Intelligent Systems with Applications 22 (2024) 200358

Contents lists available at ScienceDirect

Intelligent Systems with Applications

journal homepage: www.journals.elsevier.com/intelligent-systems-with-applications

Review

Exploration of advancements in handwritten document recognition techniques

Vanita Agrawal [a], Jayant Jagtap [b], M.V.V. Prasad Kantipudi [a,*]

[a] Symbiosis Institute of Technology (SIT), Symbiosis International (Deemed University) (SIU), Lavale, Pune, 412115, Maharashtra, India
[b] NIMS Institute of Computing, Artificial Intelligence and Machine Learning, NIMS University Rajasthan, Jaipur, India

ARTICLE INFO

Keywords:
Handwritten document recognition
Handwritten text recognition
Handwritten diagram recognition
Handwritten digit detection
Handwritten mathematical expression interpretation

ABSTRACT

Handwritten document recognition and classification are among the many computers related issues being studied for digitizing handwritten data. A handwritten document comprises text, diagrams, mathematical expressions, numerals, and tables. Due to the variety of writing styles and the intricacy of the written language, it has proven difficult to recognize handwritten material. As a result, numerous handwritten document recognition systems have been developed, each with unique benefits and drawbacks. The paper reviews the evolution of handwritten document recognition in qualitative and quantitative ways. Initially, the bibliometric survey is presented based on the number of articles, citations, countries, authors, etc., on handwritten document recognition in the Scopus database. Later, a survey is done on the learning techniques used for handwritten documents: text recognition, digit recognition, mathematical expression recognition, table recognition, and diagram recognition. This paper also presents the directions for future research in handwritten document recognition.

1. Introduction

Alonso (2015) stated that handwriting provides good logical benefits. Handwriting increases the ability to focus on what is written. It improves memory, information organization, and prioritizing skills. The solution to the conceptual question is better for students who write notes by hand than for students who type letters (Mueller & Oppenheimer, 2014).

Digitization of handwritten documents helps to store data in a better way. Compared to physical files, digital data storage is more cost-effective. Even searching for information is more straightforward with electronic data. Hence, handwritten document recognition (HDR) techniques have been the subject of extensive research. Handwritten documents are used in various fields such as education, healthcare, banking sectors, logistics companies, etc.

The recognition of handwritten text has proven challenging due to the variability in writing styles and the complexity of the written language. This has led to the development of various handwritten document recognition techniques, each with advantages and disadvantages. The benefits of optical character recognition (OCR) technology include converting physical documents into electronic format and performing searches on them. Similarly, handwriting recognition can preserve original manuscripts in electronic form.

At the interface of computer vision and artificial intelligence, handwritten document identification is a key field with significant possibilities for improving human-computer interactions, digitizing historical archives, and enabling effective data retrieval. Even though there have been great advancements recently, obtaining persistently high accuracy among many handwriting styles and languages remains a critical research problem. The main focus of this research challenge is the requirement for reliable and flexible recognition algorithms that can handle the complexities of manuscripts. It is important because it can open doors to the past, speed up data processing, improve human-computer interactions, and develop information accessibility and technology.

It is imperative to address this research topic for several reasons. First, historical writings in various forms are priceless cultural relics susceptible to deterioration over time. Second, handwritten notes and forms are still used in many businesses in modern settings, necessitating precise recognition for efficient data extraction and analysis. Furthermore, the significance goes beyond human-computer interaction since applications such as taking digital notes to verify signatures depend on the intuitive and precise identification of handwriting input.

A handwritten document does not contain only text but has different aspects, as shown in the Fig. 1. Recognition of these aspects is challenging. Hence, this paper reviews the different techniques used for

* Corresponding author.
E-mail address: prasad.kantipudi@sitpune.edu.in (M.V.V.P. Kantipudi).

https://doi.org/10.1016/j.iswa.2024.200358
Received 26 October 2023; Received in revised form 11 January 2024; Accepted 9 March 2024
Available online 15 March 2024
2667-3053/© 2024 The Authors. Published by Elsevier Ltd. This is an open access article under the CC BY-NC license (http://creativecommons.org/licenses/by-nc/4.0/).

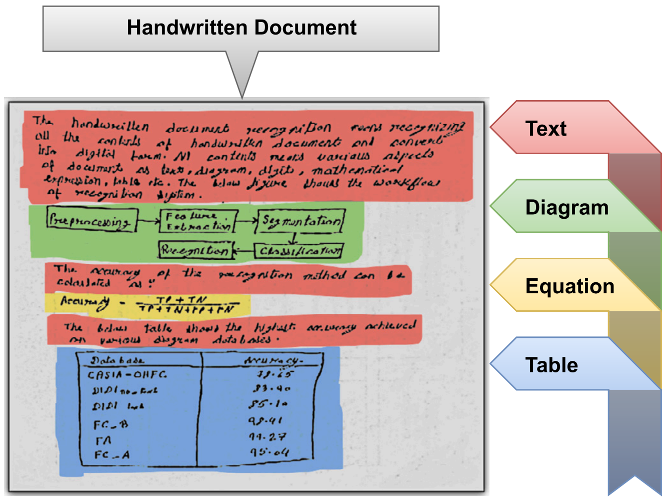

Fig. 1. Various aspects of a handwritten document.

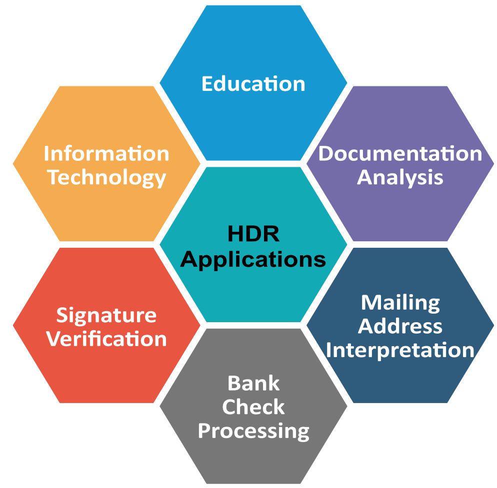

Fig. 2. Real-time applications of handwritten document recognition.

handwritten document recognition, how they have evolved, and their respective benefits and challenges. By exploring the advancements in this field, the paper sheds light on the recent methods and their potential applications in various industries.

As per our survey, the first and only attempt to provide a review of so many articles covering all aspects of handwritten documents is by Ruiz-Parrado et al. (2022). However, they presented only the bibliometric study of handwritten document analysis methods. Hence, this paper is the first attempt to provide both bibliometric and systematic reviews. It also covers the benefits and challenges of the recent techniques in each aspect of handwritten documents. This will help future researchers finalize the area and directions for their research.

Section 2 emphasizes the basics of HDR. The bibliometric survey according to the quantity of articles, citations, most prolific authors, countries with active research, and network mapping is presented in section 3. The systematic literature review of advances in HDR is tabulated in section 4. Section 5 summarizes the paper.

2. Handwritten document recognition

HDR involves the conversion of handwritten documents into digital form, and several techniques are used to accomplish this task. One of the most common techniques is template matching, which involves comparing an input image with a set of reference patterns to find the best match (Ali & Abdulrazzaq, 2023). Other techniques include feature extraction, neural networks, and support vector machines (SVM), which recognize patterns in the input image and classify new images by finding a hyperplane that separates different classes of images (Ali & Abdulrazzaq, 2023). Handwriting recognition systems are used in various real-time problems, as shown in the Fig. 2.

The types of recognition depend on when the identification takes place. Offline recognition can be done any time after the document has been written, even years later, using techniques such as image recognition and processing. Offline recognition is more challenging than traditional tasks with image data due to the requirement to categorize any handwritten word picture, regardless of form (Rajalakshmi et al., 2019). Therefore, pattern recognition and classification are the most challenging parts of the system (Rajalakshmi et al., 2019).

HDR means recognizing the handwritten document's contents and converting it to digital form. The contents might include text, diagrams, digits, mathematical expressions, tables, etc. Fig. 3 shows the workflow of the HDR system where a handwritten document is given as input, and the system outputs the digitized form of the input document. The focus of this paper is on a bibliometric survey of work done on HDR and a systematic survey of each aspect of the HDR system.

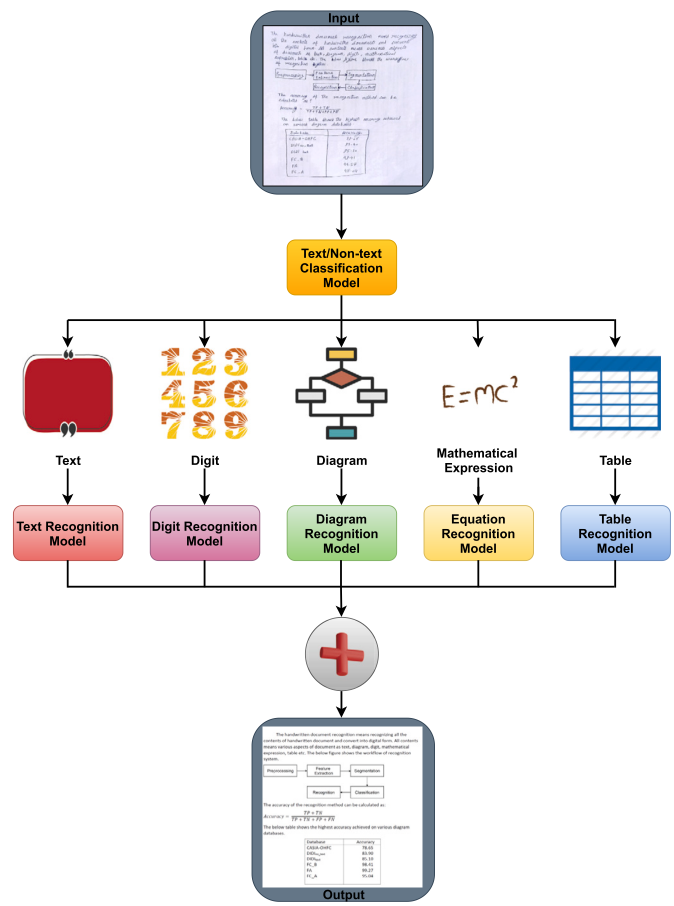

Fig. 3. Image workflow of handwritten document recognition system.

3. Bibliometric review

Web of Science and Scopus are the most widely used for analyzing bibliometric data. The paper focuses on the results of the Scopus database, as integrating citations from various databases can result in inconsistency. The bibliometric survey process began with the search of keywords on the Scopus database. Based on aspects of the handwritten document, the query is designed as shown in the Fig. 4.

The last 30 years records are extracted belonging to computer science, engineering, and mathematics subject areas and published in the

```
(TITLE-ABS-KEY(handwritten AND document AND recognition)
OR TITLE-ABS-KEY(handwritten AND text OR character AND recognition)
OR TITLE-ABS-KEY(handwritten AND digit OR number OR numeric AND recognition)
OR TITLE-ABS-KEY(handwritten AND diagram AND recognition)
OR TITLE-ABS-KEY(handwritten AND table AND recognition)
OR TITLE-ABS-KEY(handwritten AND mathematical AND expression AND recognition))
AND PUBYEAR > 1992
AND PUBYEAR < 2024
AND (
LIMIT-TO ( SUBJAREA,"COMP" )
OR LIMIT-TO ( SUBJAREA,"ENGI" )
OR LIMIT-TO ( SUBJAREA,"MATH" ))
AND (
LIMIT-TO ( LANGUAGE,"English" ))
```

Fig. 4. Query string used to retrieve the publication records from the Scopus database.

Fig. 5. Co-occurrence analysis of author keywords.

English language. The query resulted in 11,115 records on the 13th of June, 2023. The list consisted of documents on recognizing various aspects of the handwritten document as text, diagrams, digits, mathematical expressions, tables, etc. Text recognition documents from multiple languages as Arabic, Hindi, Marathi, etc., were present in the list. It also contained image recognition, object detection, and other tasks not associated with handwriting but included because initially, the testing was done on the handwritten digit dataset and then on the actual dataset. Hence the results are further filtered to include only those titles that contain words similar to handwritten, handcrafted, or handprinted. The resultant 6,812 documents are then manually refined to remove the entries without author and title details, those are mostly the proceedings, and few are the suppressed documents. The bibliometric survey was carried out on the resulting 6,800 documents.

The keywords associated with the result of the query string are analyzed and shown in the Fig. 5. Recognition is the most co-occurred keyword followed by handwritten, handwriting, feature, neural networks, etc.

3.1. Research growth

The term "research growth" describes the gradual increase in scholarly output in a particular topic. Analyzing research growth in handwritten document recognition entails assessing the rise in the number of publications. Comprehending the expansion of research offers valuable insights into the changing dynamics of the topic, enabling researchers to pinpoint periods of heightened interest and prospective domains for additional investigation.

The research on HDR started in the early 60s as per search results on the Scopus database. Kamentsky (1961) simulated three machines

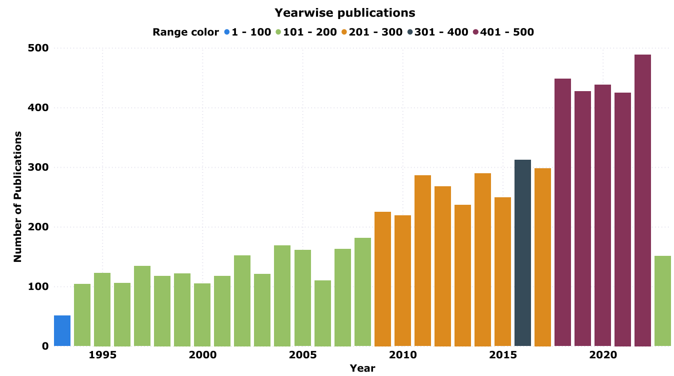

Fig. 6. Publication count per year in Scopus from 1993.

Table 1
Number of publications categorized based on both year and country.

Year	Country	Co-unt	Year	Country	Co-unt
2023	China	20	2018	India	154
2023	India	71	2017	Spain	18
2022	India	180	2017	Malaysia	10
2022	Bangladesh	18	2017	China	36
2022	Saudi Arabia	14	2017	Algeria	11
2022	Germany	13	2017	India	84
2022	China	79	2017	Bangladesh	10
2022	United States	21	2017	United States	15
2021	United States	12	2016	India	95
2021	India	141	2016	Spain	13
2021	China	59	2016	Iran	14
2021	Malaysia	10	2016	United States	15
2021	Bangladesh	19	2016	Japan	18
2021	Japan	20	2016	Tunisia	14
2021	Saudi Arabia	13	2016	China	42
2020	France	11	2016	France	15
2020	Saudi Arabia	11	2015	China	26
2020	India	144	2015	France	15
2020	Bangladesh	16	2015	India	91
2020	Japan	17	2015	Spain	17
2020	United States	18	2014	Spain	20
2020	China	69	2014	Canada	10
2019	Spain	15	2014	France	19
2019	United States	16	2014	Greece	10
2019	Japan	17	2014	China	37
2019	India	132	2014	India	75
2019	China	66	2014	United States	13
2019	Bangladesh	30	2014	Japan	16
2018	China	61	2014	Germany	10
2018	Spain	13	2013	France	11
2018	France	11	2013	Japan	14
2018	Bangladesh	23	2013	Spain	12
2018	Iran	10	2013	India	61
2018	Malaysia	10	2013	United States	10
2018	Japan	19	2013	China	41
2018	United States	29			

to read the rows of handwritten Arabic numbers. Fig. 6 shows the publication in HDR per year in the Scopus database. From the figure, it has been observed that after 2018 there was a huge spike in research on HDR as the world was fast-tracked digitization. Another reason for the increase in research is the digitization of education and Information Technology (IT) because of Covid-19. Since 2018 the publications are consistently above 400.

Table 1 shows the number of publications both year-wise and country-wise for the past ten years. It can be noticed that India has the highest count of publications, followed by China and then the United States.

The same can be observed by the Fig. 7, which shows the country-wise publications of the last 30 years categorized by the number of publications.

Table 2
Top 10 most cited publications on HDR.

Authors	Title	Cited by	HDR Aspect
Plamondon and Srihari (2000)	On-line and off-line handwriting recognition: A comprehensive survey	1936	Survey
Hull (1994)	A Database for Handwritten Text Recognition Research	1448	HTR
Graves et al. (2009)	A novel connectionist system for unconstrained handwriting recognition	1428	HTR
Deng (2012)	The MNIST database of handwritten digit images for machine learning research	1406	HDtR
Marti and Bunke (2003)	The IAM-database: An English sentence database for offline handwriting recognition	851	HTR
Graves and Schmidhuber (2009)	Offline handwriting recognition with multidimensional recurrent neural networks	699	HTR
Bottou et al. (1994)	Comparison of classifier methods: A case study in handwritten digit recognition	526	HDtR
Niu and Suen (2012)	A novel hybrid CNN-SVM classifier for recognizing handwritten digits	519	HDtR
Liu et al. (2003)	Handwritten digit recognition: Benchmarking of state-of-the-art techniques	435	HDtR
Cireşan et al. (2011)	Convolutional neural network committees for handwritten character classification	419	HCR

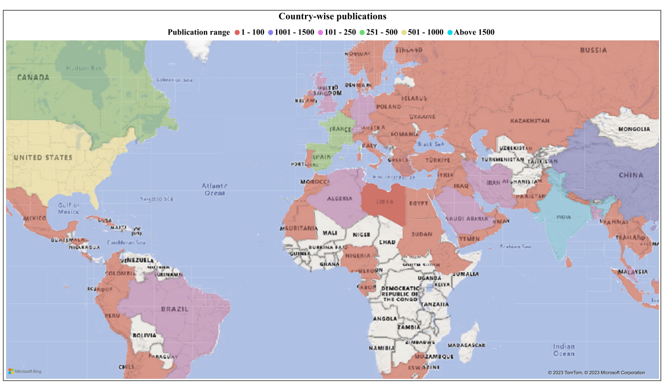

Fig. 7. Publication count from individual countries.

3.2. Citation trend

Citations indicate the level of interest an article has attracted. Citation trends are important because they help identify seminal publications and researchers who have made substantial contributions to the field's growth of handwritten document recognition. They also help gauge the effect and impact of studies within the field. Table 2 shows the top 10 most cited papers. The abbreviations used in the table are H -> handwritten, R -> recognition, T -> text, C -> character, Dt -> digit. Most of the papers are related to HTR and HDtR. The survey article written by Plamondon and Srihari (2000) has received the highest citations.

To visualize the significant change between authors and source titles over the year, the statistical information of citations is used and plotted using Alluvial diagrams, as shown in the Fig. 8. The diagram shows that the researchers mostly refer to the articles published in IEEE Transactions on Pattern Analysis and Machine Intelligence. Also, the articles from the Pattern Recognition Journal and IEEE Signal Processing Magazine are cited multiple times.

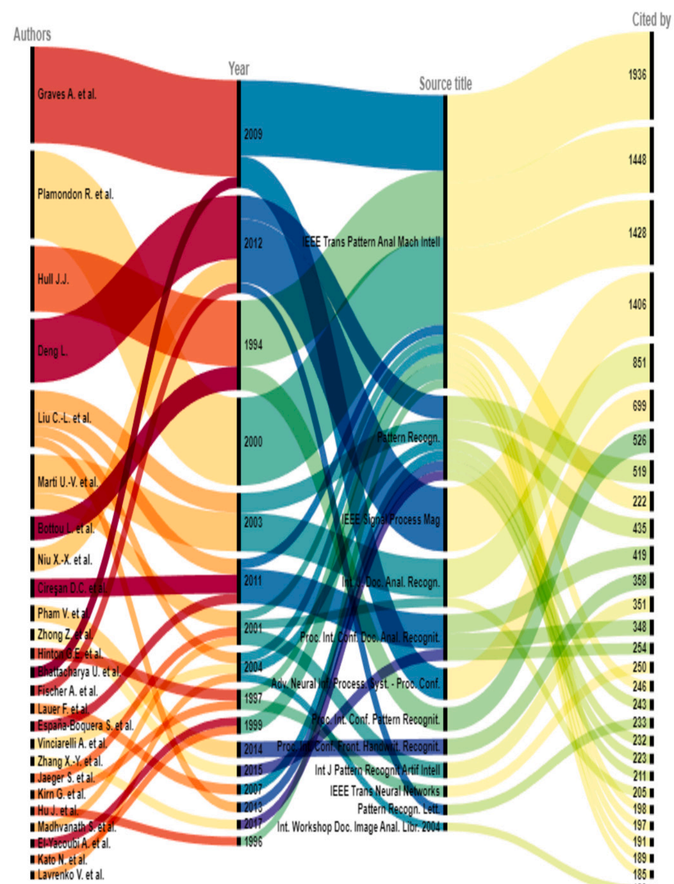

Fig. 8. Alluvial diagram displaying the relationships among the top 30 referenced documents' contributors, years, and source titles.

3.3. Research promoters

People, organizations, or publications that are essential in advancing and igniting research in a certain field are known as research promoters. Determining the research advocates facilitates comprehension of the major entities influencing the field of handwritten document identification. Research promoters help new and upcoming researchers in two ways, first by collaborating with the researchers or their institutes and secondly by funding the research. In this section, the affiliations and funding agencies of most published papers are discussed. From the survey, it was found that 25 sponsors have funded more than 10 articles. These 25 sponsors have funded a total of 875 articles. Based on the percentage of the articles sponsored the Fig. 9 is created. From the Fig. 9,

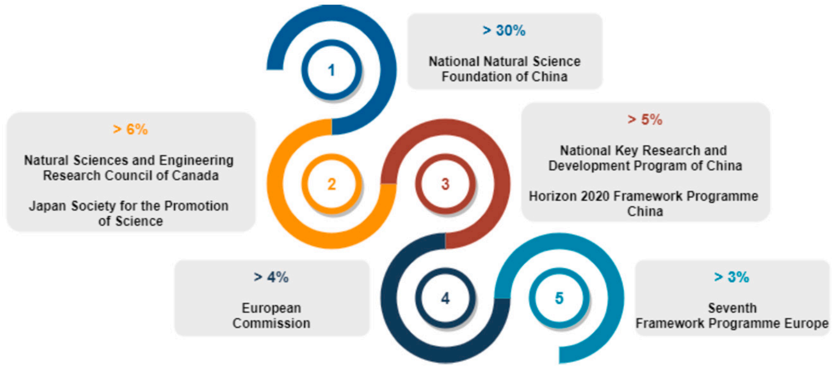

Fig. 9. Top funding sponsors based on the document count.

Fig. 10. Affiliations associated with more than 100 document counts.

it can be observed that China, Japan, Canada, and European countries are the most prominent funding sponsors.

The Fig. 10 shows the academicians who have published over 100 papers in HDR. India, Spain, the United States, China, Canada, and Japan are the most affiliated countries.

3.4. Bibliographic coupling

Bibliographic coupling counts the number of references that two papers have in common to determine how similar they are. This measure may be used to find articles that have similar references in regard to handwritten document recognition, suggesting an intellectual or conceptual relationship between them. It assists in establishing the conceptual framework of handwritten document recognition studies by offering a numerical indicator of how closely linked various publications are to one another. The detailed coupling analysis based on documents, citations, and total link strength (TLS) is shown in the Table 3. From the table, it's observed that Günter S. and Bunke H. have the highest number of documents and their TLS is 20.39. Fig. 11 provides the network analysis of the bibliographic coupling of researchers with a minimum of 5 documents. The large circle represents the fact that the researcher, H. Bunke, has many publications. The colored cluster formed in the figure represents the researcher's strong relation to each other.

Table 3
Bibliographic coupling of researchers.

Author	Documents	Citations	TLS
Günter S.; Bunke H.	15	234	20.39
Bertolami R.; Bunke H.	6	90	18.38
Marti U.-V.; Bunke H.	5	1347	15.72
Liwicki M.; Bunke H.	5	204	14
Liu C.-L. et al.	7	329	13.38
Zhu B.; Nakagawa M.	6	51	10.33
Dash K.S. et al.	9	120	7
Ma L.-L.; Wu J.	6	35	6.5
Wang Q.-F. et al.	5	208	6
Jangid M.; Srivastava S.	5	80	5.6
Kumar M. et al.	7	149	5.5
Nemmour H.; Chibani Y.	8	27	5.2
Ali A.A.A.; Suresha M.	6	51	5
Varga T.; Bunke H.	6	142	4.75
Pramanik R.; Bag S.	6	106	4
Maalej R.; Kherallah M.	6	66	4
Rajashekararadhya S.V.; Vanaja Ranjan P.	5	37	4
Serdouk Y. et al.	7	112	3.6
Elleuch M. et al.	5	124	3
Wang Y.; Huo Q.	5	39	3
Bharath A.; Madhvanath S.	5	152	2.33
Awal A.-M. et al.	5	157	2
Rahman A.F.R.; Fairhurst M.C.	6	124	2
Uchida S.; Sakoe H.	5	118	2
Alaei A. et al.	6	96	2
Abuzaraida M.A. et al.	5	48	2
Madhvanath S.; Govindaraju V.	5	232	1
Stauffer M. et al.	5	58	1
Shelke S.; Apte S.	5	51	1
Tang P. et al.	5	25	1

3.5. Bibliometric review conclusion

Research in digitizing handwritten documents to use resources efficiently has increased over the past few years. The Citation Trend section will help researchers find the most prominent source title for their article publication. The research promoters section will help find the most active research institute to collaborate with and the details of funding sponsors in case funds are required for the research. The bibliometric review also helped discover the most active researchers and their research areas.

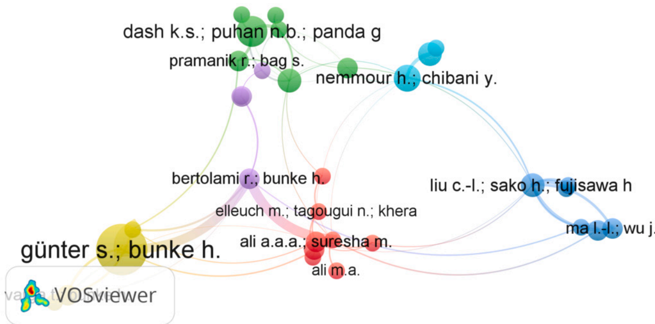

Fig. 11. Researchers' collaboration network based on the bibliography.

4. Systematic review

Now that the bibliometric survey has established the foundation for comprehending the overall environment and patterns, the emphasis is on investigating the learning strategies used in HDR. The techniques used in HDR have evolved, becoming more complex and sophisticated. Early approaches to HDR involved pure incremental, simplistic techniques (Kniazieva, 2022). However, over time, researchers have developed new and advanced techniques, such as semi-incremental ones, which involve using other approaches in addition to incremental ones (Kniazieva, 2022). Various research works have been conducted to evolve different aspects of HDR. In this section, the benefits and challenges/future work of each element of HDR are discussed in brief. The Scopus database is used to find articles on each aspect of HDR. Fifteen articles from the last five years are selected on each element with the highest citation and open access, except for table recognition. For table recognition, only a few articles are available; hence, only one filtering is applied, sorting on citation count.

4.1. Handwritten text recognition

Handwritten text or character recognition systems have seen significant advancements in recent years. Systems for reading handwritten text can be categorized as online or offline. Online platforms provide real-time character recognition when users write on touchscreens or touch-sensitive interfaces, gathering time-based data including pace, momentum, quantity of strokes, and writing position (Jain et al., 2023). The opposite is true for offline systems, which use static data—specifically scanned images—as input and frequently necessitate intensive preprocessing to function properly (Jain et al., 2023). Deep learning developments, notably transformer architectures, have also aided the development of handwritten text recognition systems. These systems have various applications in fields such as postal services, where they play a crucial role in automating address interpretation and facilitating efficient mail sorting (Jain et al., 2023). Additionally, current research is into leveraging OCR and image processing technology to recognize regional languages, such as Sinhala, Tamil, etc.

Table 4 presents the survey on current research of methods available for text recognition in HDR. The most commonly used artificial neural network (ANN) technology for handwritten text recognition is the convolutional neural network (CNN). The layers of CNN are changed or sometimes integrated with other methods such as long-short term memory (LSTM), extreme learning machine (ELM), recurrent neural network (RNN), density-based spatial clustering of applications with noise (DBSCAN), multi-layer perceptron (MLP), visual geometry group (VGG), etc. Machine learning (ML) algorithms are also used, such as fast discrete curvelet transform (FDCT), least squares-support vector machine (LS-SVM), random forests (RF), etc. IAM (Marti & Bunke, 2002) is the most commonly used dataset for text recognition. IAM contains words, lines, and documents. The algorithm's effectiveness is measured using character error rate (CER) and word error rate (WER).

Though much work has already been done, there are still many challenges and future scopes, as mentioned in the table. In the future, a more accurate feature extraction technique is needed. The work needs to be done on placing recognized words and lines in the correct order. Also, language modeling or grammar correction tools can be used to improve the accuracy of the results.

In computer vision, attention can supplement or completely replace CNN while maintaining some degree of its structural integrity. Thus, there has been a significant increase in the attention of researchers in vision transformers (ViTs) (Kolesnikov et al., 2021) and multilayer perceptrons (MLPs). Transformers use fewer resources, catch more pertinent data, and outperform CNN when focusing on a random area of interest. Hence transformers can be used for text recognition.

4.2. Handwritten digit recognition

An important application in data analysis is the recognition of handwritten digits, but it presents several challenges due to variations in writing styles and image artifacts. To address these challenges, researchers have proposed various techniques and algorithms. The development and evaluation of these techniques have been facilitated by the availability of datasets like MNIST (LeCun & Cortes, 2010), which contains many training and testing images of handwritten digits. Table 5 highlights such recent techniques and algorithms.

CNN has proven to be effective in the handwritten digit. The CNN-based approaches can calculate location-invariant features in a potentially limited amount of time, making them robust to distortions. Other advantages of CNN are local connectivity, parameter sharing, translation invariance and feature learning. Other classification algorithms like back-propagation (BP) neural networks, population extremal optimization and a fractional-order gradient descent learning mechanism (PEO-FOBP), principal component analysis (PCA), and linear discriminant analysis (LDA), threshold center-symmetric local binary CNN (TCS-LBCNN), SVM has shown improved performance in recognizing handwritten digits. The hybrid feature selection algorithm with minimum redundancy and maximum relevance (mRMR) also improves recognition accuracy. Hybrid approaches also provide benefits such as robustness, generalization, optimization, etc. The complex datasets like numerals of Oria, Bangla language, and original English digits (uncleaned) need more attention from the researchers. Overall, exploring handwritten digit recognition techniques has highlighted the importance of deep learning algorithms and their ability to overcome pattern recognition and character detection challenges.

4.3. Handdrawn diagram recognition

A hand-drawn diagram, also known as a sketch, can represent physical objects and processes. They can be used to help visualize ideas or solve problems. An example of hand-drawn diagrams is architectural drawings or engineering blueprints. Hand-drawn diagrams help understand complex systems because they are easy to understand in their natural state and don't require any special training or experience to read them properly. This makes them ideal for making decisions based on incomplete information or incomplete knowledge of the system being explored. A hand-drawn diagram is a sequence of connected points, lines, and drawn curves. The hand-drawn diagrams' recognition techniques are explored and summarized in Table 6.

Hand-drawn diagram recognition is challenging as each block of the diagram is different, and various people use different drawing styles for a single block. The diagrams can be drawn on a device (online), paper (offline), or in the air. The main task is to extract the features. Various algorithms used in literature for feature extraction are CNN, graph spectral, stroke-based, etc. The literature also shows handwriting recognition in the Artificial Intelligence of Things (AIoT). Current methods used for recognition along with CNN are depthwise separable convolu-

Table 4
The analysis of existing approaches for the recognition of text.

Author	Benefits	Challenges/Future Research Directions
Cilia et al. (2019)	Address the two main problems with feature selection methods: the high computing cost of looking for proper feature subsets and the challenges in considering the impact of connections between features.	Adoption of additional, more sophisticated, and costly computational feature selection methods with smaller feature subsets.
Sánchez et al. (2019)	This paper proposes a new state-of-the-art baseline that will improve HTR techniques.	Setting up the proper reading order of text lines is challenging.
Weng and Xia (2020)	Helps collect, process and then construct data set using lightweight network structure for OCR in mobile devices.	Need more investigation on the creation of a full deep learning model for portable devices.
Das et al. (2019)	ELM is used to solve problems in diverse domains because of its ability to learn faster, providing for general guidelines to design ELM-based classifiers	The impact of deep ELM variants on CNN can be further researched.
Neto et al. (2020)	Minimize spelling errors using optical and language methods in case of auto mechanisms for offline HTR. This technique allowed 1.5x better average sentence correction than alternative cutting-edge techniques.	Need efforts on sentences containing noise and missing words.
Geetha et al. (2021)	It uses a combination of H2TR, CNN, & RNN along with LSTM; when tested with IAM & RIMES databases, it provides competitive letter & word accuracy results	The model can be further enhanced for language based decoding.
Nurseitov et al. (2020)	Uses a combination of CNN and MLP for classifying words and then uses Bluechet & Puchserver to compare results.	Baseline techniques can be tested on the proposed dataset.
Zin et al. (2021)	Provides written English & basic calculation at the primary level for students making learning more interactive & supplement teaching.	Work can be extended from character to word recognition.
Aradillas et al. (2021)	The adverse effects of incorrect labeling are addressed, resulting in a reduction in CER.	In various few/zero-shot areas of learning, a more in-depth transfer learning technique can be applied and assessed.
Mohammed et al. (2019)	Combination of Density-based Clustering and morphological features results in higher total accuracy for character recognition.	Need to explore more patterns of Arabic writing.
Dey et al. (2022)	The results are computed using state of art ML algorithms.	It is challenging to distinguish letters from handwritten samples belonging to 62 different classes.
Sethy et al. (2022)	When used for classification, a combination of FDCT, LS-SVM, and RF provides encouraging results compared to state of art techniques.	Need to see its performance on various other character datasets.
Singh and Chatu-rvedi (2023)	The method helps build real-time HCI, helping digitize Handwritten notes for education and clinical purpose.	It can be used to create real-time interaction between humans and computers programs for intelligent classrooms that make it possible to digitize notes written by hand
Elaraby et al. (2023)	The network achieves higher recognition results in less time and a massive reduction in time for network training.	The network can be constructed using a more sophisticated transfer learning model, such as GoogleNet or VGG16.
Qureshi et al. (2022)	It helps in custom modification due to modular design, providing no requirement to retrain the neural network.	The major problem was the additional space between each word's letters, leading to inaccurate text detection.

tions net (DSCN), you only look once (YOLO), k-mean clustering, and sketch grammars (SKGs).

This domain has a vast future scope because of multiple types of diagrams such as flowcharts, unified modeling languages (UML), chemical structures, molecule structures, complex symbols, 3-dimensional (3D) shapes, etc. Also, research can be done on converting diagrams to executable code. The need for benchmarks or larger datasets is one of the challenges in diagram recognition.

4.4. Handwritten Mathematical Expression Recognition (HMER)

HMER is a sub-field of handwritten character recognition that focuses on recognizing mathematical expressions from various written forms such as graphs, tables, and formulas. HMER is the task of automatically analyzing handwritten mathematical expressions and summarizing the result of mathematical calculations. The current research in this field is focused on developing robust approaches for recognizing texts written both by hand and using computers. Three main categories of HMEs can be distinguished: speech recognition, symbolic handwriting recognition, and handwriting recognition. Handwritten mathematical expression recognition has attracted increasing attention in recent years. The main reason is that it can grasp handwritten mathematical expressions beautifully, precisely, relatively quickly, and efficiently.

If a machine can recognize handwritten mathematical expressions, it can greatly enhance our understanding of mathematics in the general community, reinforce the teachers' teaching capacity, reduce students'

Table 5
Analysis of recent approaches for handwritten digit recognition.

Author	Benefits	Challenges/Future Research Directions
Ahlawat et al. (2020)	CNN architecture achieves higher accuracy higher than ensemble architecture, and this helps in achieving very high accuracy	In the future evolutionary algorithms can be explored to optimize CNN parameters.
Zhao and Liu (2020)	CNN-based extraction using an MNIST data set can achieve encouraging results with very high accuracy	Performance can be further improved by using optimized feature selection techniques.
Chen et al. (2020)	PEO-FOBP works better than fractal-order BN neural networks and performs significantly better with regard to precision.	The method has little impact on handwriting recognition but can be used for other pattern recognition issues.
Jiang and Zhang (2020)	The edge extraction method and the triple network structure helps with the simple and effective model.	Testing on original images can be a challenge.
Ali et al. (2019)	Character recognition system helps to achieve accuracy higher than existing system without the need to train the system	As the MNIST dataset contains clean images, the proposed method needs testing on original images.
Assegie and Nair (2019)	Standardized Kaggle digits used with the decision tree approach lead to better accuracy of each number from 0 to 9	NA
Abdulhussain et al. (2021)	Numerical recognition achieves the highest recognition accuracy compared to existing scenarios under clean and realistic noise environments.	The model can be enhanced for complex digits such as Oria and Bangla numerals.
Sheikh and Patel (2019)	PCA performs better than LDA for small and recalls sets of values that are not computationally complex.	The effective dimensionality reduction method works only on smaller datasets.
Al-wajih and Ghazali (2023)	The accuracy achieved and maintained in the multi-language case TCS-LBCNN is among the best using MNIST.	The proposed model can be further enhanced for the highest accuracy.
Shuvo et al. (2022)	For HNR, by using a simple pre-processing high degree of accuracy can be achieved for Indian languages.	The proposed model fails for images with distortions and ambiguity.
Singh et al. (2021)	SBI feature descriptor, when combined with a combination of different scripts, can achieve a high degree of numerical invariant of the script class	The extracted features can be combined with other features and tested on different classifier.
Ahmed et al. (2023)	The classification of images and writing style can be achieved using cross-data sets in HDtR. This approach is also helpful in effective numerical recognition.	The model can be tested on more complex multi-lingual datasets.
Gondere et al. (2022)	By using a novel approach, HDtR outperforms baseline and conventional multi-task learning models.	It can be used as a base for developing a more robust and flexible system.
Senthil et al. (2021)	The anticipated squirrel optimizer (SO) model provides superior performance accuracy compared to current approaches like CNN.	In future research, hybrid optimizers can be used on more complex datasets.
Chin et al. (2022)	Results from hybrid mRMR + support vector machine recursive feature elimination (SVMRFE)outperform the sole support vector machine (SVM) and mRMR.	One possible future avenue is the application of microarray data interpretation and biomarker identification.

academic pressure caused by handwriting errors, and help students improve their homework habits remarkably. Handwritten mathematical expression recognition is a challenging problem. The first step in this process is the mathematical feature extraction. A mathematical expression comprises several pieces, such as addition, subtraction, or multiplication. The next step would be representing this information in a vector space where each vector consists of all possible expressions. Then a linear classifier would be trained on these vectors to recognize whether an input vector matches the training set. Table 7 explores recent works on HMER.

Various techniques are proposed in the literature, but the base of almost all methods is identical, i.e., either graph-based or tree-structured. In the graph-based approach, first, the image is converted to binary format, and symbols are extracted using image processing techniques. Then, the symbols are segmented and represented as nodes in a graph. The expression structure is analyzed using graph-based parsing algorithms and recognized using neural network models. In tree-based approaches, mathematical statements written by hand are represented as hierarchical tree structures, which are then analyzed and interpreted by parsing algorithms.

The commonly used datasets for experimentation are from the competition on recognition of online handwritten mathematical expressions (CROHME) of 2014 (Mouchère et al., 2014), 2016 (Mouchère et al., 2016), 2019 (Mahdavi et al., 2019), etc. The results are based on the recognition accuracy of the whole expression known as ExpAcc.

As the research on HMER started recently, more work needs to be done on it. Datasets need to be generated for offline recognition; Online recognition accuracy can be improved more; After recognition calculation results can be predicted; reduction of training time; application

Table 6
Summary of methods available for hand-drawn diagram recognition.

Author	Benefits	Challenges/Future Research Directions
Zhang (2021)	Using a Contour extraction algorithm and a softmax classifier helps achieve an improved recognition rate of hand-drawn sketches.	Accuracy can be further improved, and testing can be done on more complex sketches.
Alwaely and Abhayaratne (2019)	By use of an eigenvector to the lowest value of the eigenvalue helps in achieving a more robust system for different writing and drawing	The suggested model can be improved so that deaf people can use it.
Altun and Nooru-Ideen (2019)	Doing empirical research on SKETRACK helps achieve superior efficiency compared to other baseline techniques.	Database can be updated with complex symbols for the electrical circuit domain.
Polančič et al. (2020)	Solution-based and trained on TensorFlow provides for the identification of hand-drawn process diagram elements with multiple levels of accuracy.	The sketch datasets can be generated using the diagrams students created in their curriculums.
Elshenaway and Guirguis (2021)	It provides better protection than traditional four-pin digit passwords, along with better security against physical observations	The proposed model can be further enhanced to be used by people unable to speak.
Hayat et al. (2019)	DCNN helps to improve the current baseline techniques of sketch classification and retrieval	The recognition of objects through 3D shapes may be done using deep learning algorithms.
Brink-haus et al. (2022)	DECIMER helps in advancing the field of OCSR by providing standardized and openly available datasets for identifying chemical structures	As the dataset is small, it cannot be used for training the model.
Rachala and Panicker (2022)	YOLOv5 achieves very high accuracy in detecting components and provides for realtime performance	To try and develop a complete deep-learning technique in the future, a vast dataset with more significant varieties is necessary.
Fang et al. (2022)	DrawnNet shows improved accuracy as compared to current baseline method, which provides practical hand-drawn recognition.	The work can be further extended by converting the recognized flowcharts into executable code to improve productivity.
Riaz et al. (2022)	It helps designers to focus on creative tasks by automating basic repetitive tasks.	To train a model on a dataset with a variety of permutations, the dataset size needs to be huge. Also, the multi-modality has a vast scope in computer vision.
Ali et al. (2023)	Sketch-DeepNet using CNN achieves very high recognition tasks than the current baseline techniques.	To extract features from sketches, transfer learning can be explored along with late fusion.
Bourgault and Jacobs (2023)	Megafauna helps animators in real-time with the ability to directly sketch mapping functions for audio and visual generators.	Future research can focus on developing more automated methods for creating visuals, developing frameworks for producing music with more complicated melodies, and minimizing the visual appearance of user interfaces.
Murthy and Hanuman-thaiah (2022)	K-mean clustering, along with indexing, helps to achieve better accuracy enabling better system efficiency.	As the features give better accuracy model can be further enhanced for the recognition of hand-drawn sketches.
Ji (2021)	DSCN networks help in achieving better accuracy for hand-drawn sketches with the introduction of stroke order	Data simulation must be done to utilize the algorithm in real-world scenarios.
Deufe-mia and Risi (2020)	SKGs provide an efficient parsing model suitable for sketch-based interfaces in UML class diagrams.	More scalable models can be built for complex designs of engineering symbols.

of encoder-decoder and transfer learning on HMER need to be studied; and much more.

4.5. Handwritten table recognition

Handwritten tables can be converted into computer-readable formats quickly. The method enables one to read the information from the paper quickly and easily. Handwritten table recognition is a task that can be solved by using a trained classifier. Handwritten tables are recognized and converted into numerical values for further processing by pattern-matching algorithms, statistical rate estimation, or both. It is done to accomplish diverse tasks such as evaluating and classifying students' handwriting skills using their handwriting samples, estimating hand-written signatures by statistical and regression methods, extracting tables from web pages with imperfect text recognition, detecting false documents, etc.

Recent research in the Table 8 shows that the researchers mostly work on extracting tables from historical and chemistry documents. The correlation-based technique distinguishes the borders of tables and their content. The algorithms used for recognition include conditional random fields (CRF), graph attention networks, ruling-based approaches, etc.

Graph Attention Networks (GATs), a form of Graph Neural Network (GNN), successfully captured complex associations in graph-structured data. To recognize handwritten tables using GATs, the document is represented as a graph with nodes representing text sections or items, and dependencies between nodes are captured using attention methods. The attention method enables the model to concentrate on pertinent nodes

Table 7
An overview of the techniques for reading handwritten mathematical expressions.

Authors	Benefits	Challenges/Future Research Directions
Mahdavi et al. (2019)	Although graph-based techniques are optimal for printed documents, neural networks give robust results.	Math recognition is still a difficult task for modern computers.
Le et al. (2019)	The combination of distortion and decomposition has improved performance.	Proposed method is simple and hence needs more work to be done.
Zhang et al. (2019)	TAP helps in a more efficient expression recognition method on validated benchmarks and does not require symbol segmentation	The model can be enhanced for complex symbols and offline recognition.
Li et al. (2020)	Both the scale reinforcement approach and drop attention component produced better results.	The model needs to be extended for online mathematical expressions.
Wu et al. (2020)	PAL-V2 helps mathematical expression to improve the coverage. This method achieves effective results.	Future studies may focus on correct arrangement of symbols of mathematical expression.
Chan (2020)	Oversegmentation helps speed up the offline pipeline to enable on-device recognition with fewer resources.	Future researchers must explore whether specific stroke extraction tools are required for varying handwriting styles.
Zhao et al. (2021)	The proposed model used the transformer's positional encoding, encoder, and decoder to improve results.	The model needs to be enhanced to be comparable with state-of-the-art methods.
Wang et al. (2021)	SCAN obtains outstanding results by combining encoder & decoder fusion.	In future, the result of attention can be used to segment symbols.
Zhang et al. (2021)	SRD aims to build a tree structure-based decoder and encoder, enabling SRD to outperformance against state-of-the-art decoders	The proposed decoder can be further implemented to recognize offline handwritten expressions.
Yang et al. (2022)	Tree-based decoders and encoders help to fully utilize the mutual learning method to improve recognition accuracy and effectiveness.	The challenge in handwritten mathematical expression recognition is its 2-dimensional structure and less data availability.
Truong et al. (2022)	HME uses a dual-trained learning encoder and decoder, which improves performance recognition of mathematical language models. The authors also introduced the idea of data generation.	Not Available
Pal and Singh (2022)	Decoding task is done by R-GRU to generate LATEX sequences. The performance is better than baseline techniques.	Transfer learning can improve performance with less training time.
Li, Fang, et al. (2023)	YOLOv5s accuracy is better than state-of-the-art methods and is more fault-tolerant and stable than other methods.	Due to the arbitrary drafting of offline handwritten formulas, error accumulation becomes difficult.
Li, Wang, et al. (2023)	Feature extraction progress is enhanced by global spatial, better classification, and dynamic time-warping algorithms. This method outperforms state of the art method by a large margin.	Identifying similar symbols is the most challenging task.
Dong et al. (2022)	SMRT improves performance using an attention-based encoder and decoder for offline HMER.	The internal working of the model needs to be examined to reduce the training time.

when predicting a particular node. GAT uses attention coefficients to rank neighboring nodes' contributions according to significance.

As this is a recent and emerging topic, various areas need to be explored, from extracting table columns and rows to matching row and column numbers in a table. To start with table recognition work, one must understand all parts, such as how to extract data from tables, what tools are available for data extraction, and so on.

4.6. Performance comparison

The performance of the methods discussed in the above subsections on the benchmark datasets is shown in Table 9. CNN is the state-of-the-art method used in handwritten document recognition, such as text, digits, and diagrams.

The table shows enormous scope for research in word recognition of off-line handwritten text recognition. The MNIST dataset used for digit recognition has clean images, and hence, research needs to be done on real-time images with noise and distortions. New techniques must be explored to improve the expression recognition rate of mathematical expressions. Although much research has already been done on handwritten document recognition, some areas still need to be focused on.

5. Conclusion and future research

To sum up, this study aims to provide a more nuanced picture of the state of handwritten document recognition by doing two types of exploration: a thorough bibliometric survey and a detailed investigation of learning strategies. Bibliometric surveys have offered a comprehensive picture of the development of handwritten document recognition. Identifying prolific writers, prominent journals, and crucial publication epochs has provided a comprehensive picture of the collaborative efforts that have advanced the field. Building upon the bibliometric survey's foundations, various advances in handwritten document recognition have been discovered by investigating learning strategies. The

Table 8
Brief analysis of the handwritten table recognition techniques.

Authors	Benefits	Challenges/Future Research Directions
Chen and Lopresti (2011)	A correlation-based approach to analyze the integrity among neighboring text lines that might be part of the same table. This approach helps in resolving the resulting page decomposition problem using dynamic programming.	Various areas like column and ordered data need improvement and investigation.
Ghanmi and Belaid (2014)	The CRF model using a set of chemistry docs provides the universal conditional probability of given outputs of the two classifiers. This approach helps in achieving highly correct outcomes.	Further discriminative design characteristics must be created to train and evaluate the model.
Lehenmeier et al. (2020)	A custom approach is developed for the historical meteorological characters. This approach achieves a high degree of accuracy.	More complex tabular datasets need to be created and processed.
Constum et al. (2022)	They developed a comprehensive workflow that minimizes the requirement for segmentation markers and moves from the scanning of dual sections to content prediction.	The self-training technique might need further investigation.
Amarnath et al. (2019)	Entropy quantifiers are used to classify the table in the image. The effectiveness of the suggested method is assessed and reported by the proposed composite handwritten benchmark dataset.	A dataset containing diagrams, tables, and equations in a single document is needed.
Ghanmi and Belaid (2015)	Cartography is evaluated based on syntactical rules to find cell boundaries. This is tested on handwritten chemistry documents, and experimental results indicate satisfactory performance.	To be able to recreate the layout, one must thoroughly comprehend the table and all of its contents.
Andrés et al. (2022)	Document Understanding in structured historical documents improves performance by up to 0.14 F-measure points.	Not available
Chen and Lopresti (2013)	Table analysis with a ruling-based approach detects line segments and computes intersections of horizontal and vertical rulings as key points.	It is possible to strengthen the algorithm's robustness and create more functions for optimization.
Bursian and Demin (2022)	Skeleton graphs are built multiple times for blurry characters in the decision tree, using different filtering and skeletonization options	The work can be extended to be used to correct distance learning assignments.
Liu et al. (2021)	Graph attention network model to classify nodes can be used to detect tables. By combining node and edge classification results, cells in each table can be segmented.	A method for detecting complex tables and recognizing table structures must be developed.
Salazar et al. (2021)	Fusion methods help in better performance in specific experiments and the best results obtained by alpha integration.	The variation of the fusion parameters can be decreased by adding a regularization component to the cost function.

analysis explored the advantages and disadvantages of every strategy, ranging from conventional techniques to the cutting-edge field of deep learning.

With the immense advancement in computer technology and software, handwriting recognition has become one of the most critical fields. Researchers have developed numerous methodologies, technologies, and algorithms to recognize various aspects of handwritten documents. The review article discusses the evolution of these techniques over time, from the simplistic, pure incremental approaches to the more complex and sophisticated methods of today. CNN network was the most popular for feature extraction. There are many scopes for researchers to recognize handwritten non-textual data, such as electrical circuits, UML diagrams, machine structures, tables, etc. The benchmark datasets are unavailable for the mentioned non-textual content; hence, the annotated datasets must be created. The associated investigations demonstrate numerous problems regarding robustness to writer styles, increasing recognition accuracy, and the capacity to simplify across various sectors. Other challenges include integrating top-notch research methods into practical production systems and elements, including the demand for training data, processing power, and model resilience. It is essential to devise a new approach for recognizing all handwritten documents, which is successful and efficient for real-time use. Overall, the paper contributes to the ongoing advancement of knowledge in the field, providing a valuable resource for researchers and practitioners alike.

The potential areas of improvement are methods for fine-tuning machine learning algorithms to the unique properties of handwriting in specialized fields; looking into preprocessing methods and noise-resistant algorithms that help improve performance in real-world situations with imperfect document circumstances; creating real-time, high-performing, lightweight models and optimized algorithms to support interactive interfaces and live to transcribe; and incorporating human-centered design concepts to produce user-friendly interfaces that let users quickly edit or change the text that has been recognized. The emerging technologies that can be used for improvement are edge computing for on-device recognition and integrating artificial intelligence with augmented reality.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Table 9
Performance comparison on the benchmark datasets.

Author	Year	Dataset	Performance
Text Recognition			
Sánchez et al. (2019)	2019	ICFHR-2016, ICDAR-2017	CER 4.5% WER 17.5%, CER 5.8% WER 17.6%
Geetha et al. (2021)	2021	IAM, RIMES	Word Accuracy 95.20%, 98.14%
Dey et al. (2022)	2022	chars74kHnd, chars74kFnt, chars74kImg	Accuracy 81.12%, 90.45%, 64.75%
Elaraby et al. (2023)	2023	chars74kHnd	Accuracy 85.60%
Digit Recognition			
Ahlawat et al. (2020)	2020	MNIST	Accuracy 99.87%
Zhao and Liu (2020)	2020	MNIST	Classification Accuracy 98.10%
Chen et al. (2020)	2020	MNIST	Accuracy 96.54%
Jiang and Zhang (2020)	2020	MNIST	Accuracy 99.51%
Ali et al. (2019)	2019	MNIST	Accuracy 99.21%
Abdulhussain et al. (2021)	2021	MNIST	Accuracy 100.00%
Sheikh and Patel (2019)	2019	MNIST	Accuracy 90.80%
Shuvo et al. (2022)	2022	MNIST	Accuracy 99.62%
Singh et al. (2021)	2021	MNIST	Accuracy 98.33%
Ahmed et al. (2023)	2023	MNIST	Accuracy 99.83%
Senthil et al. (2021)	2021	MNIST	Accuracy 98.50%
Diagram Recognition			
Zhang (2021)	2021	TU-Berlin Sketch	Recognition Rate 73.24%
Altun and Nooru-ldeen (2019)	2019	Flowchart (FC), Finite Automata (FA), Digital Logic Circuits (DLC)	Accuracy 95.87%, 94.99%, 79.21%
Hayat et al. (2019)	2019	TU-Berlin Sketch	Accuracy 94.57%
Fang et al. (2022)	2022	Flowchart (FC_A), Flowchart (FC_B), Finite Automata (FA)	Accuracy 70.80%, 80.90%, 85.00%
Ali et al. (2023)	2023	TU-Berlin Sketch	Accuracy 95.05%
Ji (2021)	2021	TU-Berlin Sketch	Accuracy 71.80%
Mathematical Expression Recognition			
Le et al. (2019)	2019	CROHME 2014, CROHME 2016	Expression Recognition Rate (ExpRate) 48.78%, 45.60%
Zhang et al. (2019)	2019	CROHME 2014, CROHME 2016	ExpRate 61.16%, 57.02%
Li et al. (2020)	2020	CROHME 2014, CROHME 2016	ExpRate 60.45%, 58.06%
Chan (2020)	2020	CROHME 2014, CROHME 2016, CROHME 2019	ExpRate 58.22%, 65.65%, 65.22%
Zhao et al. (2021)	2021	CROHME 2014, CROHME 2016, CROHME 2019	ExpRate 53.96%, 52.31%, 52.96%
Wang et al. (2021)	2021	CROHME 2014, CROHME 2016	ExpRate 58.11%, 54.29%
Zhang et al. (2021)	2021	CROHME 2019	ExpRate 48.50%
Yang et al. (2022)	2022	CROHME 2014, CROHME 2016	ExpRate 54.87%, 57.89%
Pal and Singh (2022)	2022	CROHME 2014, CROHME 2016	ExpRate 43.72%, 41.29%
Li, Wang, et al. (2023)	2023	CROHME 2014, CROHME 2016, CROHME 2019	ExpRate 64.81%, 63.82%, 66.89%

Data availability

No data was used for the research described in the article.

References

Abdulhussain, S., Mahmmod, B., Naser, M., Alsabah, M., Ali, R., & Al-Haddad, S. (2021). A robust handwritten numeral recognition using hybrid orthogonal polynomials and moments. *Sensors*, *21*, 1–18. https://doi.org/10.3390/s21061999.

Ahlawat, S., Choudhary, A., Nayyar, A., Singh, S., & Yoon, B. (2020). Improved handwritten digit recognition using convolutional neural networks (cnn). *Sensors (Switzerland)*, *20*, 1–18. https://doi.org/10.3390/s20123344.

Ahmed, S., Mehmood, Z., Awan, I., & Yousaf, R. (2023). A novel technique for handwritten digit recognition using deep learning. *Journal of Sensors*, *2023*. https://doi.org/10.1155/2023/2753941.

Al-wajih, E., & Ghazali, R. (2023). Threshold center-symmetric local binary convolutional neural networks for bilingual handwritten digit recognition. *Knowledge-Based Systems*, *259*. https://doi.org/10.1016/j.knosys.2022.110079.

Ali, S., Aslam, N., Kim, D., Abbas, A., Tufail, S., & Azhar, B. (2023). Context awareness based sketch-deepnet architecture for hand-drawn sketches classification and recognition in aiot. *PeerJ Computer Science*, *9*. https://doi.org/10.7717/PEERJ-CS.1186.

Ali, S., Shaukat, Z., Azeem, M., Sakhawat, Z., Mahmood, T., & ur Rehman, K. (2019). An efficient and improved scheme for handwritten digit recognition based on convolutional neural network. *SN Applied Sciences*, *1*. https://doi.org/10.1007/s42452-019-1161-5.

Ali, S. H., & Abdulrazzaq, M. B. (2023). A comprehensive overview of handwritten recognition techniques: A survey. *Journal of Computer Science*, *19*, 569–587. https://doi.org/10.3844/jcssp.2023.569.587.

Alonso, M. A. P. (2015). Metacognition and sensorimotor components underlying the process of handwriting and keyboarding and their impact on learning. An analysis from the perspective of embodied psychology. *Procedia – Social and Behavioral Sciences*, *176*, 263–269. https://doi.org/10.1016/j.sbspro.2015.01.470.

Altun, O., & Nooru-ldeen, O. (2019). Sketrack: Stroke-based recognition of online hand-drawn sketches of arrow-connected diagrams and digital logic circuit diagrams. *Scientific Programming*, *2019*. https://doi.org/10.1155/2019/6501264.

Alwaely, B., & Abhayaratne, C. (2019). Graph spectral domain feature learning with application to in-air hand-drawn number and shape recognition. *IEEE Access*, *7*, 159661–159673. https://doi.org/10.1109/ACCESS.2019.2950643.

Amarnath, R., Sindhushree, G., Nagabhushan, P., & Javed, M. (2019). Automatic localization and extraction of tables from handheld mobile-camera captured handwritten document images. *Journal of Intelligent & Fuzzy Systems*, *36*, 2527–2544. https://doi.org/10.3233/JIFS-181242.

Andrés, J., Prieto, J., Granell, E., Romero, V., Sánchez, J., & Vidal, E. (2022). Information extraction from handwritten tables in historical documents. In *Lecture notes in computer science, LNCS: Vol. 13237* (pp. 184–198) (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).

Aradillas, J., Murillo-Fuentes, J., & Olmos, P. (2021). Boosting offline handwritten text recognition in historical documents with few labeled lines. *IEEE Access*, *9*, 76674–76688. https://doi.org/10.1109/ACCESS.2021.3082689.

Assegie, T., & Nair, P. (2019). Handwritten digits recognition with decision tree classification: A machine learning approach. *International Journal of Electrical and Computer Engineering*, *9*, 4446–4451. https://doi.org/10.11591/ijece.v9i5.pp4446-4451.

Bottou, L., Cortes, C., Denker, J. S., Drucker, H., Guyon, I., Jackel, L., LeCun, Y., Müller, U. A., Säckinger, E., Simard, P., & Vapnik, V. (1994). Comparison of classifier methods: A case study in handwritten digit recognition. In *Proceedings - international conference on pattern recognition* (pp. 77–82).

Bourgault, S., & Jacobs, J. (2023). Preserving hand-drawn qualities in audiovisual performance through sketch-based interaction. *Journal of Computer Languages*, *74*. https://doi.org/10.1016/j.cola.2022.101186.

Brink-haus, H., Zielesny, A., Steinbeck, C., & Rajan, K. (2022). Decimer—hand-drawn molecule images dataset. *Journal of Cheminformatics*, *14*. https://doi.org/10.1186/s13321-022-00620-9.

Bursian, E., & Demin, A. (2022). Automatic recognition of fuzzy characters in the transport task tables of scanned handwritten student papers. In *Lecture notes in information systems and organisation* (pp. 39–48).

Chan, C. (2020). Stroke extraction for offline handwritten mathematical expression recognition. *IEEE Access*, *8*, 61565–61575. https://doi.org/10.1109/ACCESS.2020.2984627.

Chen, J., & Lopresti, D. (2011). Table detection in noisy off-line handwritten documents. In *Proceedings of the international conference on document analysis and recognition, ICDAR* (pp. 399–403).

Chen, J., & Lopresti, D. (2013). *Ruling-based table analysis for noisy handwritten documents. ACM international conference proceeding series*.

Chen, M. R., Chen, B. P., Zeng, G. Q., Lu, K. D., & Chu, P. (2020). An adaptive fractional-order bp neural network based on extremal optimization for handwritten digits recognition. *Neurocomputing*, *391*, 260–272. https://doi.org/10.1016/j.neucom.2018.10.090.

Chin, F., Lem, K., & Wong, K. (2022). Improving handwritten digit recognition using hybrid feature selection algorithm. *Applied Computing and Informatics*. https://doi.org/10.1108/ACI-02-2022-0054.

Cilia, N., De Stefano, C., Fontanella, F., & Scotto di Freca, A. (2019). A ranking-based feature selection approach for handwritten character recognition. *Pattern Recognition Letters*, *121*, 77–86. https://doi.org/10.1016/j.patrec.2018.04.007.

Cireşan, D. C., Meier, U., Gambardella, L. M., & Schmidhuber, J. (2011). Convolutional neural network committees for handwritten character classification. In *Proceedings of the international conference on document analysis and recognition, ICDAR* (pp. 1135–1139).

Constum, T., Kempf, N., Paquet, T., Tranouez, P., Chatelain, C., Brée, S., & Merveille, F. (2022). Recognition and information extraction in historical handwritten tables: Toward understanding early 20 th century Paris census. In *Lecture notes in computer science, LNCS: Vol. 13237* (pp. 143–157) (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).

Das, D., Nayak, D., Dash, R., & Majhi, B. (2019). An empirical evaluation of extreme learning machine: Application to handwritten character recognition. *Multimedia Tools and Applications*, *78*, 19495–19523. https://doi.org/10.1007/s11042-019-7330-0.

Deng, L. (2012). The mnist database of handwritten digit images for machine learning research. *IEEE Signal Processing Magazine*, *29*, 141–142. https://doi.org/10.1109/MSP.2012.2211477.

Deufe-mia, V., & Risi, M. (2020). Multi-domain recognition of hand-drawn diagrams using hierarchical parsing. *Multimodal Technologies and Interaction*, *4*, 1–30. https://doi.org/10.3390/mti4030052.

Dey, R., Balabantaray, R., & Mohanty, S. (2022). Sliding window based off-line handwritten text recognition using edit distance. *Multimedia Tools and Applications*, *81*, 22761–22788. https://doi.org/10.1007/s11042-021-10988-9.

Dong, L. F., Liu, H. C., & Zhang, X. M. (2022). Synthetic data generation and shuffled multi-round training based offline handwritten mathematical expression recognition. *Journal of Computer Science and Technology*, *37*, 1427–1443. https://doi.org/10.1007/s11390-021-0722-4.

Elaraby, N., Barakat, S., & Rezk, A. (2023). A novel Siamese network for few/zero-shot handwritten character recognition tasks. *Computers, Materials & Continua*, *74*, 1837–1854. https://doi.org/10.32604/cmc.2023.032288.

Elshenaway, A., & Guirguis, S. (2021). On-air hand-drawn doodles for iot devices authentication during Covid-19. *IEEE Access*, *9*, 161723–161744. https://doi.org/10.1109/ACCESS.2021.3131551.

Fang, J., Feng, Z., & Cai, B. (2022). Drawnnet: Offline hand-drawn diagram recognition based on keypoint prediction of aggregating geometric characteristics. *Entropy*, *24*. https://doi.org/10.3390/e24030425.

Geetha, R., Thilagam, T., & Padmavathy, T. (2021). Effective offline handwritten text recognition model based on a sequence-to-sequence approach with cnn–rnn networks. *Neural Computing & Applications*, *33*, 10923–10934. https://doi.org/10.1007/s00521-020-05556-5.

Ghanmi, N., & Belaid, A. (2014). Table detection in handwritten chemistry documents using conditional random fields. In *Proceedings of international conference on frontiers in handwriting recognition, ICFHR* (pp. 146–151).

Ghanmi, N., & Belaid, A. (2015). Separator and content based approach for table extraction in handwritten chemistry documents. In *Proceedings of the international conference on document analysis and recognition, ICDAR* (pp. 296–300).

Gondere, M., Schmidt-Thieme, L., Sharma, D., & Scholz, R. (2022). Multi-script handwritten digit recognition using multi-task learning. *Journal of Intelligent & Fuzzy Systems*, *43*, 355–364. https://doi.org/10.3233/JIFS-212233.

Graves, A., Liwicki, M., Fernández, S., Bertolami, R., Bunke, H., & Schmidhuber, J. (2009). A novel connectionist system for unconstrained handwriting recognition. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *31*, 855–868. https://doi.org/10.1109/TPAMI.2008.137.

Graves, A., & Schmidhuber, J. (2009). Offline handwriting recognition with multidimensional recurrent neural networks. In *Advances in neural information processing systems 21 - proceedings of the 2008 conference* (pp. 545–552).

Hayat, S., She, K., Yu, Y., & Mateen, M. (2019). Deep cnn-based features for hand-drawn sketch recognition via transfer learning approach. *International Journal of Advanced Computer Science and Applications*, *10*, 438–448. https://doi.org/10.14569/ijacsa.2019.0100958.

Hull, J. J. (1994). A database for handwritten text recognition research. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *16*, 550–554. https://doi.org/10.1109/34.291440.

Jain, P. H., Kumar, V., Samuel, J., Singh, S., Mannepalli, A., & Anderson, R. (2023). Artificially intelligent readers: An adaptive framework for original handwritten numerical digits recognition with ocr methods. *Information*, *14*. https://doi.org/10.3390/info14060305.

Ji, Q. (2021). Research on recognition effect of dscn network structure in hand-drawn sketch. *Computational Intelligence and Neuroscience*, *2021*. https://doi.org/10.1155/2021/4056454.

Jiang, W., & Zhang, L. (2020). Edge-siamnet and edge-triplenet: New deep learning models for handwritten numeral recognition. *IEICE Transactions on Information and Systems*, *E103D*, 720–723. https://doi.org/10.1587/transinf.2019EDL8199.

Kamentsky, L. A. (1961). The simulation of three machines which read rows of handwritten Arabic numbers. *IRE Transactions on Electronic Computers*, *EC-10*, 489–501. https://doi.org/10.1109/TEC.1961.5219238.

Kniazieva, Y. (2022). What is handwritten text recognition with ocr? Retrieved from https://labelyourdata.com/articles/ai-handwriting-recognition.

Kolesnikov, A., Dosovitskiy, A., Weissenborn, D., Heigold, G., Uszkoreit, J., Beyer, L., Minderer, M., Dehghani, M., Houlsby, N., Gelly, S., Unterthiner, T., & Zhai, X. (2021). An image is worth 16x16 words: Transformers for image recognition at scale. In *9th international conference on learning representations, ICLR 2021*.

Le, A., Indurkhya, B., & Nakagawa, M. (2019). Pattern generation strategies for improving recognition of handwritten mathematical expressions. *Pattern Recognition Letters*, *128*, 255–262. https://doi.org/10.1016/j.patrec.2019.09.002.

LeCun, Y., & Cortes, C. (2010). MNIST handwritten digit database. Retrieved from http://yann.lecun.com/exdb/mnist/.

Lehenmeier, C., Burghardt, M., & Mischka, B. (2020). Layout detection and table recognition – recent challenges in digitizing historical documents and handwritten tabular data. In *Lecture notes in computer science, LNCS: Vol. 12246* (pp. 229–242) (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).

Li, F., Fang, H., Wang, D., Liu, R., Hou, Q., & Xie, B. (2023). Offline handwritten mathematical expression recognition based on yolov5s. *The Visual Computer*. https://doi.org/10.1007/s00371-023-02859-1.

Li, Z., Jin, L., Lai, S., & Zhu, Y. (2020). Improving attention-based handwritten mathematical expression recognition with scale augmentation and drop attention. In *Proceedings of international conference on frontiers in handwriting recognition, ICFHR* (pp. 175–180).

Li, Z., Wang, X., Liu, Y., Jin, L., Huang, Y., & Ding, K. (2023). Improving handwritten mathematical expression recognition via similar symbol distinguishing. *IEEE Transactions on Multimedia*, 1–13. https://doi.org/10.1109/TMM.2023.3260648.

Liu, C. L., Nakashima, K., Sako, H., & Fujisawa, H. (2003). Handwritten digit recognition: Benchmarking of state-of-the-art techniques. *Pattern Recognition*, *36*, 2271–2285. https://doi.org/10.1016/S0031-3203(03)00085-2.

Liu, Y., Zhang, H., Yun, X. L., Ye, J. Y., & Liu, C. L. (2021). Table detection and cell segmentation in online handwritten documents with graph attention networks. In *Proceedings of the 2nd ACM international conference on multimedia in Asia, MMAsia 2020*.

Mahdavi, M., Zanibbi, R., Mouchere, H., Viard-Gaudin, C., & Garain, U. (2019). Icdar 2019 crohme + tfd: Competition on recognition of handwritten mathematical expressions and typeset formula detection. In *Proceedings of the international conference on document analysis and recognition, ICDAR* (pp. 1533–1538).

Marti, U. V., & Bunke, H. (2002). The iam-database: An English sentence database for offline handwriting recognition. *International Journal on Document Analysis and Recognition*, 39–46. https://doi.org/10.1007/s100320200071.

Marti, U. V., & Bunke, H. (2003). The iam-database: An English sentence database for offline handwriting recognition. *International Journal on Document Analysis and Recognition*, *5*, 39–46. https://doi.org/10.1007/s100320200071.

Mohammed, D., Mezher, A., & Hadi, H. (2019). Off-line handwritten character recognition using an integrated dbscan-ann scheme. *Indonesian Journal of Electrical Engineering and Computer Science*, *14*, 1443–1451. https://doi.org/10.11591/ijeecs.v14.i3.pp1443-1451.

Mouchère, H., Viard-Gaudin, C., Zanibbi, R., & Garain, U. (2014). Icfhr 2014 competition on recognition of on-line handwritten mathematical expressions (crohme 2014). In *Proceedings of international conference on frontiers in handwriting recognition, ICFHR*.

Mouchère, H., Viard-Gaudin, C., Zanibbi, R., & Garain, U. (2016). Icfhr2016 crohme: Competition on recognition of online handwritten mathematical expressions. In *International conference on frontiers in handwriting recognition (ICFHR)* (pp. 607–612).

Mueller, P. A., & Oppenheimer, D. M. (2014). The pen is mightier than the keyboard: Advantages of longhand over laptop note taking. *Psychological Science*, *25*(6), 1159–1168. https://doi.org/10.1177/0956797614524581.

Murthy, P., & Hanumanthaiah, S. (2022). A simplified and novel technique to retrieve color images from hand-drawn sketch by human. *International Journal of Electrical and Computer Engineering*, *12*, 6140–6148. https://doi.org/10.11591/ijece.v12i6.pp6140-6148.

Neto, A., Bezerra, B., & Toselli, A. (2020). Towards the natural language processing as spelling correction for offline handwritten text recognition systems. *Applied Sciences (Switzerland)*, *10*, 1–29. https://doi.org/10.3390/app10217711.

Niu, X. X., & Suen, C. Y. (2012). A novel hybrid cnn-svm classifier for recognizing handwritten digits. *Pattern Recognition*, *45*, 1318–1325. https://doi.org/10.1016/j.patcog.2011.09.021.

Nurseitov, D., Bostanbekov, K., Kanatov, M., Alimova, A., Abdallah, A., & Abdimanap, G. (2020). Classification of handwritten names of cities and handwritten text recognition using various deep learning models. *Advances in Science, Technology and Engineering Systems*, *5*, 934–943. https://doi.org/10.25046/AJ0505114.

Pal, A., & Singh, K. (2022). R-gru: Regularized gated recurrent unit for handwritten mathematical expression recognition. *Multimedia Tools and Applications*, *81*, 31405–31419. https://doi.org/10.1007/s11042-022-12889-x.

Plamondon, R., & Srihari, S. N. (2000). On-line and off-line handwriting recognition: A comprehensive survey. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*, 63–84. https://doi.org/10.1109/34.824821.

Polančič, G., Jagečić, S., & Kous, K. (2020). An empirical investigation of the effectiveness of optical recognition of hand-drawn business process elements by applying machine learning. *IEEE Access*, *8*, 206118–206131. https://doi.org/10.1109/ACCESS.2020.3034603.

Qureshi, F., Rajput, A., Mujtaba, G., & Fatima, N. (2022). A novel offline handwritten text recognition technique to convert ruled-line text into digital text through deep neural networks. *Multimedia Tools and Applications*, *81*, 18223–18249. https://doi.org/10.1007/s11042-022-12097-7.

Rachala, R., & Panicker, M. (2022). Hand-drawn electrical circuit recognition using object detection and node recognition. *SN Computer Science*, *3*. https://doi.org/10.1007/s42979-022-01159-0.

Rajalakshmi, M., Saranya, P., & Shanmugavadivu, P. (2019). Pattern recognition-recognition of handwritten document using convolutional neural networks. In *2019 IEEE international conference on intelligent techniques in control, optimization and signal processing (INCOS)* (pp. 1–7).

Riaz, S., Arshad, A., Band, S., & Mosavi, A. (2022). Transforming hand drawn wireframes into front-end code with deep learning. *Computers, Materials & Continua*, *72*, 4302–4321. https://doi.org/10.32604/cmc.2022.024819.

Ruiz-Parrado, V., Heradio, R., Aranda-Escolastico, E., Sánchez, Á., & Vélez, J. F. (2022). A bibliometric analysis of off-line handwritten document analysis literature (1990–2020). *Pattern Recognition*, *125*, Article 108513. https://doi.org/10.1016/j.patcog.2021.108513.

Salazar, A., Prieto, J., Vidal, E., Safont, G., & Vergara, L. (2021). Fusion of visual and textual features for table header detection in handwritten text images. In *Proceedings - 2021 international conference on computational science and computational intelligence, CSCI 2021* (pp. 1560–1566).

Sánchez, J., Romero, V., Toselli, A., Villegas, M., & Vidal, E. (2019). A set of benchmarks for handwritten text recognition on historical documents. *Pattern Recognition*, *94*, 122–134. https://doi.org/10.1016/j.patcog.2019.05.025.

Senthil, T., Rajan, C., & Deepika, J. (2021). An efficient cnn model with squirrel optimizer for handwritten digit recognition. *International Journal of Advanced Technology and Engineering Exploration*, *8*, 2394–7454. https://doi.org/10.19101/IJATEE.2021.874073.

Sethy, A., Patra, P., & Nayak, S. (2022). A hybrid system for handwritten character recognition with high robustness. *Traitement du Signal*, *39*, 567–576. https://doi.org/10.18280/ts.390218.

Sheikh, R., & Patel, M. (2019). Handwritten digit recognition using different dimensionality reduction techniques. *International Journal of Recent Technology and Engineering*, *8*, 999–1002. https://doi.org/10.35940/ijrte.B1798.078219.

Shuvo, M., Akhand, M., & Siddique, N. (2022). Handwritten numeral recognition through superimposition onto printed form. *Journal of King Saud University: Computer and Information Sciences*, *34*, 7751–7764. https://doi.org/10.1016/j.jksuci.2022.06.019.

Singh, P., Chatterjee, I., Sarkar, R., Smith, E., & Nasipuri, M. (2021). A new feature extraction approach for script invariant handwritten numeral recognition. *Expert Systems*, *38*. https://doi.org/10.1111/exsy.12699.

Singh, S. K., & Chatu-rvedi, A. (2023). Leveraging deep feature learning for wearable sensors based handwritten character recognition. *Biomedical Signal Processing and Control*, *80*. https://doi.org/10.1016/j.bspc.2022.104198.

Truong, T. N., Nguyen, C., & Nakagawa, M. (2022). Syntactic data generation for handwritten mathematical expression recognition. *Pattern Recognition Letters*, *153*, 83–91. https://doi.org/10.1016/j.patrec.2021.12.002.

Wang, J., Du, J., Zhang, J., Wang, B., & Ren, B. (2021). Stroke constrained attention network for online handwritten mathematical expression recognition. *Pattern Recognition*, *119*. https://doi.org/10.1016/j.patcog.2021.108047.

Weng, Y., & Xia, C. (2020). A new deep learning-based handwritten character recognition system on mobile computing devices. *Mobile Networks and Applications*, *25*, 402–411. https://doi.org/10.1007/s11036-019-01243-5.

Wu, J. W., Yin, F., Zhang, Y. M., Zhang, X. Y., & Liu, C. L. (2020). Handwritten mathematical expression recognition via paired adversarial learning. *International Journal of Computer Vision*, *128*, 2386–2401. https://doi.org/10.1007/s11263-020-01291-5.

Yang, C., Du, J., Zhang, J., Wu, C., Chen, M., & Wu, J. (2022). Tree-based data augmentation and mutual learning for offline handwritten mathematical expression recognition. *Pattern Recognition*, *132*. https://doi.org/10.1016/j.patcog.2022.108910.

Zhang, J., Du, J., & Dai, L. (2019). Track, attend, and parse (tap): An end-to-end framework for online handwritten mathematical expression recognition. *IEEE Transactions on Multimedia*, *21*, 221–233. https://doi.org/10.1109/TMM.2018.2844689.

Zhang, J., Du, J., Yang, Y., Song, Y. Z., & Dai, L. (2021). Srd: A tree structure based decoder for online handwritten mathematical expression recognition. *IEEE Transactions on Multimedia*, *23*, 2471–2480. https://doi.org/10.1109/TMM.2020.3011316.

Zhang, L. (2021). Hand-drawn sketch recognition with a double-channel convolutional neural network. *EURASIP Journal on Advances in Signal Processing*, *2021*. https://doi.org/10.1186/s13634-021-00752-4.

Zhao, H. H., & Liu, H. (2020). Multiple classifiers fusion and cnn feature extraction for handwritten digits recognition. *Granular Computing*, *5*, 411–418. https://doi.org/10.1007/s41066-019-00158-6.

Zhao, W., Gao, L., Yan, Z., Peng, S., Du, L., & Zhang, Z. (2021). Handwritten mathematical expression recognition with bidirectionally trained transformer. In *Lecture notes in computer science, LNCS: Vol. 12822* (pp. 570–584) (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics).

Zin, T., Thant, S., Pwint, M., & Ogino, T. (2021). Handwritten character recognition on Android for basic education using convolutional neural network. *Electronics (Switzerland)*, *10*. https://doi.org/10.3390/electronics10080904.