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

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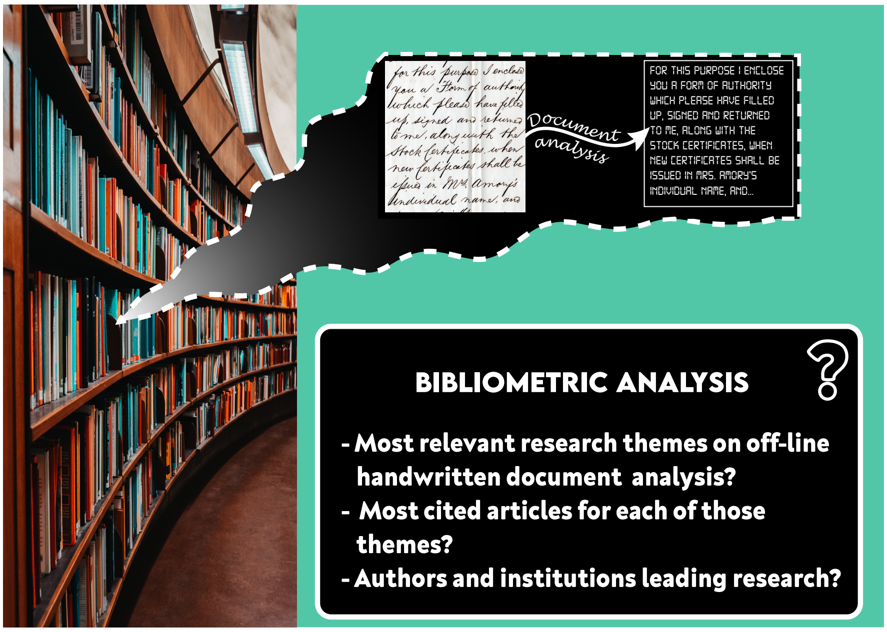
# Appendix: Most Influential Papers



# 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:

Providing 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 published along years was 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

# List of Tables

# 1 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 [67] 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. [148] 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.

| **Author** | **Year** | **Article** | **Publisher** | **Topic** | **#Cit** |
|---|---|---|---|---|---|
| *Plamondon and Srihari* [167]. | 2000 | On-line and off-line handwriting recognition: A comprehensive survey | IEEE T Pattern Anal | HTR | 1,749 |
| *Xu et al.* [234]. | 1992 | Methods of Combining Multiple Classifiers and Their Applications to Handwriting Recognition | IEEE T syst Man Cyb | HTR | 1,655 |
| *Hull* [93]. | 1994 | A Database for Handwritten Text Recognition Research | IEEE T Pattern Anal | HTR | 1,029 |

| Author | Year | Article | Publisher | Topic | #Cit |
|---|---|---|---|---|---|
| *Graves et al.* [70]. | 2009 | A novel connectionist system for unconstrained handwriting recognition | IEEE T Pattern Anal | HTR | 982 |
| *Marti and Bunke* [147]. | 2003 | The IAM-database: An English sentence database for offline handwriting recognition | Int J Doc Anal Recog | HTR | 588 |
| *Graves and Schmidhuber* [71]. | 2009 | Offline handwriting recognition with multidimensional recurrent neural networks | NeurIPS | HTR | 522 |
| *Huang and Suen* [92]. | 1995 | A Method of Combining Multiple Experts for the Recognition of Unconstrained Handwritten Numerals | IEEE T Pattern Anal | HNR | 418 |
| *Liu et al.* [129]. | 2003 | Handwritten digit recognition: Benchmarking of state-of-the-art techniques | Pattern Recogn | HDR | 401 |
| *Lorigo and Govindaraju* [139]. | 2006 | Offline Arabic handwriting recognition: A survey | IEEE T Pattern Anal | HTR | 342 |
| *Marti and Bunke* [146]. | 2001 | sing a statistical language model to improve the performance of an HMM-based cursive handwriting recognition system | Int J Pattern Recogn | LM | 314 |
| *Suen et al.* [207]. | 1992 | Computer Recognition of Unconstrained Handwritten Numerals | P IEEE | HNR | 300 |
| *Arica and Yarman-Vural* [14]. | 2001 | An overview of character recognition focused on off-line handwriting | IEEE T Syst Man Cy C | HCR | 291 |
| *Said et al.* [183]. | 2000 | personal identification based on handwriting | Pattern Recogn | WI | 246 |
| *Pham et al.* [166]. | 2014 | Dropout Improves Recurrent Neural Networks for Handwriting Recognition | ICFHR | HTR | 239 |
| *Liu et al.* [130]. | 2004 | Handwritten digit recognition: Investigation of normalization and feature extraction techniques | Pattern Recogn | HDR | 226 |
| *Bhattacharya and Chaudhuri* [18]. | 2009 | Handwritten numeral databases of Indian scripts and multistage recognition of mixed numerals | IEEE T Pattern Anal | HNR | 210 |
| *Kimura et al.* [104]. | 1991 | Handwritten numerical recognition based on multiple algorithms | Pattern Recogn | HNR | 203 |
| *Vinciarelli et al.* [222]. | 2004 | Offline recognition of unconstrained handwritten texts using HMMs and statistical language models | IEEE T Pattern Anal | HTR | 201 |

| Author | Year | Article | Publisher | Topic | #Cit |
|---|---|---|---|---|---|
| *Lauer et al.* [116]. | 2007 | A trainable feature extractor for handwritten digit recognition | Pattern Recogn | HDR | 194 |
| *Kirn and Govindaraju* [106]. | 1997 | A lexicon driven approach to handwritten word recognition for real-time applications | IEEE T Pattern Anal | Lexicon | 189 |
| *Fischer et al.* [59]. | 2012 | Lexicon-free handwritten word spotting using character HMMs | Pattern Recogn Lett | WS | 186 |
| *Madhvanath and Govindaraju* [143]. | 2001 | The role of holistic paradigms in handwritten word recognition | IEEE T Pattern Anal | HTR | 177 |
| *Kato* [99]. | 1999 | A handwritten character recognition system using directional element feature and asymmetric mahalanobis distance | IEEE T Pattern Anal | HCR | 177 |
| *Manmatha et al.* [144]. | 1996 | Word spotting: a new approach to indexing handwriting | CVPR | WS | 176 |
| *El-Yacoubi et al.* [54]. | 1999 | An HMM-based approach for off-line unconstrained handwritten word modeling and recognition | IEEE T Pattern Anal | HTR | 173 |
| *Chen et al.* [31]. | 1994 | OffLine Handwritten Word Recognition Using a Hidden Markov Model Type Stochastic Network | IEEE T Pattern Anal | HTR | 173 |
| *Senior and Robinson* [189]. | 1998 | An off-line cursive handwriting recognition system | IEEE T Pattern Anal | HTR | 172 |
| *Liu et al.* [134]. | 2013 | Online and offline handwritten Chinese character recognition: Benchmarking on new databases | Pattern Recogn | HCR | 169 |
| *España-Boquera et al.* [56]. | 2011 | Improving offline handwritten text recognition with hybrid HMM/ANN models | IEEE T Pattern Anal | HTR | 168 |
| *Oliveira et al.* [157]. | 2002 | Automatic recognition of handwritten numerical strings: A Recognition and Verification strategy | IEEE T Pattern Anal | HNR | 165 |
| *Zhong et al.* [247]. | 2015 | High performance offline handwritten Chinese character recognition using GoogLeNet and directional feature maps | ICDAR | HCR | 158 |

| Author | Year | Article | Publisher | Topic | #Cit |
|---|---|---|---|---|---|
| *Lavrenko et al.* [117]. | 2004 | Holistic Word Recognition for Handwritten Historical Documents | DIAL | HTR | 155 |
| *Marti and Bunke* [145]. | 1999 | A full English sentence database for off-line handwriting recognition | ICDAR | HTR | 154 |
| *Zheng and Doermann* [246]. | 2004 | Machine Printed Text and Handwriting Identification in Noisy Document Images | IEEE T Pattern Anal | WI | 142 |
| *Plötz and Fink* [168]. | 2009 | Markov models for offline handwriting recognition: A survey | Int J Doc Anal Recog | HTR | 141 |
| *Adankon and Cheriet* [4]. | 2009 | Model selection for the LS-SVM. Application to handwriting recognition | Pattern Recogn | HTR | 140 |
| *Fukushima and Wake* [62]. | 1991 | Handwritten Alphanumeric Character Recognition by the Neocognitron | IEEE T Neural Netwo | HCR | 140 |
| *Louloudis et al.* [140]. | 2009 | Text line and word segmentation of handwritten documents | Pattern Recogn | Segmentation | 138 |
| *Rodríghez-Serrano and Perronnin* [179]. | 2009 | Handwritten word-spotting using hidden Markov models and universal vocabularies | Pattern Recogn | WS | 136 |
| *C.L Liu et al.* [126]. | 2002 | Lexicon-driven segmentation and recognition of handwritten character strings for Japanese address reading | IEEE T Pattern Anal | HTR | 134 |
| *Ha and Bunke* [76]. | 1997 | Off-line, handwritten numeral recognition by perturbation method | IEEE T Pattern Anal | HNR | 133 |
| *Zhang et al.* [244]. | 2017 | Online and offline handwritten Chinese character recognition: A comprehensive study and new benchmark | Pattern Recogn | HCR | 132 |
| *Li et al.* [122]. | 2008 | Script-independent text line segmentation in freestyle handwritten documents | IEEE T Pattern Anal | Segmentation | 132 |
| *Jain and Zongker* [95]. | 1997 | Representation and recognition of handwritten digits using deformable templates | IEEE T Pattern Ana | HDR | 132 |
| *Shi et al.* [194]. | 2002 | Handwritten numeral recognition using gradient and curvature of gray scale image | Pattern Recogn | HNR | 130 |

| Author | Year | Article | Publisher | Topic | #Cit |
|---|---|---|---|---|---|
| *Chacko et al.* [27]. | 2012 | Handwritten character recognition using wavelet energy and extreme learning machine | Int J Mach Learn Cyb | HCR | 126 |
| *Kimura et al.* [105]. | 1997 | Improvement of handwritten Japanese character recognition using weighted direction code histogram | Pattern Recogn | HCR | 126 |
| *Hildebrant and Liu* [88]. | 1993 | Optical recognition of handwritten Chinese characters: Advances since 1980 | Pattern Recogn | HCR | 126 |
| *Lu and Shridhar* [142]. | 1996 | Character segmentation in handwritten words - An overview | Pattern Recogn | Segmentation | 124 |
| *Wunsch and Laine* [232]. | 1995 | Wavelet descriptors for multiresolution recognition of handprinted characters | Pattern Recogn | HCR | 123 |
| *El-Hajj et al.* [52]. | 2005 | Arabic handwriting recognition using baseline dependant features and hidden Markov modeling | ICDAR | HTR | 122 |
| *Lee* [120]. | 1996 | Off-line recognition of totally unconstrained handwritten numerals using multilayer cluster neural network | IEEE T Pattern Anal | HNR | 122 |
| *Yamada et al.* [235]. | 1990 | A nonlinear normalization method for handprinted kanji character recognition-line density equalization | Pattern Recogn | HCR | 121 |
| *Koerich et al.* [108]. | 2003 | Large vocabulary off-line handwriting recognition: A survey | Pattern Anal Appl | HTR | 119 |
| *Pal et al.* [161]. | 2007 | Handwritten numeral recognition of six popular Indian scripts | ICDAR | HNR | 118 |
| *Bunke et al.* [25]. | 2003 | Recognition of cursive roman handwriting - past, present and future | ICDAR | HTR | 118 |
| *Chen and Wang* [32]. | 2000 | Segmentation of single- or multiple-touching handwritten numeral string using background and foreground analysis | | Segmentation | 118 |
| *Guerbai et al.* [72]. | 2015 | The effective use of the one-class SVM classifier for handwritten signature verification based on writer-independent parameters | Pattern Recogn | SV | 117 |
| *Mohamed and Gader* [153]. | 1996 | Handwritten word recognition using segmentation-free hidden Markov modeling and segmentation-based dynamic programming techniques | IEEE T Pattern Anal | HTR | 117 |

| Author | Year | Article | Publisher | Topic | #Cit |
|---|---|---|---|---|---|
| *Liu et al.* [135]. | 2011 | ICDAR 2011 Chinese handwriting recognition competition | ICDAR | HTR | 113 |
| *Al-HajjMohamad et al.* [6]. | 2009 | Combining slanted-frame classifiers for improved HMM-based Arabic handwriting recognition | IEEE T Pattern Anal | HTR | 113 |
| *Liu and Nakagawa* [128]. | 2001 | Evaluation of prototype learning algorithms for nearest-neighbor classifier in application to handwritten character recognition | Pattern Recogn | HCR | 112 |
| *Arica and Yarman-Vural* [15]. | 2002 | | | | 111 |
| *Knerr et al.* [107]. | 1992 | Handwritten Digit Recognition by Neural Networks with Single-Layer Training | IEEE T Neural Networ | HDR | 111 |
| *Pal and Datta* [160]. | 2003 | Segmentation of Bangla unconstrained handwritten text | ICDAR | Segmentation | 109 |
| *Cao et al.* [26]. | 1995 | Recognition of handwritten numerals with multiple feature and multistage classifier | Pattern Recogn | HNR | 108 |
| *Papavassiliou et al.* [162]. | 2010 | Handwritten document image segmentation into text lines and words | Pattern Recogn | Segmentation | 106 |
| *Sudholt and Fink* [205]. | 2016 | PHOCNet: A deep convolutional neural network for word spotting in handwritten documents | ICFHR | WS | 106 |
| *Yin and Liu* [238]. | 2009 | Handwritten Chinese text line segmentation by clustering with distance metric learning | Pattern Recogn | Segmentation | 106 |
| *Liu* [124]. | 2007 | Normalization-cooperated gradient feature extraction for handwritten character recognition | IEEE T Pattern Anal | HCR | 105 |
| *Revow et al.* [178]. | 1996 | Using generative models for handwritten digit recognition | IEEE T Pattern Anal | HDR | 105 |
| *Pechwitz and Maergner* [165]. | 2003 | | | | 104 |
| *Heutte et al.* [87]. | 1998 | HMM based approach for handwritten Arabic word recognition using the IFN/ENIT - database | ICDAR | HTR | 104 |

| Author | Year | Article | Publisher | Topic | #Cit |
|---|---|---|---|---|---|
| *Salah et al.* [184]. | 2002 | A selective attention-based method for visual pattern recognition with application to handwritten digit recognition and face recognition | IEEE T Pattern Anal | HDR | 102 |
| *Wang et al.* [226]. | 2012 | Handwritten Chinese text recognition by integrating multiple contexts | IEEE T Pattern Anal | HTR | 101 |
| *Stamatopoulos et al.* [202]. | 2013 | ICDAR 2013 handwriting segmentation contest | ICDAR | Segmentation | 100 |
| *Yin et al.*. [239]. | 2013 | ICDAR 2013 Chinese handwriting recognition competition | ICDAR | HTR | 100 |
| *Su et al.* [204]. | 2009 | Off-line recognition of realistic Chinese handwriting using segmentation-free strategy | Pattern Recogn | HTR | 100 |
| *He et al.* [85]. | 2008 | Writer identification of Chinese handwriting documents using hidden Markov tree model | Pattern Recogn | WI | 100 |
| *Su et al.* [203]. | 2007 | Corpus-based HIT-MW database for offline recognition of general-purpose Chinese handwritten text | Int J Doc Anal Recog | HTR | 100 |
| *Seni and Cohen* [188]. | 1994 | External word segmentation of off-line handwritten text lines | V | Segmentation | 99 |
| *Si Wei Lu et al.* [141]. | 1991 | Hierarchical attributed graph representation and recognition of handwritten chinese characters | Pattern Recogn | HTR | 99 |
| *Hafemann et al.* [77]. | 2017 | Learning features for offline handwritten signature verification using deep convolutional neural networks | Pattern Recogn | SV | 98 |
| *Toselli et al.* [215]. | 2003 | Integrated handwriting recognition and interpretation using finite-state models | Int J Pattern Recogn | HTR | 98 |
| *Oliveira et al.* [158]. | 2003 | A methodology for feature selection using multiobjective genetic algorithms for handwritten digit string recognition | Int J Pattern Recogn | HDR | 98 |
| *Dehghan et al.* [45]. | 2001 | Handwritten Farsi(Arabic) word recognition: A holistic approach using discrete HMM | Pattern Recogn | HTR | 98 |

| Author | Year | Article | Publisher | Topic | #Cit |
|---|---|---|---|---|---|
| *Gader et al.* [65]. | 1997 | Handwritten word recognition with character and inter-character neural networks | IEEE T syst Man Cyb B | HTR | 98 |
| *Van Breukelen et al.* [220]. | 1998 | Handwritten digit recognition by combined classifier | Kybernetika | HDR | 96 |
| *Favata and Srikantan* [57]. | 1996 | A multiple feature/resolution approach to handprinted digit and character recognition | Int J Imag syst Tech | HCR | 96 |
| *Chi et al.* [37]. | 1995 | | | | 95 |
| *H. Liu and Ding.* [136]. | 2005 | Handwritten numeral recognition using self-organizing maps and fuzzy rules | Pattern Recogn | HNR | 94 |
| *Sako et al.* [131]. | 2004 | Discriminative learning quadratic discriminant function for handwriting recognition | IEEE T Neural Networ | HTR | 93 |
| *Al-Ohali et al.* [7]. | 2003 | Databases for recognition of handwritten Arabic cheques | Pattern Recogn | HNR | 93 |

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

# 2 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 $[\text{reference}]_{\#\text{citations}}$, e.g., $[207]_{300}$ means that [207] has been cited 300 times since its publication.

| Thematic network | Network's keywords | #Papers | h-index | Top 10 papers |
|---|---|---|---|---|
| Character Recognition | Character Recognition, Statistical Model, Graph, Decision Tree, MLP, NN, Numeral Recognition, Preprocessing, Arabic Text Recognition, Template Matching, Japanese Text Recognition, Ensemble Classification | 43 | 22 | $[207]_{300}$ $[104]_{203}$ $[31]_{173}$ $[88]_{126}$ $[235]_{121}$ $[141]_{99}$ $[201]_{80}$ $[119]_{78}$ $[3]_{71}$ $[63]_{51}$ |

| Thematic network | Network's keywords | #Papers | h-index | Top 10 papers |
|---|---|---|---|---|
| Text Recognition | Text Recognition, Segmentation, Feature Extraction | 14 | 11 | $[93]_{1029}$ $[188]_{99}$ $[201]_{80}$ $[206]_{72}$ $[224]_{49}$ $[53]_{42}$ $[191]_{38}$ $[229]_{34}$ $[163]_{19}$ $[13]_{18}$ |

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

## 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.

| Thematic network | Network's keywords | #Papers | h-index | Top 10 papers |
|---|---|---|---|---|
| Character Recognition | Character Recognition, Structural Features, Statistical Model, MLP, Character Segmentation, Feature Extraction, NN, Classification, HMM, Word Recognition, Template Matching, Japanese Text Recognition | 162 | 37 | $[106]_{189}$ $[144]_{176}$ $[54]_{173}$ $[189]_{172}$ $[76]_{133}$ $[95]_{132}$ $[105]_{126}$ $[142]_{124}$ $[232]_{123}$ $[120]_{122}$ |
| Numeral Recognition | Numeral Recognition, Ensemble Classification, Structural Classification, Segmentation, GA, Clustering, Fuzzy Logic | 75 | 29 | $[92]_{418}$ $[106]_{189}$ $[54]_{173}$ $[76]_{133}$ $[95]_{132}$ $[120]_{122}$ $[26]_{108}$ $[37]_{95}$ $[237]_{78}$ $[212]_{77}$ |

| **Thematic network** | **Network's keywords** | **#Papers** | **h-index** | **Top 10 papers** |
|---|---|---|---|---|
| Chinese Character Recognition | Chinese Character Recognition, Directional Feature, Preprocessing, Graph | 41 | 15 | [99]$_{177}$ [54]$_{173}$ [189]$_{172}$ [95]$_{132}$ [105]$_{126}$ [212]$_{77}$ [11]$_{66}$ [217]$_{63}$ [137]$_{49}$ [28]$_{48}$ |
| Word Spotting | Word Spotting, Information Retrieval, Text Recognition | 27 | 14 | [92]$_{418}$ [144]$_{176}$ [145]$_{154}$ [156]$_{69}$ [102]$_{46}$ [34]$_{43}$ [2]$_{35}$ [101]$_{32}$ [79]$_{31}$ [38]$_{29}$ |
| Digit Recognition | Digit Recognition, KNN, Feature Selection | 16 | 8 | [76]$_{133}$ [95]$_{132}$ [82]$_{69}$ [64]$_{45}$ [195]$_{38}$ [33]$_{22}$ [150]$_{17}$ [109]$_{14}$ [103]$_{7}$ [149]$_{5}$ |

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

## 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.

| **Thematic network** | **Network's keywords** | **#Papers** | **h-index** | **Top 10 papers** |
|---|---|---|---|---|
| HMM | HMM, Sentence Recognition, Dictionary, Large Vocabulary, Text Recognition, Feature Selection, Preprocessing, Word Recognition, Arabic Text Recognition, Language Model, Ensemble Classification, Synthetic Data | 122 | 29 | [167]$_{1749}$ [147]$_{588}$ [146]$_{314}$ [14]$_{291}$ [130]$_{226}$ [222]$_{201}$ [143]$_{177}$ [246]$_{142}$ [126]$_{134}$ [108]$_{119}$ |

| **Thematic network** | **Network's keywords** | **#Papers** | **h-index** | **Top 10 papers** |
|---|---|---|---|---|
| Character Recognition | Character Recognition, Statistical Model, Graph, SOM, Character Segmentation, Feature Extraction, Segmentation, NN, Classification, Template Matching, Fuzzy Logic, Structural Features | 164 | 35 | $[129]_{401}$ $[14]_{291}$ $[157]_{165}$ $[126]_{134}$ $[194]_{130}$ $[32]_{118}$ $[128]_{112}$ $[15]_{111}$ $[45]_{98}$ $[131]_{93}$ |
| Chinese Character Recognition | Chinese Character Recognition, PCA, Active Shape Model, SVM, GA, Wavelet, Supervised Learning, Postprocessing | 59 | 19 | $[129]_{401}$ $[246]_{142}$ $[194]_{130}$ $[128]_{112}$ $[125]_{85}$ $[132]_{74}$ $[200]_{59}$ $[245]_{52}$ $[193]_{50}$ $[29]_{38}$ |
| Writer Identification | Writer Identification, Signature Verification, Mathematical Transform, Texture Features | 23 | 10 | $[167]_{1749}$ $[183]_{246}$ $[246]_{142}$ $[187]_{56}$ $[221]_{45}$ $[86]_{29}$ $[241]_{29}$ $[90]_{16}$ $[69]_{15}$ $[152]_{11}$ |
| Numeral Recognition | Digit Recognition, Structural Classification, Decision Tree, Clustering | 63 | 22 | $[129]_{401}$ $[130]_{226}$ $[157]_{165}$ $[194]_{130}$ $[25]_{118}$ $[184]_{102}$ $[131]_{93}$ $[61]_{89}$ $[115]_{78}$ $[132]_{74}$ |

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

## 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.

| Thematic network | Network's keywords | #Papers | h-index | Top 10 papers |
|---|---|---|---|---|
| SVM | SVM, Indian Text Recognition, Elastic Mesh, RBF, Feature Extraction, Character Recognition, Digit Recognition, Classification, Chinese Character Recognition, Feature Selection, Arabic Text Recognition, KNN | 254 | 32 | $[139]_{342}$ $[18]_{210}$ $[116]_{194}$ $[4]_{140}$ $[6]_{113}$ $[124]_{105}$ $[204]_{100}$ $[85]_{100}$ $[203]_{100}$ $[228]_{84}$ |
| HMM | HMM, Sentence Recognition, Moments, Dictionary, Text Recognition, Chinese Text Recognition, Word Recognition, RNN, Language Model, Ensemble Classification, Statistical Model, Graph | 198 | 27 | $[70]_{982}$ $[168]_{141}$ $[140]_{138}$ $[179]_{136}$ $[122]_{132}$ $[6]_{113}$ $[238]_{106}$ $[204]_{100}$ $[85]_{100}$ $[243]_{79}$ |
| Segmentation | Segmentation, Structural Features, Bank Check Recognition, Digit Segmentation, NN, Writer Identification, Numeral Recognition, Preprocessing, Historical Documents, Script Identification, Fuzzy Logic | 206 | 28 | $[179]_{136}$ $[6]_{113}$ $[124]_{105}$ $[204]_{100}$ $[85]_{100}$ $[243]_{79}$ $[49]_{70}$ $[133]_{66}$ $[127]_{65}$ $[218]_{64}$ |
| Signature Verification | Signature Verification, Verification, Wavelet, DTW, Mathematical Transform | 55 | 14 | $[85]_{100}$ $[24]_{92}$ $[73]_{51}$ $[171]_{36}$ $[23]_{35}$ $[75]_{34}$ $[170]_{19}$ $[176]_{19}$ $[213]_{14}$ $[66]_{12}$ |

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

## 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.

| Thematic network | Network's keywords | #Papers | h-index | Top 10 papers |
|---|---|---|---|---|
| Character Recognition | Character Recognition, Statistical Model, Mathematical Transform, Zonning, Feature Extraction, NN, SVM, Preprocessing, Arabic Text Recognition, KNN, Wavelet, Indian Text Recognition | 632 | 35 | [56]$_{168}$ [27]$_{126}$ [135]$_{113}$ [162]$_{106}$ [239]$_{100}$ [20]$_{86}$ [225]$_{85}$ [164]$_{84}$ [219]$_{80}$ [230]$_{79}$ |
| 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 | [166]$_{239}$ [59]$_{186}$ [134]$_{169}$ [56]$_{168}$ [135]$_{113}$ [162]$_{106}$ [226]$_{101}$ [202]$_{100}$ [239]$_{100}$ [42]$_{86}$ |
| HMM | HMM, Sentence Recognition, Bayesian Network, Viterbi Algorithm, DBNN, Word Spotting, Word Recognition, RNN, Clustering, Music Recognition, Roman Script, GMM | 219 | 29 | [166]$_{239}$ [59]$_{186}$ [56]$_{168}$ [162]$_{106}$ [20]$_{86}$ [58]$_{83}$ [48]$_{82}$ [9]$_{75}$ |
| 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 | [164]$_{84}$ [219]$_{80}$ [41]$_{75}$ [154]$_{56}$ [94]$_{49}$ [112]$_{41}$ [50]$_{38}$ [46]$_{36}$ [80]$_{30}$ [16]$_{29}$ |

| Thematic network | Network's keywords | #Papers | h-index | Top 10 papers |
|---|---|---|---|---|
| Writer Identification | Writer Identification, Histogram, Texture Features, Feature Selection, Forensics | 79 | 14 | [42]$_{86}$ [44]$_{80}$ [47]$_{53}$ [60]$_{49}$ [30]$_{33}$ [89]$_{28}$ [113]$_{23}$ [121]$_{23}$ [1]$_{22}$ [174]$_{22}$ |
| MLP | MLP, PFGA, Numeral Recognition, Moments | 73 | 10 | [56]$_{168}$ [12]$_{64}$ [227]$_{30}$ [151]$_{20}$ [114]$_{20}$ [199]$_{15}$ [97]$_{13}$ [173]$_{12}$ [192]$_{11}$ [180]$_{10}$ |
| Historical Documents | Historical Documents, Language Model, Morphology Operator | 57 | 12 | [226]$_{101}$ [240]$_{44}$ [138]$_{39}$ [30]$_{33}$ [100]$_{24}$ [68]$_{22}$ [174]$_{22}$ [186]$_{21}$ [110]$_{19}$ [185]$_{14}$ |

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

## 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.

| Thematic network | Network's keywords | #Papers | h-index | Top 10 papers |
|---|---|---|---|---|
| DNN | DNN, Text Recognition, Character Recognition,CNN, Digit Recognition, RNN, Transfer Learning, Indian Text Recognition, Data Augmentation, Dropout, DCNN, DBNN | 1,1138 | 30 | [247]$_{158}$ [244]$_{132}$ [205]$_{106}$ [77]$_{98}$ [55]$_{82}$ [236]$_{70}$ [233]$_{68}$ [223]$_{68}$ [231]$_{66}$ [91]$_{65}$ |

| **Thematic network** | **Network's keywords** | **#Papers** | **h-index** | **Top 10 papers** |
|---|---|---|---|---|
| SVM | SVM, Texture Features, Decision Tree, PCA, Feature Extraction, NN, Classification, Signature Verification, Arabic Text Recognition, KNN, HOG, Statistical Model, Texture Features | 902 | 23 | $[72]_{117}$ $[55]_{82}$ $[209]_{54}$ $[159]_{53}$ $[190]_{48}$ $[98]_{29}$ $[22]_{25}$ $[169]_{23}$ $[197]_{20}$ $[21]_{16}$ |
| Segmentation | Segmentation, Histogram, Character Segmentation, Text Line Segmentation, Word Spotting, Preprocessing, Word Recognition, Math Recognition, Historical Documents, Sliding Window, FCNN, Projection Features | 455 | 18 | $[72]_{117}$ $[205]_{106}$ $[181]_{52}$ $[242]_{46}$ $[111]_{45}$ $[8]_{35}$ $[172]_{34}$ $[35]_{27}$ $[51]_{26}$ $[216]_{25}$ |
| Ensemble Classification | Ensemble Classification, Moments, ResNet,Chinese Character Recognition, Chinese Text Recognition, Feature Selection, GA, Script Identification, Fuzzy Logic, Structural Features, Mathematical Transform, Graph | 379 | 20 | $[247]_{158}$ $[244]_{132}$ $[40]_{73}$ $[233]_{68}$ $[231]_{66}$ $[17]_{44}$ $[177]_{42}$ $[43]_{35}$ $[39]_{34}$ $[123]_{33}$ |
| HMM | HMM, Embedding,Tibetan Text Recognition, Language Model, Music Recognition, Roman Text Recognition, Multi-Script Recognition, N-Grams, Sentence Recognition, Bayesian Network | 165 | 14 | $[231]_{66}$ $[181]_{52}$ $[84]_{52}$ $[111]_{52}$ $[35]_{45}$ $[210]_{25}$ $[78]_{25}$ $[214]_{20}$ $[19]_{18}$ $[36]_{18}$ |
| Writer Identification | Writer Identification, Siamese Network, Verification, Template Matching, Wavelet, Forensics, SIFT, Autoencoder | 155 | 12 | $[81]_{58}$ $[84]_{52}$ $[175]_{29}$ $[196]_{29}$ $[96]_{23}$ $[118]_{22}$ $[83]_{17}$ $[10]_{16}$ $[36]_{15}$ $[155]_{14}$ |

| **Thematic network** | **Network's keywords** | **#Papers** | **h-index** | **Top 10 papers** |
|---|---|---|---|---|
| Numeral Recognition | Numeral Recognition, MLP, Attention Mechanism, Graphology, End-to-end, ELM | 141 | 12 | [242]$_{46}$ [172]$_{34}$ [123]$_{33}$ [118]$_{22}$ [5]$_{19}$ [198]$_{19}$ [74]$_{18}$ [211]$_{16}$ [182]$_{15}$ [208]$_{14}$ |

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

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