]_{29}$ $[96]_{16}$	
				[74] ₁₅ [161] ₁₁	
Numeral	Digit Recognition, Structural Classi-	63	22	$[137]_{401}$ $[138]_{226}$	
Recognition	fication, Decision Tree, Clustering			$[166]_{165}$ $[203]_{130}$	
				$[27]_{118}$ $[193]_{102}$	
				$[139]_{93}$ $[65]_{89}$	
				$[123]_{78}$ $[140]_{74}$	

2.4 Period 4: 2005-2009

Table 2.4 summarizes the top ten cited papers for the most relevant research themes from 2005 to 2009.

Table 2.4: Thematic networks' performance (Period 4: 2005-2009).

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
SVM	SVM, Indian Text Recognition, Elas-	254	32	$[147]_{342}$ $[20]_{210}$
	tic Mesh, RBF, Feature Extraction,			$[124]_{194}$ $[4]_{140}$
	Character Recognition, Digit Recog-			$[7]_{113}$ $[132]_{105}$
	nition, Classification, Chinese Char-			$[213]_{100}$ $[91]_{100}$
	acter Recognition, Feature Selection,			$[212]_{100} [238]_{84}$
	Arabic Text Recognition, KNN			
HMM	HMM, Sentence Recognition, Mo-	198	27	[75] ₉₈₂ [177] ₁₄₁
	ments, Dictionary, Text Recognition,			$[148]_{138}$ $[188]_{136}$
	Chinese Text Recognition, Word			$[130]_{132}$ $[7]_{113}$
	Recognition, RNN, Language Model,			$[248]_{106}$ $[213]_{100}$
	Ensemble Classification, Statistical			$[91]_{100}$ $[253]_{79}$
	Model, Graph			
Segmentation	Segmentation, Structural Features,	206	28	$[188]_{136}$ $[7]_{113}$
	Bank Check Recognition, Digit Seg-			$[132]_{105}$ $[213]_{100}$
	mentation, NN, Writer Identification,			$[91]_{100}$ $[253]_{79}$
	Numeral Recognition, Preprocessing,			$[53]_{70}$ $[141]_{66}$
	Historical Documents, Script Identi-			$[135]_{65}$ $[228]_{64}$
	fication, Fuzzy Logic			
Signature	Signature Verification, Verifica-	55	14	$[91]_{100}$ $[26]_{92}$
Verification	tion, Wavelet, DTW, Mathematical			$[78]_{51}$ $[180]_{36}$
	Transform			$[25]_{35}$ $[80]_{34}$
				$[179]_{19}$ $[185]_{19}$
				$[223]_{14} [70]_{12}$

2.5 Period 5: 2010-2014

Table 2.5 summarizes the top ten cited papers for the most relevant research themes from 2010 to 2014.

Table 2.5: Thematic networks' performance (Period 5: 2010-2014).

14 Most Influential Papers per Period and Thematic Area

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
Character Recognition	Character Recognition, Statistical Model, Mathematical Transform, Zonning, Feature Extraction, NN, SVM, Preprocessing, Arabic Text Recognition, KNN, Wavelet, Indian Text Recognition	632	35	[60] ₁₆₈ [29] ₁₂₆ [143] ₁₁₃ [171] ₁₀₆ [249] ₁₀₀ [22] ₈₆ [235] ₈₅ [173] ₈₄ [229] ₈₀ [240] ₇₉
Segmentation	Segmentation, SOM, Character Segmentation, Text Line Segmentation, Text Recognition, Chinese Text Recognition, GA, Math Recognition, Dymanic Programming, Structural Features, Postprocessing, Projection Features	386	33	[175] ₂₃₉ [63] ₁₈₆ [142] ₁₆₉ [60] ₁₆₈ [143] ₁₁₃ [171] ₁₀₆ [236] ₁₀₁ [211] ₁₀₀ [249] ₁₀₀ [44] ₈₆
HMM	HMM, Sentence Recognition, Bayesian Network, Viterbi Algo- rithm, DBNN, Word Spotting, Word Recognition, RNN, Clustering, Music Recognition, Roman Script, GMM	219	29	[175] ₂₃₉ [63] ₁₈₆ [60] ₁₆₈ [171] ₁₀₆ [22] ₈₆ [62] ₈₃ [52] ₈₂ [10] ₇₅
Classification	Classification, Feature Reduction, RBF, BKS, Chinese Character Recognition, Digit Recognition, Signature Verification, Script Identification, Fuzzy Logic, Ensemble Classification, HOG, Chain Code, Feature Reduction	292	22	

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
Writer Identi-	Writer Identification, Histogram,	79	14	[44] ₈₆ [46] ₈₀ [51] ₅₃
fication	Texture Features, Feature Selection,			[64]49 [32]33 [95]28
	Forensics			$[121]_{23}$ $[129]_{23}$
				$[1]_{22}$ $[183]_{22}$
MLP	MLP, PFGA, Numeral Recognition,	73	10	$[60]_{168}$ $[13]_{64}$
	Moments			$[237]_{30}$ $[160]_{20}$
				$[122]_{20}$ $[208]_{15}$
				$[104]_{13}$ $[182]_{12}$
				$[201]_{11} [189]_{10}$
Historical	Historical Documents, Language	57	12	$[236]_{101}$ $[250]_{44}$
Documents	Model, Morphology Operator			$[146]_{39}$ $[32]_{33}$
				$[107]_{24}$ $[72]_{22}$
				$[183]_{22}$ $[195]_{21}$
				$[117]_{19} [194]_{14}$

2.6 Period 6: 2015-2020

Table 2.6 summarizes the top ten cited papers for the most relevant research themes from 2015 to 2020.

Table 2.6: Thematic networks' performance (Period 6: 2015-2020).

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
DNN	DNN, Text Recognition, Charac-	1,1138	30	$[258]_{158}$ $[254]_{132}$
	ter Recognition, CNN, Digit Recogni-			$[214]_{106}$ $[82]_{98}$
	tion, RNN, Transfer Learning, Indian			$[59]_{82}$ $[246]_{70}$
	Text Recognition, Data Augmenta-			$[243]_{68}$ $[233]_{68}$
	tion, Dropout, DCNN, DBNN			[241] ₆₆ [97] ₆₅

Thematic	Network's keywords	#Papers	h-index	Top 10 p	papers
network					
SVM	SVM, Texture Features, Decision	902	23	[77]117	[59]82
	Tree, PCA, Feature Extraction, NN,			[219]54	[168]53
	Classification, Signature Verification,			[199]48	$[105]_{29}$
	Arabic Text Recognition, KNN,			$[24]_{25}$	$[178]_{23}$
	HOG, Statistical Model, Texture			[206] ₂₀ [23	3]16
	Features				
Segmentation	Segmentation, Histogram, Character	455	18	[77]117	$[214]_{106}$
	Segmentation, Text Line Segmenta-			$[190]_{52}$	$[252]_{46}$
	tion, Word Spotting, Preprocessing,			$[118]_{45}$	$[9]_{35}$
	Word Recognition, Math Recogni-			[181] ₃₄	$[37]_{27}$
	tion, Historical Documents, Sliding			[55] ₂₆ [220	$6]_{25}$
	Window, FCNN, Projection Features				
Ensemble	Ensemble Classification, Moments,	379	20	[258] ₁₅₈	$[254]_{132}$
Classification	ResNet, Chinese Character Recogni-			$[42]_{73}$	$[243]_{68}$
	tion, Chinese Text Recognition, Fea-			[241]66	$[18]_{44}$
	ture Selection, GA, Script Iden-			$[186]_{42}$	$[45]_{35}$
	tification, Fuzzy Logic, Structural			[41] ₃₄ [13	1]33
	Features, Mathematical Transform,				
	Graph				
HMM	HMM, Embedding, Tibetan Text	165	14	[241]66	$[190]_{52}$
	Recognition, Language Model, Music			$[90]_{52}$	$[118]_{52}$
	Recognition, Roman Text Recog-			$[37]_{45}$	$[220]_{25}$
	nition, Multi-Script Recognition,			[84] ₂₅	$[224]_{20}$
	N-Grams, Sentence Recognition,			[21] ₁₈ [38]	18
	Bayesian Network				
Writer Identi-	Writer Identification, Siamese Net-	155	12	[87] ₅₈	$[90]_{52}$
fication	work, Verification, Template Match-			[184] ₂₉	$[205]_{29}$
	ing, Wavelet, Forensics, SIFT, Au-			$[103]_{23}$	$[126]_{22}$
	toencoder			[89] ₁₇ [11]	$]_{16} [38]_{15}$
				$[164]_{14}$	

Thematic	Network's keywords	#Papers	h-index	Top 10 papers
network				
Numeral	Numeral Recognition, MLP, Atten-	141	12	$[252]_{46}$ $[181]_{34}$
Recognition	tion Mechanism, Graphology, End-			$[131]_{33}$ $[126]_{22}$
	to-end, ELM			$[6]_{19}$ $[207]_{19}$ $[79]_{18}$
				$[221]_{16}$ $[191]_{15}$
				[218] ₁₄

- [1] G. A. Abandah, F. T. Jamour, and E. A. Qaralleh. Recognizing hand-written Arabic words using grapheme segmentation and recurrent neural networks. *Int J Doc Anal Recog*, 17(3):275–291, 2014.
- [2] I. S. I. Abuhaiba, M. J. J. Holt, and S. Datta. Recognition of off-line cursive handwriting. *Comput Vis Image Und*, 71(1):19–38, 1998.
- [3] I. S. I. Abuhaiba, S. A. Mahmoud, and R. J. Green. Recognition of handwritten cursive Arabic characters. *IEEE T Pattern Anal*, 16(6):664–672, 1994.
- [4] M. M. Adankon and M. Cheriet. Model selection for the LS-SVM. application to handwriting recognition. *Pattern Recogn*, 42(12):3264–3270, 2009.
- [5] Savita Ahlawat, Amit Choudhary, Anand Nayyar, Saurabh Singh, and Byungun Yoon. Improved handwritten digit recognition using convolutional neural networks (CNN). *Sensors*, 20(12):3344, 2020.
- [6] M. A. H. Akhand, M. Ahmed, and M. M. H. Rahman. Convolutional neural network training with artificial pattern for Bangla handwritten numeral recognition. In 5th ICIEV, pages 625–630, Dhaka, Bangladesh, 2016.
- [7] R. Al-Hajj Mohamad, L. Likforman-Sulem, and C. Mokbel. Combining slanted-frame classifiers for improved HMM-based Arabic handwriting recognition. *IEEE T Pattern Anal*, 31(7):1165–1177, 2009.
- [8] Y. Al-Ohali, M. Cheriet, and C. Suen. Databases for recognition of handwritten Arabic cheques. *Pattern Recogn*, 36(1):111–121, 2003.

[9] David Aldavert, Marçal Rusiñol, Ricardo Toledo, and Josep Lladós. A study of Bag-of-Visual-Words representations for handwritten keyword spotting. *Int J Doc Anal Recog*, 18(3):223–234, 2015.

- [10] J. H. Alkhateeb, J. Ren, J. Jiang, and H. Al-Muhtaseb. Offline handwritten Arabic cursive text recognition using hidden Markov models and re-ranking. *Pattern Recogn Lett*, 32(8):1081–1088, 2011.
- [11] J. Almotiri, K. Elleithy, and A. Elleithy. Comparison of autoencoder and principal component analysis followed by neural network for elearning using handwritten recognition. In *LISAT*, Farmingdale, USA, 2017.
- [12] A. Amin, H. Al-Sadoun, and S. Fischer. Hand-printed Arabic character recognition system using an artificial network. *Pattern Recogn*, 29(4):663–675, 1996.
- [13] C. Amma, M. Georgi, and T. Schultz. Airwriting: Hands-free mobile text input by spotting and continuous recognition of 3d-space handwriting with inertial sensors. In 16th ISWC, pages 52–59, Newcastle, UK, 2012.
- [14] W. An-Bang, F. Kuo-Chin, and J. S. Huang. Recognition of handwritten Chinese characters by modified relaxation methods. *Image Vision Comput*, 12(8):509–522, 1994.
- [15] N. Arica and F. T. Yarman-Vural. An overview of character recognition focused on off-line handwriting. *IEEE T Syst Man Cy C*, 31(2):216– 233, 2001.
- [16] N. Arica and F. T. Yarman-Vural. Optical character recognition for cursive handwriting. *IEEE T Pattern Anal*, 24(6):801–813, 2002.
- [17] U. R. Babu, Y. Venkateswarlu, and A. K. Chintha. Handwritten digit recognition using k-nearest neighbour classifier. In 2014, pages 60–65.
- [18] A. Baldominos, Y. Saez, and P. Isasi. Evolutionary convolutional neural networks: An application to handwriting recognition. *Neurocomputing*, 283:38–52, 2018.
- [19] Alejandro Baldominos, Yago Saez, and Pedro Isasi. A survey of handwritten character recognition with MNIST and EMNIST. Appl Sci, 9(15):3169, 2019.

REFERENCES 21

[20] U. Bhattacharya and B. B. Chaudhuri. Handwritten numeral databases of Indian scripts and multistage recognition of mixed numerals. *IEEE T Pattern Anal*, 31(3):444–457, 2009.

- [21] A. K. Bhunia, A. Das, P. P. Roy, and U. Pal. A comparative study of features for handwritten Bangla text recognition. In 13th ICDAR, volume 2015-November, pages 636–640, Tunis, Tunisia, 2015.
- [22] A.-L. Bianne-Bernard, F. Menasri, R. Al-Hajj Mohamad, C. Mokbel, C. Kermorvant, and L. Likforman-Sulem. Dynamic and contextual information in HMM modeling for handwritten word recognition. *IEEE T Pattern Anal*, 33(10):2066–2080, 2011.
- [23] N. Bouadjenek, H. Nemmour, and Y. Chibani. Robust soft-biometrics prediction from off-line handwriting analysis. Applied Soft Computing Journal, 46:980–990, 2016.
- [24] A. Boukharouba and A. Bennia. Novel feature extraction technique for the recognition of handwritten digits. Appl Comput Inform, 13(1):19– 26, 2017.
- [25] A. Broumandnia, J. Shanbehzadeh, and M. Rezakhah Varnoosfaderani. Persian/Arabic handwritten word recognition using M-band packet wavelet transform. *Image Vision Comput*, 26(6):829–842, 2008.
- [26] M. Bulacu, L. Schomaker, and A. Brink. Text-independent writer identification and verification on offline Arabic handwriting. In 9th ICDAR, volume 2, pages 769–773, Parana, Brazil, 2007.
- [27] H. Bunke. Recognition of cursive roman handwriting past, present and future. In 7th ICDAR, pages 448–459, Edinburgh, UK, 2003.
- [28] J. Cao, M. Ahmadi, and M. Shridhar. Recognition of handwritten numerals with multiple feature and multistage classifier. *Pattern Recogn*, 28(2):153–160, 1995.
- [29] B. P. Chacko, V. R. Vimal Krishnan, G. Raju, and P. Babu Anto. Handwritten character recognition using wavelet energy and extreme learning machine. *Int J Mach Learn Cyb*, 3(2):149–161, 2012.
- [30] H.-H. Chang and H. Yan. Analysis of stroke structures of handwritten chinese characters. *IEEE T Syst Man Cyb B*, 29(1):47–61, 1999.

[31] G. Y. Chen, T. D. Bui, and A. Krzyzak. Contour-based handwritten numeral recognition using multiwavelets and neural networks. *Pattern Recogn*, 36(7):1597–1604, 2003.

- [32] K. Chen, H. Wei, J. Hennebert, R. Ingold, and M. Liwicki. Page segmentation for historical handwritten document images using color and texture features. In 14th ICFHR, pages 488–493, Heraklion, Greece, 2014.
- [33] M. Y. Chen, A. Kundu, and J. Zhou. Offline handwritten word recognition using a hidden Markov model type stochastic network. *IEEE T Pattern Anal*, 16(5):481–496, 1994.
- [34] Y.-K. Chen and J.-F. Wang. Segmentation of single- or multiple-touching handwritten numeral string using background and foreground analysis. *IEEE T Pattern Anal*, 22(11):1304–1317, 2000.
- [35] D. Cheng and H. Yan. Recognition of handwritten digits based on contour information. *Pattern Recognition*, 31(3):235–255, 1998.
- [36] K.-W. Cheung, D.-V. Yeung, and R. T. Chin. A bayesian framework for deformable pattern recognition with application to handwritten character recognition. *IEEE T Pattern Anal*, 20(12):1382–1388, 1998.
- [37] Y. Chherawala, P. P. Roy, and M. Cheriet. Feature set evaluation for offline handwriting recognition systems: Application to the recurrent neural network model. *IEEE T Cybernetics*, 46(10), 2015.
- [38] Y. Chherawala, P.P. Roy, and M. Cheriet. Combination of context-dependent bidirectional long short-term memory classifiers for robust offline handwriting recognition. *Pattern Recogn Lett*, 90:58–64, 2017.
- [39] Z. Chi, J. Wu, and H. Yan. Handwritten numeral recognition using self-organizing maps and fuzzy rules. *Pattern Recogn*, 28(1):59–66, 1995.
- [40] J.-H. Chiang. A hybrid neural network model in handwritten word recognition. *Neural Networks*, 11(2):337–346, 1998.
- [41] N. D. Cilia, C. De Stefano, F. Fontanella, and A. Scotto di Freca. A ranking-based feature selection approach for handwritten character recognition. *Pattern Recogn Lett*, 121:77–86, 2019.
- [42] K. Cpałka, M. Zalasiński, and L. Rutkowski. A new algorithm for identity verification based on the analysis of a handwritten dynamic signature. *Appl Soft Comput*, 43:47–56, 2016.

REFERENCES 23

[43] N. Das, J. M. Reddy, R. Sarkar, S. Basu, M. Kundu, M. Nasipuri, and D. K. Basu. A statistical-topological feature combination for recognition of handwritten numerals. *Appl Soft Comput*, 12(8):2486–2495, 2012.

- [44] N. Das, R. Sarkar, S. Basu, M. Kundu, M. Nasipuri, and D. K. Basu. A genetic algorithm based region sampling for selection of local features in handwritten digit recognition application. *Appl Soft Comput* J, 12(5):1592–1606, 2012.
- [45] N. Das, R. Sarkar, S. Basu, P. K. Saha, M. Kundu, and M. Nasipuri. Handwritten Bangla character recognition using a soft computing paradigm embedded in two pass approach. *Pattern Recogn*, 48(6):2054– 2071, 2015.
- [46] C. De Stefano, F. Fontanella, C. Marrocco, and A. Scotto Di Freca. A GA-based feature selection approach with an application to handwritten character recognition. *Pattern Recogn Lett*, 35(1):130–141, 2014.
- [47] Claudio De Stefano, Francesco Fontanella, Donato Impedovo, Giuseppe Pirlo, and Alessandra Scotto di Freca. Handwriting analysis to support neurodegenerative diseases diagnosis: A review. *Pattern Recogn Lett*, 121:37–45, 2019.
- [48] M. Dehghan, K. Faez, M. Ahmadi, and M. Shridhar. Handwritten Farsi(Arabic) word recognition: A holistic approach using discrete hmm. *Pattern Recogn*, 34(5):1057–1065, 2001.
- [49] M. Diaz, M. A. Ferrer, D. Impedovo, M. I. Malik, G. Pirlo, and R. Plamondon. A perspective analysis of handwritten signature technology. ACM Comput Surv, 51(6), 2019.
- [50] M. Diem, S. Fiel, A. Garz, M. Keglevic, F. Kleber, and R. Sablatnig. ICDAR 2013 competition on handwritten digit recognition (HDRC 2013). In 12th ICDAR, pages 1422–1427, Washington, USA, 2013.
- [51] C. Djeddi, I. Siddiqi, L. Souici-Meslati, and A. Ennaji. Text-independent writer recognition using multi-script handwritten texts. *Pattern Recogn Lett*, 34(10):1196–1202, 2013.
- [52] P. Doetsch, M. Kozielski, and H. Ney. Fast and robust training of recurrent neural networks for offline handwriting recognition. In 14th ICFHR, pages 279–284, 2014.

[53] J.-X. Dong, A. Krzyzak, and C.Y. Suen. An improved handwritten Chinese character recognition system using support vector machine. *Pattern Recogn Lett*, 26(12):1849–1856, 2005.

- [54] P. Drotár, J. Mekyska, I. Rektorová, L. Masarová, Z. Smékal, and M. Faundez-Zanuy. Analysis of in-air movement in handwriting: A novel marker for Parkinson's disease. Comput Meth Prog Bio, 117(3):405-411, 2014.
- [55] K. Dutta, P. Krishnan, M. Mathew, and C. V. Jawahar. Improving CNN-RNN hybrid networks for handwriting recognition. In 16th ICFHR, volume 2018-August, pages 80–85, Niagara Falls, USA, 2018.
- [56] R. El-Hajj, L. Likforman-Sulem, and C. Mokbel. Arabic handwriting recognition using baseline dependant features and hidden Markov modeling. In 8th ICDAR, volume 2005, pages 893–897, Seoul, South Korea, 2005.
- [57] T. S. El-Sheikh and S. G. El-Taweel. Real-time Arabic handwritten character recognition. *Pattern Recogn*, 23(12):1323–1332, 1990.
- [58] A. El-Yacoubi, M. Gilloux, R. Sabourin, and C. Y. Suen. An HMM-based approach for off-line unconstrained handwritten word modeling and recognition. *IEEE T Pattern Anal*, 21(8):752–760, 1999.
- [59] M. Elleuch, R. Maalej, and M. Kherallah. A new design based-SVM of the CNN classifier architecture with dropout for offline arabic handwritten recognition. In *Procedia Comput Sci*, volume 80, pages 1712–1723, 2016.
- [60] S. España-Boquera, M. J. Castro-Bleda, J. Gorbe-Moya, and F. Zamora-Martinez. Improving offline handwritten text recognition with hybrid HMM/ANN models. *IEEE T Pattern Anal*, 33(4):767– 779, 2011.
- [61] J. T. Favata and G. Srikantan. A multiple feature/resolution approach to handprinted digit and character recognition. Int J Imag syst Tech, 7(4):304–311, 1996.
- [62] A. Fischer, A. Keller, V. Frinken, and H. Bunke. HMM-based word spotting in handwritten documents using subword models. pages 3416– 3419, Istanbul, Turkey, 2010.

REFERENCES 25

[63] A. Fischer, A. Keller, V. Frinken, and H. Bunke. Lexicon-free handwritten word spotting using character HMMs. Pattern Recogn Lett, 33(7):934–942, 2012.

- [64] A. Fornés, A. Dutta, A. Gordo, and J. Lladós. CVC-MUSCIMA: A ground truth of handwritten music score images for writer identification and staff removal. *Int J Doc Anal Recog*, 15(3):243–251, 2012.
- [65] K. Fukushima. Neocognitron for handwritten digit recognition. *Neu-rocomputing*, 51:161–180, 2003.
- [66] K. Fukushima and N. Wake. Handwritten alphanumeric character recognition by the neocognitron. *IEEE T Neural Networ*, 2(3):355–365, 1991.
- [67] P. Gader, B. Forester, M. Ganzberger, A. Gillies, B. Mitchell, M. Whalen, and T. Yocum. Recognition of handwritten digits using template and model matching. *Pattern Recogn*, 24(5):421–431, 1991.
- [68] P. D. Gader and M. A. Khabou. Automatic feature generation for handwritten digit recognition. *IEEE T Pattern Anal*, 18(12):1256– 1261, 1996.
- [69] P.D. Gader, M. Mohamed, and J.-H. Chiang. Handwritten word recognition with character and inter-character neural networks. *IEEE T syst Man Cyb B*, 27(1):158–164, 1997.
- [70] J. Galbally, J. Fierrez, M. Martinez-Diaz, and J. Ortega-Garcia. Synthetic generation of handwritten signatures based on spectral analysis. In *Proc SPIE - Int Soc Opt Eng*, volume 7306, 2009.
- [71] E. Garfield. Introducing citation classics. The human side of scientific reports. *Curr Comments*, 1:5–7, 1977.
- [72] B. Gatos, G. Louloudis, and N. Stamatopoulos. Segmentation of historical handwritten documents into text zones and text lines. In 14th ICFHR, pages 464–469, Heraklion, Greece, 2014.
- [73] Subhankar Ghosh, Palaiahnakote Shivakumara, Prasun Roy, Umapada Pal, and Tong Lu. Graphology based handwritten character analysis for human behaviour identification. *CAAI T Intell Technol*, 5(1):55–65, 2020.
- [74] R. Göcke. Building a system for writer identification on handwritten music scores. pages 250–255, Rhodes, Greece, 2003.

[75] A. Graves, M. Liwicki, S. Fernández, R. Bertolami, H. Bunke, and J. Schmidhuber. A novel connectionist system for unconstrained handwriting recognition. *IEEE T Pattern Anal*, 31(5):855–868, 2009.

- [76] A. Graves and J. Schmidhuber. Offline handwriting recognition with multidimensional recurrent neural networks. In *NeurIPS 21*, pages 545–552, Vancouver, Canada, 2009.
- [77] Y. Guerbai, Y. Chibani, and B. Hadjadji. The effective use of the oneclass SVM classifier for handwritten signature verification based on writer-independent parameters. *Pattern Recogn*, 48(1):103–113, 2015.
- [78] R. Guest. Age dependency in handwritten dynamic signature verification systems. *Pattern Recogn Lett*, 27(10):1098–1104, 2006.
- [79] L. Guo and S. Ding. A hybrid deep learning CNN-ELM model and its application in handwritten numeral recognition. *J Comput Inf Syst*, 11(7):2673–2680, 2015.
- [80] I. Güler and M. Meghdadi. A different approach to off-line handwritten signature verification using the optimal dynamic time warping algorithm. Digit Signal Process Rev J, 18(6):940–950, 2008.
- [81] T. M. Ha and H. Bunke. Off-line, handwritten numeral recognition by perturbation method. *IEEE T Pattern Anal*, 19(5):535–539, 1997.
- [82] L. G. Hafemann, R. Sabourin, and L. S. Oliveira. Learning features for offline handwritten signature verification using deep convolutional neural networks. *Pattern Recogn*, 70:163–176, 2017.
- [83] L. G. Hafemann, R. Sabourin, and L. S. Oliveira. Offline handwritten signature verification — Literature review. In 7th IPTA, pages 1–8, Montreal, Canada, 2018.
- [84] J. Hajic and P. Pecina. The MUSCIMA++ dataset for handwritten optical music recognition. In 14th ICDAR, volume 1, pages 39–46, Kyoto, Japan, 2017.
- [85] K. Han and I. K. Sethi. Handwritten signature retrieval and identification. *Pattern Recogn Lett*, 17(1):83–90, 1996.
- [86] M. Hangarge, K. C. Santosh, and R. Pardeshi. Directional discrete cosine transform for handwritten script identification. In 12th ICDAR, pages 344–348, Washington, USA, 2013.

REFERENCES 27

[87] Y. Hannad, I. Siddiqi, and M. E. Y. El Kettani. Writer identification using texture descriptors of handwritten fragments. *Expert Syst Appl*, 47:14–22, 2016.

- [88] T. Hastie and P. Y. Simard. Metrics and models for handwritten character recognition. *Stat Sci*, 13(1):54–65, 1998.
- [89] S. He and L. Schomaker. Deep adaptive learning for writer identification based on single handwritten word images. *Pattern Recogn*, 88:64–74, 2019.
- [90] S. He, M. Wiering, and L. Schomaker. Junction detection in handwritten documents and its application to writer identification. *Pattern Recogn*, 48(12):4036–4048, 2015.
- [91] Z. He, X. You, and Y. Y. Tang. Writer identification of Chinese handwriting documents using hidden Markov tree model. *Pattern Recogn*, 41(4):1295–1307, 2008.
- [92] Z. Y. He and Y. Y. Tang. Chinese handwriting-based writer identification by texture analysis. In *ICMLC*, volume 6, pages 3488–3491, Shanghai, China, 2004.
- [93] L. Heutte, T. Paquet, J. V. Moreau, Y. Lecourtier, and C. Olivier. A structural/statistical feature based vector for handwritten character recognition. *Pattern Recogn Lett*, 19(7):629-641, 1998.
- [94] T. H. Hildebrandt and W. Liu. Optical recognition of handwritten Chinese characters: Advances since 1980. Pattern Recogn, 26(2):205– 225, 1993.
- [95] P. S. Hiremath, S. Shivashankar, J. D. Pujari, and V. Mouneswara. Script identification in a handwritten document image using texture features. In *2nd IACC*, pages 110–114, Patiala, India, 2010.
- [96] C. Hook, J. Kempf, and G. Scharfenberg. New pen device for biometrical 3D pressure analysis of handwritten characters, words and signatures. pages 38–44, Berkeley, USA, 2003.
- [97] Y.-L. Hsu, C.-L. Chu, Y.-J. Tsai, and J.-S. Wang. An inertial pen with dynamic time warping recognizer for handwriting and gesture recognition. *IEEE Sens J*, 15(1):154–163, 2015.

[98] Y. S. Huang and C. Y. Suen. A method of combining multiple experts for the recognition of unconstrained handwritten numerals. *IEEE T Pattern Anal*, 17(1):90–94, 1995.

- [99] J. J. Hull. A database for handwritten text recognition research. *IEEE T Pattern Anal*, 16(5):550–554, 1994.
- [100] D. Impedovo, G. Pirlo, and R. Plamondon. Handwritten signature verification: New advancements and open issues. In *IWFHR*, pages 367–372, Bari, Italy, 2012.
- [101] A. K. Jain and D. Zongker. Representation and recognition of handwritten digits using deformable templates. *IEEE T Pattern Anal*, 19(12):1386–1391, 1997.
- [102] Weiwei Jiang and Le Zhang. Edge-SiamNet and Edge-TripleNet: New deep learning models for handwritten numeral recognition. *IEICE T Inf Syst*, 103(3):720–723, 2020.
- [103] L. W. Jin, Z.-Y. Zhong, Z. Yang, W.-X. Yang, Z.-C. Xie, and J. Sun. Applications of deep learning for handwritten Chinese character recognition: A review. *Acta Autom Sinica*, 42(8):1125–1141, 2016.
- [104] K. V. Kale, P. D. Deshmukh, S. V. Chavan, M. M. Kazi, and Y. S. Rode. Zernike moment feature extraction for handwritten Devanagari compound character recognition. In SAI, pages 459–466, 2013.
- [105] P. M. Kamble and R. S. Hegadi. Handwritten Marathi character recognition using R-HOG feature. In *Procedia Comput Sci*, volume 45, pages 266–274, 2015.
- [106] N. Kato. A handwritten character recognition system using directional element feature and asymmetric mahalanobis distance. *IEEE T Pattern Anal*, 21(3):258–262, 1999.
- [107] M. Khayyat, L. Lam, and C. Y. Suen. Learning-based word spotting system for Arabic handwritten documents. *Pattern Recogn*, 47(3):1021– 1030, 2014.
- [108] G. Kim and V. Govindaraju. Handwritten phrase recognition as applied to street name images. *Pattern Recogn*, 31(1):41–51, 1998.
- [109] G. Kim, V. Govindaraju, and S. N. Srihari. An architecture for handwritten text recognition systems. Int J Doc Anal Recog, 2(1):37–44, 1999.

[110] F. Kimura, S. Nishikawa, T. Wakabayashi, Y. Miyaket, and T. Tsutsumida. Evaluation and synthesis of feature vectors for handwritten numeral recognition. *IEICE T Inf Syst*, E79-D(5):436–442, 1996.

- [111] F. Kimura and M. Shridhar. Handwritten numerical recognition based on multiple algorithms. *Pattern Recogn*, 24(10):969–983, 1991.
- [112] F. Kimura, T. Wakabayashi, S. Tsuruoka, and Y. Miyake. Improvement of handwritten Japanese character recognition using weighted direction code histogram. *Pattern Recogn*, 30(8):1329–1337, 1997.
- [113] G. Kirn and V. Govindaraju. A lexicon driven approach to handwritten word recognition for real-time applications. *IEEE T Pattern Anal*, 19(4):366–379, 1997.
- [114] S. Knerr, L. Personnaz, and G. Dreyfus. Handwritten digit recognition by neural networks with single-layer training. *IEEE T Neural Networ*, 3(6):962–968, 1992.
- [115] A. L. Koerich, R. Sabourin, and C. Y. Suen. Large vocabulary off-line handwriting recognition: A survey. *Pattern Anal Appl*, 6(2):97–121, 2003.
- [116] ZS. M. Kovács-V. and R. Guerrieri. Massively-parallel handwritten character recognition based on the distance transform. *Pattern Recogn*, 28(3):293–301, 1995.
- [117] M. Kozielski, D. Rybach, S. Hahn, R. Schluter, and H. Ney. Open vocabulary handwriting recognition using combined word-level and character-level language models. In *ICASSP*, pages 8257–8261, Vancouver, Canada, 2013.
- [118] P. Krishnan, K. Dutta, and C. V. Jawahar. Deep feature embedding for accurate recognition and retrieval of handwritten text. In 15th ICFHR, volume 0, pages 289–294, Shenzhen, China, 2016.
- [119] Shruti R Kulkarni and Bipin Rajendran. Spiking neural networks for handwritten digit recognition—supervised learning and network optimization. *Neural Networks*, 103:118–127, 2018.
- [120] M. Kumar, M. K. Jindal, and R. K. Sharma. Classification of characters and grading writers in offline handwritten Gurmukhi script. In *ICIIP*, Shimla, India, 2011.

[121] M. Kumar, M.K. Jindal, and R.K. Sharma. A novel hierarchical technique for offline handwritten Gurmukhi character recognition. *Natl Acad Sci Lett*, 37(6):567–572, 2014.

- [122] M. Kumar, R. Sharma, and M. Jindal. A novel feature extraction technique for offline handwritten gurmukhi character recognition. *IETE Journal of Research*, 59(6):687–691, 2013.
- [123] E. Kussul and T. Baidyk. Improved method of handwritten digit recognition tested on MNIST database. *Image Vision Comput*, 22(12 SPEC. ISS.):971–981, 2004.
- [124] F. Lauer, C. Y. Suen, and G. Bloch. A trainable feature extractor for handwritten digit recognition. *Pattern Recogn*, 40(6):1816–1824, 2007.
- [125] V. Lavrenko, T. M. Rath, and R. Manmatha. Holistic word recognition for handwritten historical documents. In 1st DIAL, pages 278–287, Palo Alto, USA, 2004.
- [126] A. D. Le and M. Nakagawa. Training an end-to-end system for handwritten mathematical expression recognition by generated patterns. In 14th ICDAR, volume 1, pages 1056–1061, Kyoto, Japan, 2017.
- [127] S.-W. Lee and J.-S. Park. Nonlinear shape normalization methods for the recognition of large-set handwritten characters. *Pattern Recogn*, 27(7):895–902, 1994.
- [128] S.W. Lee. Off-line recognition of totally unconstrained handwritten numerals using multilayer cluster neural network. *IEEE T Pattern Anal*, 18(6):648–652, 1996.
- [129] W. Y. Leng and S. M. Shamsuddin. Writer identification for Chinese handwriting. *Int J Adv Soft Comput Appl*, 2(2):142–173, 2010.
- [130] Y. Li, Y. Zheng, D. Doermann, and S. Jaeger. Script-independent text line segmentation in freestyle handwritten documents. *IEEE T Pattern Anal*, 30(8):1313–1329, 2008.
- [131] L. Likforman-Sulem, A. Esposito, M. Faundez-Zanuy, S. Clemencon, and G. Cordasco. EMOTHAW: A novel database for emotional state recognition from handwriting and drawing. *IEEE T Hum-Mach Syst*, 47(2):273–284, 2017.

[132] C.-L. Liu. Normalization-cooperated gradient feature extraction for handwritten character recognition. *IEEE T Pattern Anal*, 29(8):1465–1469, 2007.

- [133] C.-L. Liu, I.-J. Kim, and J. H. Kim. Model-based stroke extraction and matching for handwritten Chinese character recognition. *Pattern Recogn*, 34(12):2339–2352, 2001.
- [134] C.-L. Liu, M. Koga, and H. Fujisawa. Lexicon-driven segmentation and recognition of handwritten character strings for japanese address reading. *IEEE T Pattern Anal*, 24(11):1425–1437, 2002.
- [135] C.-L. Liu and K. Marukawa. Pseudo two-dimensional shape normalization methods for handwritten Chinese character recognition. *Pattern Recogn*, 38(12):2242–2255, 2005.
- [136] C.-L. Liu and M. Nakagawa. Evaluation of prototype learning algorithms for nearest-neighbor classifier in application to handwritten character recognition. *Pattern Recogn*, 34(3):601–615, 2001.
- [137] C.-L. Liu, K. Nakashima, H. Sako, and H. Fujisawa. Handwritten digit recognition: Benchmarking of state-of-the-art techniques. *Pattern Recogn*, 36(10):2271–2285, 2003.
- [138] C.-L. Liu, K. Nakashima, H. Sako, and H. Fujisawa. Handwritten digit recognition: Investigation of normalization and feature extraction techniques. *Pattern Recogn*, 37(2):265–279, 2004.
- [139] C.-L. Liu, H. Sako, and H. Fujisawa. Discriminative learning quadratic discriminant function for handwriting recognition. *IEEE T Neural Net*wor, 15(2):430–444, 2004.
- [140] C.-L. Liu, H. Sako, and H. Fujisawa. Effects of classifier structures and training regimes on integrated segmentation and recognition of handwritten numeral strings. *IEEE T Pattern Anal*, 26(11):1395–1407, 2004.
- [141] C.-L. Liu and C. Y. Suen. A new benchmark on the recognition of handwritten Bangla and Farsi numeral characters. *Pattern Recogn*, 42(12):3287–3295, 2009.
- [142] C. L. Liu, F. Yin, D. H. Wang, and Q. F. Wang. Online and offline handwritten Chinese character recognition: Benchmarking on new databases. *Pattern Recogn*, 46(1):155–162, 2013.

[143] C.-L. Liu, F. Yin, Q.-F. Wang, and D.-H. Wang. ICDAR 2011 Chinese handwriting recognition competition. In 11th ICDAR, pages 1464—1469, Beijing, China, 2011.

- [144] H. Liu and X. Ding. Handwritten character recognition using gradient feature and quadratic classifier with multiple discrimination schemes. In 8th ICDAR, volume 2005, pages 19–23, Seoul, South Korea, 2005.
- [145] K. Liu, Y. S. Huang, and C. Y. Suen. Identification of fork points on the skeletons of handwritten Chinese characters. *IEEE T Pattern Anal*, 21(10):1095–1100, 1999.
- [146] J. Lladós, M. Rusiñol, A. Fornés, D. Fernández, and A. Dutta. On the influence of word representations for handwritten word spotting in historical documents. *Int J Pattern Recogn*, 26(5), 2012.
- [147] L. M. Lorigo and V. Govindaraju. Offline Arabic handwriting recognition: A survey. *IEEE T Pattern Anal*, 28(5):712–724, 2006.
- [148] G. Louloudis, B. Gatos, I. Pratikakis, and C. Halatsis. Text line and word segmentation of handwritten documents. *Pattern Recogn*, 42(12):3169–3183, 2009.
- [149] Si Wei Lu, Y. Ren, and C. Y. Suen. Hierarchical attributed graph representation and recognition of handwritten chinese characters. *Pattern Recogn*, 24(7):617–632, 1991.
- [150] Y. Lu and M. Shridhar. Character segmentation in handwritten words an overview. *Pattern Recogn*, 29(1):77–96, 1996.
- [151] S. Madhvanath and V. Govindaraju. The role of holistic paradigms in handwritten word recognition. *IEEE T Pattern Anal*, 23(2):149–164, 2001.
- [152] Samir Malakar, Manosij Ghosh, Showmik Bhowmik, Ram Sarkar, and Mita Nasipuri. A GA based hierarchical feature selection approach for handwritten word recognition. *Neural Comput Appl*, 32(7):2533–2552, 2020.
- [153] R. Manmatha, Chengfeng Han, and E. M. Riseman. Word spotting: a new approach to indexing handwriting. In CVPR, pages 631–637, San Francisco, USA, 1996.

[154] U. V. Marti and H. Bunke. A full English sentence database for offline handwriting recognition. In 5th ICDAR, pages 709–712, Bangalore, India, 1999.

- [155] U. V. Marti and H. Bunke. Using a statistical language model to improve the performance of an hmm-based cursive handwriting recognition system. *Int J Pattern Recogn*, 15(1):65–90, 2001.
- [156] U. V. Marti and H. Bunke. The IAM-database: An English sentence database for offline handwriting recognition. *Int J Doc Anal Recog*, 5(1):39–46, 2003.
- [157] M. A. Martinez, M. Herrera, J. Lopez-Gijon, and E. Herrera-Viedma. H-classics: characterizing the concept of citation classics through H-index. *Scientometrics*, 98(3):1971–1983, 2014.
- [158] O. MayoraIbarra and F. Curatelli. Handwritten digit recognition by means of a holographic associative memory. Expert Syst Appl, 15(3-4):399–403, 1998.
- [159] L. Micó and J. Oncina. Comparison of fast nearest neighbour classifiers for handwritten character recognition. *Pattern Recogn Lett*, 19(3-4):351–356, 1998.
- [160] T. K. Mishra, B. Majhi, and S. Panda. A comparative analysis of image transformations for handwritten Odia numeral recognition. In ICACCI, pages 790–793, Mysore, India, 2013.
- [161] N. Mogharreban, S. Rahimi, and M. Sabharwal. A combined crisp and fuzzy approach for handwriting analysis. volume 1, pages 351–356, 2004.
- [162] M. Mohamed and P. Gader. Handwritten word recognition using segmentation-free hidden Markov modeling and segmentation-based dynamic programming techniques. *IEEE T Pattern Anal*, 18(5):548–554, 1996.
- [163] K. Neamah, D. Mohamad, T. Saba, and A. Rehman. Discriminative features mining for offline handwritten signature verification. 3D Res, 5(1):1-6, 2014.
- [164] S. M. Obaidullah, C. Halder, N. Das, and K. Roy. Numeral script identification from handwritten document images. In *Procedia Comput Sci*, volume 54, pages 585–594, 2015.

[165] I. I.-S. Oh, J.-S. Lee, and C.Y. Suen. Analysis of class separation and combination of class-dependent features for handwriting recognition. *IEEE T Pattern Anal*, 21(10):1089–1094, 1999.

- [166] L. S. Oliveira, R. Sabourin, F. Bortolozzi, and C. Y. Suen. Automatic recognition of handwritten numerical strings: A recognition and verification strategy. *IEEE T Pattern Anal*, 24(11):1438–1454, 2002.
- [167] L. S. Oliveira, R. Sabourin, F. Bortolozzi, and C. Y. Suen. A methodology for feature selection using multiobjective genetic algorithms for handwritten digit string recognition. *Int J Pattern Recogn*, 17(6):903– 929, 2003.
- [168] S. Y. Ooi, A. B. J. Teoh, Y. H. Pang, and B. Y. Hiew. Image-based handwritten signature verification using hybrid methods of discrete Radon transform, principal component analysis and probabilistic neural network. Appl Soft Comput, 40:274–282, 2016.
- [169] U. Pal and S. Datta. Segmentation of Bangla unconstrained handwritten text. In 7th ICDAR, pages 1128–1132, Edinburgh, UK, 2003.
- [170] U. Pal, T. Wakabayashi, N. Sharma, and F. Kimura. Handwritten numeral recognition of six popular Indian scripts. In 9th ICDAR, volume 2, pages 749–753, Parana, Brazil, 2007.
- [171] V. Papavassiliou, T. Stafylakis, V. Katsouros, and G. Carayannis. Handwritten document image segmentation into text lines and words. *Pattern Recogn*, 43(1):369–377, 2010.
- [172] T. Paquet and Y. Lecourtier. Recognition of handwritten sentences using a restricted lexicon. *Pattern Recogn*, 26(3):391–407, 1993.
- [173] M. T. Parvez and S. A. Mahmoud. Offline Arabic handwritten text recognition: A survey. *ACM Comput Surv*, 45(2), 2013.
- [174] M. Pechwitz and V. Maergner. HMM based approach for handwritten Arabic word recognition using the IFN/ENIT database. In 7th ICDAR, volume 2003-January, pages 890–894, Edinburgh, UK, 2003.
- [175] V. Pham, T. Bluche, C. Kermorvant, and J. Louradour. Dropout improves recurrent neural networks for handwriting recognition. In 14th ICFHR, volume 2014-December, pages 285–290, Hersonissos, Greece, 2014.

[176] R. Plamondon and S. N. Srihari. On-line and off-line handwriting recognition: A comprehensive survey. *IEEE T Pattern Anal*, 22(1):63–84, 2000.

- [177] T. Plötz and G. A. Fink. Markov models for offline handwriting recognition: A survey. *Int J Doc Anal Recog*, 12(4):269–298, 2009.
- [178] P. Porwik, R. Doroz, and T. Orczyk. The k-NN classifier and self-adaptive Hotelling data reduction technique in handwritten signatures recognition. *Pattern Anal Appl*, 18(4):983–1001, 2015.
- [179] P. Porwik and T. Para. Some handwritten signature parameters in biometric recognition process. In 29th ITI, pages 185–190, Cavtat, Croatia, 2007.
- [180] M. R. Pourshahabi, M. H. Sigari, and H. R. Pourreza. Offline handwritten signature identification and verification using contourlet transform. In 1st SoCPaR, pages 670–673, Malacca, Malaysia, 2009.
- [181] R. Pramanik and S. Bag. Shape decomposition-based handwritten compound character recognition for Bangla OCR. J Vis Commun Image R, 50:123–134, 2018.
- [182] P. Purkait and B. Chanda. Off-line recognition of hand-written bengali numerals using morphological features. In *Proceedings 12th ICFHR*, *ICFHR 2010*, pages 363–368, 2010.
- [183] P. Purkait, R. Kumar, and B. Chanda. Writer identification for handwritten Telugu documents using directional morphological features. In 12th ICFHR, pages 658–663, Kolkata, India, 2010.
- [184] J. Qiao, G. Wang, W. Li, and M. Chen. An adaptive deep Q-learning strategy for handwritten digit recognition. *Neural Networ*, 107:61–71, 2018.
- [185] G. Raju. Recognition of unconstrained handwritten malayalam characters using zero-crossing of wavelet coefficients. In *Proceedings 2006 14th International Conference on Advanced Computing and Communications, ADCOM 2006*, pages 217–221, 2006.
- [186] Z. Rao, C. Zeng, M. Wu, Z. Wang, N. Zhao, M. Liu, and X. Wan. Research on a handwritten character recognition algorithm based on an extended nonlinear kernel residual network. *KSII T Internet Inf*, 12(1):413–435, 2018.

[187] M. Revow, C. K. I. Williams, and G. E. Hinton. Using generative models for handwritten digit recognition. *IEEE T Pattern Anal*, 18(6):592–606, 1996.

- [188] J. A. Rodríguez-Serrano and F. Perronnin. Handwritten word-spotting using hidden Markov models and universal vocabularies. *Pattern Recogn*, 42(9):2106–2116, 2009.
- [189] D. V. Rojatkar, K. D. Chinchkhede, and G. G. Sarate. Handwritten Devnagari consonants recognition using MLPNN with five fold cross validation. In *ICCPCT*, pages 1222–1226, Nagercoil, India, 2013.
- [190] P. P. Roy, A. K. Bhunia, A. Das, P. Dey, and U. Pal. HMM-based Indic handwritten word recognition using zone segmentation. *Pattern Recogn*, 60:1057–1075, 2016.
- [191] J. Sadri, M.R. Yeganehzad, and J. Saghi. A novel comprehensive database for offline persian handwriting recognition. *Pattern Recogn*, 60:378–393, 2016.
- [192] H. E. S. Said, T. N. Tan, and K. D. Baker. Personal identification based on handwriting. *Pattern Recogn*, 33(1):149–160, 2000.
- [193] A. A. Salah, E. Alpaydin, and L. Akarun. A selective attention-based method for visual pattern recognition with application to handwritten digit recognition and face recognition. *IEEE T Pattern Anal*, 24(3):420–425, 2002.
- [194] A. Sánchez, C. A. B. Mello, P.D. Suárez, and A. Lopes. Automatic line and word segmentation applied to densely line-skewed historical handwritten document images. *Integr Comput-Aid E*, 18(2):125–142, 2011.
- [195] J. A. Sánchez, V. Bosch, V. Romero, K. Depuydt, and J. De Does. Handwritten text recognition for historical documents in the transcriptorium project. In ACM Int Conf Proc Series, pages 111–117, 2014.
- [196] A. Schlapbach and H. Bunke. Off-line handwriting identification using HMM based recognizers. In 17th ICPR, volume 2, pages 654–655, Cambridge, UK, 2004.
- [197] G. Seni and E. Cohen. External word segmentation of off-line hand-written text lines. *Pattern Recogn*, 27(1):41–52, 1994.

[198] A. W. Senior and A. J. Robinson. An off-line cursive handwriting recognition system. *IEEE T Pattern Anal*, 20(3):309–321, 1998.

- [199] Y. Serdouk, H. Nemmour, and Y. Chibani. New off-line handwritten signature verification method based on artificial immune recognition system. *Expert Syst Appl*, 51:186–194, 2016.
- [200] V. Shapiro, G. Gluhchev, and V. Sgurev. Handwritten document image segmentation and analysis. *Pattern Recogn Lett*, 14(1):71–78, 1993.
- [201] N. Sharma, B. Kumar, and V. Singh. Recognition of off-line hand printed english characters, numerals and special symbols. In *Proceedings of the 5th International Conference on Confluence 2014: The Next Generation Information Technology Summit*, pages 640–645, 2014.
- [202] D. Shi, S. R. Gunn, and R. I. Damper. Handwritten Chinese radical recognition using nonlinear active shape models. *IEEE T Pattern Anal*, 25(2):277–280, 2003.
- [203] M. Shi, Y. Fujisawa, T. Wakabayashi, and F. Kimura. Handwritten numeral recognition using gradient and curvature of gray scale image. *Pattern Recogn*, 35(10):2051–2059, 2002.
- [204] Z. Shi and V. Govindaraju. Segmentation and recognition of connected handwritten numeral strings. *Pattern Recogn*, 30(9):1501–1504, 1997.
- [205] M. Shopon, N. Mohammed, and M. A. Abedin. Bangla handwritten digit recognition using autoencoder and deep convolutional neural network. In *IWCI*, pages 64–68, Dhaka, Bangladesh, 2017.
- [206] I. Siddiqi, C. Djeddi, A. Raza, and L. Souici-meslati. Automatic analysis of handwriting for gender classification. *Pattern Anal Appl*, 18(4):887–899, 2015.
- [207] G. Singh and M. Sachan. Multi-layer perceptron (mlp) neural network technique for offline handwritten gurmukhi character recognition. In 2014 IEEE International Conference on Computational Intelligence and Computing Research, IEEE ICCIC 2014, 2015.
- [208] P. K. Singh, R. Sarkar, N. Das, S. Basu, and M. Nasipuri. Identification of Devanagari and roman scripts from multi-script handwritten documents. 8251:509–514, 2013.

[209] H. Soltanzadeh and M. Rahmati. Recognition of Persian handwritten digits using image profiles of multiple orientations. *Pattern Recogn Lett*, 25(14):1569–1576, 2004.

- [210] S. N. Srihari. Recognition of handwritten and machine-printed text for postal address interpretation. *Pattern Recogn Lett*, 14(4):291–302, 1993.
- [211] N. Stamatopoulos, B. Gatos, G. Louloudis, U. Pal, and A. Alaei. IC-DAR 2013 handwriting segmentation contest. In *12th ICDAR*, pages 1402–1406, Washington, USA, 2013.
- [212] T. Su, T. Zhang, and D. Guan. Corpus-based hit-mw database for offline recognition of general-purpose chinese handwritten text. *Int J Doc Anal Recog*, 10(1):27–38, 2007.
- [213] T. H. Su, T. W. Zhang, D. J. Guan, and H. J. Huang. Off-line recognition of realistic Chinese handwriting using segmentation-free strategy. *Pattern Recogn*, 42(1):167–182, 2009.
- [214] S. Sudholt and G. A. Fink. PHOCNet: A deep convolutional neural network for word spotting in handwritten documents. In 15th ICFHR, volume 0, pages 277–282, Shenzhen, China, 2016.
- [215] J. Sueiras, V. Ruiz, A. Sanchez, and J.F. Velez. Offline continuous handwriting recognition using sequence to sequence neural networks. *Neurocomputing*, 289:119–128, 2018.
- [216] C. Y. Suen, R. Legault, C. Nadal, M. Cheriet, and L. Lam. Building a new generation of handwriting recognition systems. *Pattern Recogn Lett*, 14(4):303–315, 1993.
- [217] C. Y. Suen, C. Nadal, R. Legault, L. Lam, and T. A. Mai. Computer recognition of unconstrained handwritten numerals. *P IEEE*, 80(7):1162–1180, 1992.
- [218] Z. Sun, L. Jin, Z. Xie, Z. Feng, and S. Zhang. Convolutional multidirectional recurrent network for offline handwritten text recognition. In *Proceedings of ICFHR*, ICFHR, volume 0, pages 240–245, 2016.
- [219] O. Surinta, M. F. Karaaba, L. R. B. Schomaker, and M. A. Wiering. Recognition of handwritten characters using local gradient feature descriptors. *Eng Appl Artif Intel*, 45:405–414, 2015.

[220] D. Suryani, P. Doetsch, and H. Ney. On the benefits of convolutional neural network combinations in offline handwriting recognition. In 15th ICFHR, volume 0, pages 193–198, Shenzhen, China, 2016.

- [221] Z. Tamen, H. Drias, and D. Boughaci. An efficient multiple classifier system for Arabic handwritten words recognition. *Pattern Recogn Lett*, 93:123–132, 2017.
- [222] Y. Y. Tang, L. T. Tu, J. Liu, S. W. Lee, W. W. Lin, and I.-S. Shyu. Offline recognition of Chinese handwriting by multifeature and multilevel classification. *IEEE T Pattern Anal*, 20(5):556–561, 1998.
- [223] S. O. Thian, H. K. Wee, and B. J. T. Andrew. Dynamic handwritten signature verification based on statistical quantization mechanism. In *ICCET*, volume 2, pages 312–316, Chengdu, China, 2009.
- [224] S. Thomas, C. Chatelain, L. Heutte, T. Paquet, and Y. Kessentini. A deep HMM model for multiple keywords spotting in handwritten documents. *Pattern Anal Appl*, 18(4):1003–1015, 2015.
- [225] A. H. Toselli, A. Juan, J. González, I. Salvador, E. Vidal, F. Casacuberta, D. Keysers, and H. Ney. Integrated handwriting recognition and interpretation using finite-state models. *Int J Pattern Recogn*, 18(4):519–539, 2004.
- [226] A. H. Toselli, E. Vidal, V. Romero, and V. Frinken. HMM word graph based keyword spotting in handwritten document images. *Inform Sciences*, 370-371:497–518, 2016.
- [227] Y.-H. Tseng and H.-J. Lee. Recognition-based handwritten chinese character segmentation using a probabilistic Viterbi algorithm. *Pattern Recogn Lett*, 20(8):791–806, 1999.
- [228] S. Uchida and H. Sakoe. A survey of elastic matching techniques for handwritten character recognition. *IEICE T Inf Syst*, E88-D(8):1781–1790, 2005.
- [229] G. Vamvakas, B. Gatos, and S. J. Perantonis. Handwritten character recognition through two-stage foreground sub-sampling. *Pattern Recogn*, 43(8):2807–2816, 2010.
- [230] M. Van Breukelen, R. P. W. Duin, D. M. J. Tax, and J. E. Den Hartog. Handwritten digit recognition by combined classifiers. *Kybernetika*, 34(4):381–386, 1998.

[231] C. Vielhauer and R. Steinmetz. Handwriting: Feature correlation analysis for biometric hashes. *Eurasip J Appl Sig Pr*, 2004(4):542–558, 2004.

- [232] A. Vinciarelli, S. Bengio, and H. Bunke. Offline recognition of unconstrained handwritten texts using HMMs and statistical language models. *IEEE T Pattern Anal*, 26(6):709–720, 2004.
- [233] P. Voigtlaender, P. Doetsch, and H. Ney. Handwriting recognition with large multidimensional long short-term memory recurrent neural networks. In *15th ICFHR*, volume 0, pages 228–233, Shenzhen, China, 2016.
- [234] T. Wakahara. Shape matching using LAT and its application to hand-written numeral recognition. *IEEE T Pattern Anal*, 16(6):618–629, 1994.
- [235] J.-S. Wang and F.-C. Chuang. An accelerometer-based digital pen with a trajectory recognition algorithm for handwritten digit and gesture recognition. *IEEE T Ind Electron*, 59(7):2998–3007, 2012.
- [236] Q.-F. Wang, F. Yin, and C.-L. Liu. Handwritten Chinese text recognition by integrating multiple contexts. *IEEE T Pattern Anal*, 34(8):1469–1481, 2012.
- [237] Y. Wen and L. He. A classifier for Bangla handwritten numeral recognition. *Expert Syst Appl*, 39(1):948–953, 2012.
- [238] Y. Wen, Y. Lu, and P. Shi. Handwritten Bangla numeral recognition system and its application to postal automation. *Pattern Recogn*, 40(1):99–107, 2007.
- [239] J. M. Westall and M. S. Narasimha. Vertex directed segmentation of handwritten numerals. *Pattern Recogn*, 26(10):1473–1486, 1993.
- [240] C. Wu, W. Fan, Y. He, J. Sun, and S. Naoi. Handwritten character recognition by alternately trained relaxation convolutional neural network. In 14th ICFHR, volume 2014-December, pages 291–296, Hersonissos, Greece, 2014.
- [241] Y.-C. Wu, F. Yin, and C.-L. Liu. Improving handwritten Chinese text recognition using neural network language models and convolutional neural network shape models. *Pattern Recogn*, 65:251–264, 2017.

[242] P. Wunsch and A. F. Laine. Wavelet descriptors for multiresolution recognition of handprinted characters. *Pattern Recogn*, 28(8):1237– 1249, 1995.

- [243] X. Xiao, L. Jin, Y. Yang, W. Yang, J. Sun, and T. Chang. Building fast and compact convolutional neural networks for offline handwritten Chinese character recognition. *Pattern Recogn*, 72:72–81, 2017.
- [244] L. Xu, A. Krzyżak, and C. Y. Suen. Methods of combining multiple classifiers and their applications to handwriting recognition. *IEEE T* syst Man Cyb, 22(3):418–435, 1992.
- [245] H. Yamada, K. Yamamoto, and T. Saito. A nonlinear normalization method for handprinted kanji character recognition-line density equalization. *Pattern Recogn*, 23(9):1023–1029, 1990.
- [246] W. Yang, L. Jin, D. Tao, Z. Xie, and Z. Feng. DropSample: A new training method to enhance deep convolutional neural networks for large-scale unconstrained handwritten Chinese character recognition. *Pattern Recogn*, 58:190–203, 2016.
- [247] B. Yanikoglu and P. A. Sandon. Segmentation of off-line cursive hand-writing using linear programming. *Pattern Recogn*, 31(12):1825–1833, 1998.
- [248] F. Yin and C.-L. Liu. Handwritten Chinese text line segmentation by clustering with distance metric learning. *Pattern Recogn*, 42(12):3146–3157, 2009.
- [249] F. Yin, Q.-F. Wang, X.-Y. Zhang, and C.-L. Liu. ICDAR 2013 Chinese handwriting recognition competition. In *12th ICDAR*, pages 1464–1470, Washington, USA, 2013.
- [250] F. Zamora-Martínez, V. Frinken, S. España-Boquera, M. J. Castro-Bleda, A. Fischer, and H. Bunke. Neural network language models for off-line handwriting recognition. *Pattern Recogn*, 47(4):1642–1652, 2014.
- [251] B. Zhang and S. N. Srihari. Binary vector dissimilarity measures for handwriting identification. In *Proc SPIE - Int Soc Opt Eng*, volume 5010, pages 28–38, 2003.

[252] J. Zhang, J. Du, S. Zhang, D. Liu, Y. Hu, J. Hu, S. Wei, and L. Dai. Watch, attend and parse: An end-to-end neural network based approach to handwritten mathematical expression recognition. *Pattern Recogn*, 71:196–206, 2017.

- [253] P. Zhang, T. D. Bui, and C. Y. Suen. A novel cascade ensemble classifier system with a high recognition performance on handwritten digits. *Pattern Recogn*, 40(12):3415–3429, 2007.
- [254] X. Y. Zhang, Y. Bengio, and C. L. Liu. Online and offline handwritten Chinese character recognition: A comprehensive study and new benchmark. *Pattern Recogn*, 61:348–360, 2017.
- [255] Hui-huang Zhao and Han Liu. Multiple classifiers fusion and CNN feature extraction for handwritten digits recognition. *Granul Comput*, 5(3):411–418, 2020.
- [256] S. Zhao, Z. Chi, P. Shi, and H. Yan. Two-stage segmentation of unconstrained handwritten Chinese characters. *Pattern Recogn*, 36(1):145– 156, 2003.
- [257] Y. Zheng, H. Li, and D. Doermann. Machine printed text and hand-writing identification in noisy document images. *IEEE T Pattern Anal*, 26(3):337–353, 2004.
- [258] Z. Zhong, L. Jin, and Z. Xie. High performance offline handwritten Chinese character recognition using GoogLeNet and directional feature maps. In 13th ICDAR, pages 846–850, Tunis, Tunisia, 2015.