



Offline Handwritten Text Recognition: A Systematic Literature Review with Comparative Study of Techniques

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ABSTRACT

Offline Handwritten Text Recognition (HTR) is required for practical applications such as the recognition of old documents, students' study material, postal code recognition for letter delivery, recognition of entrance examination forms or admission form assessment, optical mark recognition (OMR), and recognition of medical prescriptions, which depend on reliable models. This systematic literature review (SLR) examines several technologies used in offline HTR, including machine_learning and optimization methods. This study selected a sample of 60 research papers, written in English and published between 2016 and 2026, from the Scopus database. Of these, 36 were Articles, chosen using appropriate inclusion-exclusion criteria, to analyze offline handwritten text recognition approaches.

KEYWORD: Offline handwritten, text recognition, digits, machine_learning, MNIST.

1 Introduction

Offline HTR is a significant field within computer vision, pattern recognition, and artificial intelligence (AI) that converts handwritten text or documents into digital text. Text produced by online or offline printing can be easily scanned and converted to a digital format. However, OHTR is challenging because of its diverse writing styles, which can vary among individuals depending on their emotional state, and because the ink, characters, font, and size are often blurry or compromised. Standard datasets and machine learning algorithms are required for language recognition.

Post-processing in HTR presents significant issues, such as the requirement for a comprehensive lexicon, distortion of the scanned image, and choice of writing instrument [1]. Several online datasets are available in Hindi, Urdu, English, Arabic, Punjabi, etc.

The author focuses on machine learning techniques/models trained on the Modified National Institute of Standards and Technology MNIST() dataset. 1st step was to install Anaconda Navigator on Windows 11 and launch the Jupyter Notebook Lab. We performed all coding on a Jupyter Notebook and ran it in this environment. Next, import and utilize the publicly accessible MNSIT dataset online, making it available. The dataset consisted of sufficient images with ten classes ranging from 0 to 9. There are 70,000 images, of which 60,000 are used for training and 10,000 are used for model testing [2]. Handwritten digit recognition (HDR) is a technology that allows machines to identify human-written digits. Handwritten digits exhibit inherent idiosyncrasies that differ among people and can be created in different styles. As a result, this presents computer difficulties in successfully performing the task. Digit recognition applications involve multiple tasks, such as filling out forms, processing bank checks, and sorting mail. The primary obstacle is developing an effective algorithm that can precisely decipher handwritten numbers from scanners, tablets, and other digital devices. Handwritten digit recognition is a prevalent task for categorizing many classes in banking systems. Users can conveniently and automatically deposit paper cheques using mobile banking applications and traditional automated teller machines. Various parameters were used to measure the performance of the different machine-learning techniques. After importing the dataset for recognition tasks, such as MNIST digit classification, the next step typically involves preprocessing the data, splitting it into training and testing sets, choosing a machine learning model, training the model on the training set, evaluating the model's performance on the testing set, and then potentially fine-tuning the model or trying different models to improve effectiveness.

1.1 Need for offline handwritten text recognition and associated Challenges

Offline Handwritten recognition refers to the ability to identify information recorded from handwritten documents and interpret their written text. Nevertheless, the deterioration over time presents several difficulties in identifying distinct writing styles (multi-style), which vary depending on emotional state,

blurred or damaged ink, characters, font, and size, inadequate quality of device documentation, significant ambiguity, varying structure, age of the selected personnel, gender, and stroke variability. Segmenting a picture into many segments, each representing a distinct digit, and accurately classifying them for recognition poses substantial challenges in human word recognition (HWR). The recognition of noisy datasets is also a significant challenge. Considering the considerable computing expenses involved in recognizing letters, text, and sequences and the existence of several approaches, it is challenging to determine the most effective strategies, models, and metrics that yield the best results on different datasets. The author conducted a Systematic Literature Review (SLR) on article 60, found on Scopus, after the inclusion and exclusion processes to obtain solutions to these issues.

1.2 Objectives of the SLR

Upon thorough examination of the chosen research, we identified the following aims:

- Systematically classify and identify offline handwritten text recognition methods often employed in machine learning and deep learning.
- To discuss simulation tools and methodologies for evaluating recognition models.
- This research seeks to explore and monitor the development of offline HTR systems over time. Additionally, the aim is to explore the domain applications in which offline handwritten recognition is widely used and to investigate the language diversity among these systems.
- The objective was to perform a comparative examination of several machine learning algorithm categories using the MNIST dataset and determine the most effective technique with the best evaluation parameters.
- An analysis of the main challenges, research gaps, and areas for further development in existing research on offline handwritten recognition systems.

1.3 Motivation and Contribution

This systematic literature review of Offline HTR comes from the increasing demand for digitization in areas such as education, banking, and healthcare. With the increasing importance of recognising handwritten text, it is necessary to find effective methods to address problems such as a variety of handwriting styles and document quality. The purpose of this review is to investigate the latest developments and research trends to address knowledge gaps and enhance understanding in the area. The following is a summary of the novel contributions of this study:

- This work summarizes 36 articles from the Scopus database to assess which language is currently the most widely recognized and the year in which maximal recognition occurred to utilize various strategies.
- It highlights offline HTR challenges and areas for future research and innovation.
- Comparative analysis: The review contains comparative analysis of machine learning models applied on MNIST dataset, which helps in identifying the best machine learning technique for specific recognition task.
- This documentation of the existing methods and limitations offers guidance and direction for future research, which can lead to improvements in model development and practical applications.

Section-wise organisation of the SLR

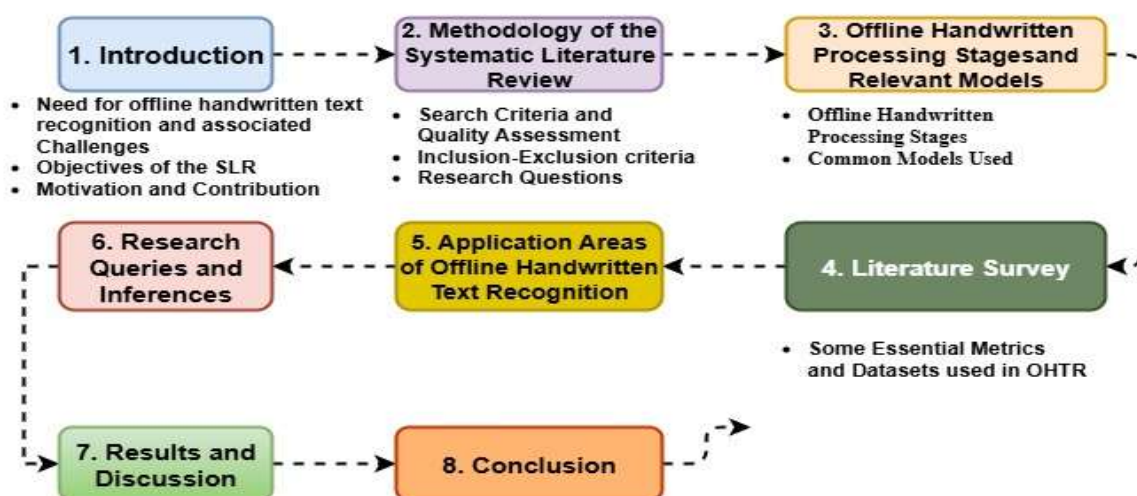


Figure 1 Various Sections and subsections of the SLR

This paper is arranged into eight sections and subsections, which you can see in Figure 1.

2 Methodology of the SLR

This section describes the elements of this systematic literature review: the search criteria, the review process, and the research questions. This includes clarifying research questions or objectives, determining relevant databases and sources, and conducting a systematic search and screening for eligible studies. The search term was a string containing all key terms from the research questions, along with any synonyms used with these terms.

2.1 Search Criteria and Quality Assessment:

The keywords used to compose the search strings are "Offline", "handwritten", "text", and "recognition". The following advanced search query was used in the Scopus Database to extract relevant papers:

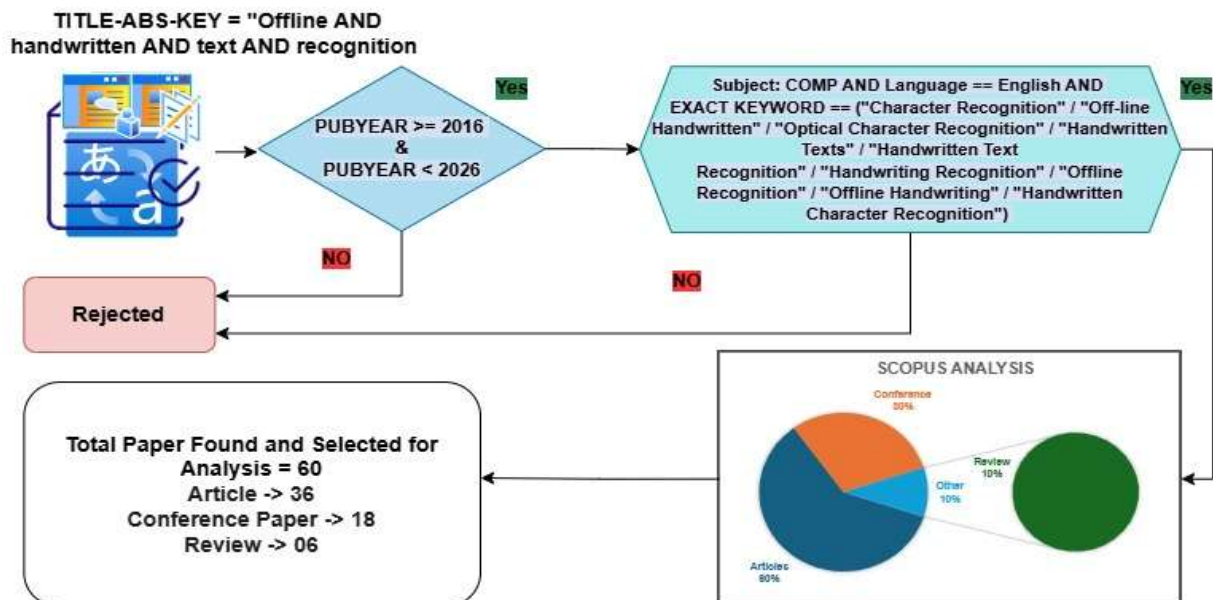


Figure 2 Selection Criteria

TITLE-ABS-KEY (Offline handwritten text recognition) AND PUBYEAR > 2015 AND PUBYEAR < 2026 AND (LIMIT-TO (OA,"all")) AND (LIMIT-TO (PUBSTAGE,"final")) AND (LIMIT-TO (EXACTKEYWORD,"Character Recognition") OR LIMIT-TO (EXACTKEYWORD,"Off-line Handwritten") OR LIMIT-TO (EXACTKEYWORD,"Optical Character Recognition") OR LIMIT-TO (EXACTKEYWORD,"Handwritten Texts") OR LIMIT-TO (EXACTKEYWORD,"Hand-written Text Recognition") OR LIMIT-TO (EXACTKEYWORD,"Handwriting Recognition") OR LIMIT-TO (EXACTKEYWORD,"Offline Handwriting Recognition") OR LIMIT-TO (EXACTKEYWORD,"Offline Handwriting") OR LIMIT-TO (EXACTKEYWORD,"Hand Written Character Recognition")) AND (LIMIT-TO (SUBJAREA,"COMP")) AND (LIMIT-TO (LANGUAGE,"English"))

Numerous published libraries in the field of computer science were manually searched. The SLR was performed in the Scopus database, IEEE Computer Society, ResearchGate, ScienceDirect, Springer and ACM Digital Archive. The above-mentioned advanced query resulted in the discovery of 60 documents/papers, of which 36 were Articles, 18 were conference papers, and 6 were reviews, as shown in Figure 2 above. The inclusion–exclusion criteria listed in Table 2 were then used. About 24 publications were excluded because they were of a particular document type, e.g., conference papers (18) and review papers (06). Only open-access papers were included in the query above; others were not included because of the necessity to pay to read and view, or for other reasons. We included research that has been cross-referenced to obtain a more complete and higher-quality analysis. We chose 34 cross-references from the list of extracted cross-references, carefully selected and rigorously meeting the search criteria, to provide a broader spectrum of research that can be trusted. Sixty papers were selected, including 36 research articles, which served as the basis for the technology survey and subsequent analyses.

2.2 Inclusion-Exclusion criteria

The acceptance or rejection criteria for this SLR are explained in Table 2.

Table 1 Inclusion-exclusion Criteria for filtering relevant articles for SLA.

Inclusion:	Exclusion:
All papers including keywords "offline handwritten text recognition".	Papers that do not include the keywords "offline handwritten text recognition"
The period chosen is 2016-2026	Papers Excluded that did not come under the time frame of 2016-2026
The chosen area as a Subject is "Computer Science."	All those research papers that do not contain keywords and emphasize the answers related to the research questions.
"Research Article" is the type of Document	Conference Papers and Review paper do not included in the review table
The language chosen is English.	Papers that were not in the English language were not considered
Citations of at least 0 must be included.	review papers/books/conference review/retracted/ Research Article which focuses literature study
Most papers that are relevant and are published in "all open access" journals that meet the above criteria are manually checked and included.	Research papers that are commercial and demand a purchase to retrieve.

Data extraction was conducted to gather essential information from each study, including design, methodologies or approaches, research constraints, future implications, instruments, assessment criteria, and other noteworthy discoveries. The collected data were subsequently consolidated and examined using a methodical and organized methodology and presented in tabular form to offer valuable insights and derive conclusions regarding the study inquiries.

2.3 Research Questions

RQ1: Which techniques and models have been observed as most frequently used in term of higher accuracy in offline handwritten-text recognition in the last decade?

RQ2: Which evaluation metrics, such as CER, WER, accuracy, and F1-score, are most appropriate for evaluating offline handwritten text recognition across different scripts and writing styles?

RQ3: Which datasets and benchmark standards are frequently used in HTR research?

RQ4: What is the effectiveness of offline handwritten recognition systems in applications such as banking, postal services, healthcare (medical prescriptions), academic digitization, and document archiving?

RQ5: Which script or language has shown the most promise in the past 10 years for offline handwritten-text recognition?

RQ6: Which recognition level (Character/word/line/paragraph/person/signature/writer ID/Gender) has been most effectively used in offline handwritten text recognition over the past decade?

RQ7: Which Platform has been used with the most promise in the past 10 years for offline handwritten-text recognition?

3 Offline Handwritten Processing Stages and Relevant Models

3.1 Offline Handwritten Processing Stages

There are various offline handwriting processing stages which are being employed while recognizing offline handwritten text, as shown in Figure 3 below and as explained below.

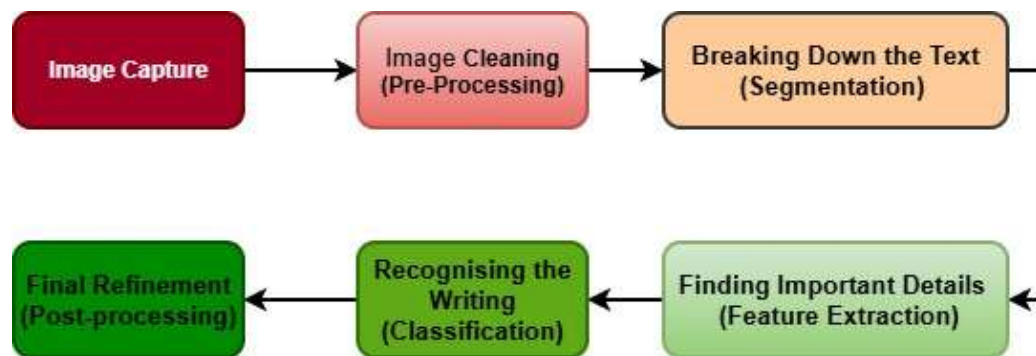


Figure 3 Offline Handwritten Processing Stages

- **Image Capture**

The first step is to digitise the handwritten document by scanning or photographing it, thereby converting it into a digital image. This is the initial processing stage, known as the image-acquisition phase, which converts offline documents into digital form so that subsequent processing stages can be applied to these images.

- **Image Cleaning (Preprocessing)**

These digital images were then cleaned or processed to enhance the scanned image quality, making the handwriting easier to analyse, and converted into a format more convenient for the next processing stage (segmentation). This included removing smudges, adjusting brightness and contrast, fixing tilted or skewed images, without losing essential information and converting the image into black and white for clarity [3].

- **Breaking Down the Text (Segmentation)**

The cleaned or scanned images which contain handwritten text are separated or divided into smaller parts, such as lines, words, and individual characters, so that the system can focus on each piece one at a time. The most important action taken here is to split them into individual characters, lines, or words, i.e., line segmentation. To be analysed further, these can also be changed into a binary process, which completely removes noises the boundaries of words [3].

- **Finding Important Details (Feature Extraction)**

The system examines the unique details of each character or word, such as their shapes, thickness, curves, and spaces, to better understand what is written. This phase plays the most important role in any system designed to recognise handwritten text. Almost all CNNs were used in many papers in previous scenarios, as they are known for their capacity to extract features from images using convolution layers [4].

- **Recognising the Writing (Classification)**

In this phase, the features extracted in the previous stage are used to determine which division an entered part belongs to. Using advanced computer models, the system compares these details to known handwriting styles and symbols to determine which letter or word each segment represents and is built using various classification methods, such as CNNs, SVMs, and KNNs [5].

- **Final Refinement (Post-processing)**

Post-processing is the last part of offline HTR, which is accountable for recognizing. The recognized text is then processed to fix errors, adjust formatting, and confirm that the end part is understandable and correct, often by checking against dictionaries or language rules.

3.2 Common Models Used

Different models/techniques are utilised to answer the Research Queries, and the Inferences, which will be discussed under Section 6, are explained here with specific properties and uses. Here are some of the above-mentioned methods:

1. **CNN (Convolutional Neural Networks):** CNNs are extensively used in image processing. They utilize convolutional layers to automatically detect features from raw image data, making them effective for various applications, including image classification and object detection. CNNs are specialists in image analysis and can be used to analyse visual patterns in handwritten characters to recognise them accurately.
2. **Pix2Pix:** Pix2Pix is a GAN specifically designed for image-to-image translation, such as converting sketches to photos or aerial images to maps. It consists of a generator and a discriminator to enhance the quality of generated images.
3. **TL DenseNet (Transfer Learning with DenseNet):** This is a family of convolutional networks, where each layer is connected to all the other layers. Transfer learning with DenseNet involves fine-tuning a pre-trained model for a specific task, resulting in shorter training times and better performance on smaller datasets.

4. KNN (K-Nearest Neighbours): KNN is an instance-based learning algorithm that is simple and used in classification problems. It categorises the new data point according to the most predominant class in its k-nearest neighbours in the feature space. Easy to implement but may be computationally expensive for large datasets.

5. Structural MATLAB: Use MATLAB's computational environment and tools to structure and analyse data, such as modelling, simulation and algorithm development. Various statistical and machine learning functions in MATLAB can facilitate complex analyses.

6. SVM (Support Vector Machine): SVM is a supervised learning algorithm which is applied in classification and regression tasks. It tries to divide the class lines in the feature space in the best possible way. The strength of SVMs is that they work well in high-dimensional spaces and can learn non-linear boundaries by applying kernel functions. SVMs take the extracted features and use them to classify parts of handwriting, thus recognizing each character from the others.

7. Fuzzy Features: Fuzzy logic is used to model imprecise or uncertain information. Fuzzy features can be added to multiple models to improve decision-making, especially when the data is fuzzified, not crisp, or not very clear.

8. Gradient + Segmentation: This is usually a combination of gradient-based methods (such as gradient descent) and segmentation techniques to detect and segment objects in images.

The 9th method is called the Histogram of Oriented Gradients + Long Short-Term Memory (HOG + LSTM): HOG is a technique for extracting features from images that defines edge directions and shapes. If used in conjunction with LSTM (a variant of a recurrent neural network), it can solve problems that require learning sequences over time, such as action recognition in videos.

The 10th is CRNN (Convolutional Recurrent Neural Network), designed to process sequential data with spatial-temporal features. The model is especially suitable for applications such as handwriting recognition and speech-to-text. These are intended to learn sequences and context, so are particularly well suited for cursive or joined writing and will remember the previous character.

The 11th Model is FCN + CTC (Fully Convolutional Network + Connectionist Temporal Classification): FCNs are employed for pixel-wise classification, such as semantic segmentation. In combination with CTC, it enables training models predicting sequences, for example, speech or video frames, without segmentation. This implies the machine learning algorithms are used along with the normalization techniques to normalise the data. Normalization is useful to enhance models' performance by normalizing the features, so they have the same importance in calculating distance.

Hybrid models or combining several models at the end, which were based on combining CNNs with RNNs and Hidden Markov Models (HMMs) (which are good at learning sequences) with other models for obtaining the maximum accuracy and adaptability.

All of these are relevant and can be employed to answer various parts of the research question and to provide approaches to data analysis, prediction and interpretation. By using different models and using the handwritten document in a step-by-step manner, the systems can effectively convert handwritten text to digital text, even if handwriting styles are subjected to significant variation among the individuals.

4 Literature survey

The entries are diverse research papers that provide a brief description of the author(s), year of publication, handwritten text recognition methods, challenges, applications, pros, cons, and future directions. Based on the extensive diversity in handwriting styles, Karthi et al. (2023) argued that previous studies failed to correctly identify cursive writing styles and their overlapping effects. To tackle this problem, Ruiz-Parrado et al. [6] presented a study by using bibliometric techniques on 5389 articles and found that mostly published research articles area is recognition on multi languages such as Japanese, Chinese, Arabic, and Roman scripts by using ML Techniques such as HMMs, SVMs, and NNs by mostly authors in their publications.

Sousa Neto et al. [7] presented a study on the English language to recognise characters and words on five well-known datasets named (IAM, RIMES, Bentham, Washington, Saint Gall), and found 87.25% and 71.54% for character and word accuracy, respectively.

Toiganbayeva et al. [3] studied the Kazakh language for word and line recognition by using dataset Kazakh Offline Handwritten Text Dataset (KOHTD) (3000 handwritten exam papers at Satbayev University and Al-Farabi Kazakh National University) that consists of approximately 922010 symbols by using CRNN models, such as Flor, Abdallah, Bluche, and Puigcerver HTR models to find which one performed best among them and showed 6.52% character error rate (CER), 24.52% word error rate (WER).

Hamdan et al. [8] worked on new model named Joint attention model by using handwritten paragraph recognition datasets, such as RIMES, IAM, and READ 2016 and found CER rate 5.32, 2.18, and 4.2 for IAM, Rimes and READ datasets, respectively.

Singh et al. [9] study on online Punjabi script recognition by using fine-tuned Deep Convolutional Neural Network (DCNN) and above 97% accuracy have been achieved by their model. They provide a broad level literature overview on many languages in this article.

Wang (2021) discusses the challenges of Chinese character recognition and the use of language models to improve accuracy. Annanurov (2021) works on Khmer character recognition with moderate accuracy in a low calculation environment. Lamtougui (2023) is another study that focuses on Arabic recognition but suffers from Arabic handwriting and aims to improve it using attention models. The style-variance issue in multi-script recognition is discussed in [Barreiro 2024], where a hybrid model approach is proposed. Momeni (2024) uses Seq2Seq (s2s) models for Arabic line recognition but requires large computational resources and achieves higher accuracy. Gender Bias in Biometric Signature Verification: A study and solutions (2022) examines gender bias in biometric signature verification and proposes solutions to address domain shift. El Khayati (2024) discusses the problems associated with Arabic word recognition and recommends standardising this process. Other studies address various problems, such as segmentation difficulties, style variations, and limitations in datasets across several languages, reflecting the importance of improving recognition accuracy and expanding datasets to build improved recognition models.

Dahbali et al. in 2024 [4] presented a hybrid model by using CNN-CBAM AND BLSTM for recognition of ARABIC SCRIPT, with results CER=3.25%, WER- 14.55% and addresses the existing problems related to the recognition of Arabic handwritten lines with ligatures, which requires large scale datasets.

In 2023, Yadav et al. [5] Presented a study on Devanagari script by using CNN technique by designing a model HDevCharNet (Handwritten Devanagari Character Recognition Network) and dataset taken is Devanagari handwritten character dataset (DHCD) and showed an accuracy of 98.75%, to 99.17. It is about recognizing Hindi consonants and numerals in the context of banking, but vowels are still a challenge.

The author introduced a new method called the "Residual Bidirectional Network-based Self-Adaptive Dwarf Mongoose (RBN-SADM)" using the IAM and EMNIST datasets to accurately and effectively recognize cursive overlapped English handwritten text. This approach achieved higher performance of 98.7%, 98.6%, 98.2%, 97.8%, and 97.9% in terms of accuracy, precision, recall, specificity, and F1-measure, respectively [1].

Khan et al. [10] concluded that standard datasets and machine learning algorithms are required for language recognition. Although online datasets for Hindi, Urdu, English, Arabic, and Punjabi exist, there is a paucity of data for Pashto characters and difficulty in selecting adequate machine learning algorithms for recognizing meaningful insights. Thus, the author proposes a handwritten Pashto character image dataset (HPCID) with 14784 samples on A4-sized paper from university students and faculty.

4.1 Some Essential Datasets and Recognition Level of scripts (Languages) used in OHTR

Author / Year	Recog. Script	Recognition Level	Challenge / Gap	Applications	Advantages	Disadvantage	Future Work	Result
Sousa Neto et al., 2022 [7]	English, French, Latin	character and word	high computational cost	Historical manuscripts	perform well even with small training datasets	slower in the decoding	paragraph and page-level recognition	Accuracy rate: Character- 87.25%, word- 71.54%
Toiganbayeva et al. 2022 [3]	Kazakh	Line and Word	Dataset absence	Education	First large DB	State of comparison only, no new method purposed	Handwriting identification based on gender	WER- 24.52% , CER- 6.52%
Hamdan 2023 [8]	English	Paragraph	Line segmentation errors	Historical Manuscripts	End-to-end	Complex training	Improvement in recursive slanted text adjustment	CER rate 5.32, 2.18 and 4.2 for IAM, Rimes, and READ, respectively

Singh 2021 [11]	Punjab	Word	Indic scarcity	Education	Word-based recognition	Small dataset	Multilingual model	97% Accuracy
Dahbali 2024 [4]	Arabic	Line	Ligatures	Postal/Bank	Segmentation free	Needs large data	Hybrid models	CER=3.25%, WER-14.55%
Yadav 2023 [5]	Hindi	Character	Dataset unavailability	Banking	consonants and numerals recognized	Vowels not recognized	modifiers or text with Devanagari characters	99.17%
Wang 2021 [12]	Chinese	Character	Touching chars	Office automation	Recognize variant writing styles	Script complexity	Integrate language model	97.9%
Annanurov 2021 [13]	Khmer	Character	Low compute env	healthcare, finance	Low memory	Moderate accuracy	Edge OCR	93–98%
Lamtougui 2023 [14]	Arabic	Word	Cursive nature	Arabic OCR (banking, postal, document digitization)	No segmentation	Needs LM	Attention models	Improved CER
Barreiro 2024 [15]	Multi	Word	Style variance	Document digitization	Learnable norm	GAN instability	Joint HTR-GAN	Reduced WER
Momeni 2024 [16]	Arabic	Line	RNN seq limits	Document digitization	Parallelizable	Large compute	Seq2Seq models	Higher Accuracy
Aradillas 2021 [17]	English	Line	Few labels	Historical document recognition	Few-shot TL	Label noise	Self-supervision	CER ↓6%
Agduk 2022 [18]	English	Person	Gender bias	Signature verification (biometrics)	Biometric use	Domain shift	Multiwriter	92.77%
Huang 2021 [20]	Pashto	Character	Dataset absence	Education	Simple model	Low acc	Deep models	80.34%
Riaz et al., 2022 [21]	Urdu	Text-line	Ligature complexity	Document digitization	CER reduction	Heavy compute	Efficient transformer	CER: 5.31%
El Mamouni et al., 2019 [22]	Arabic	Character	Segmentation difficulty	Handwritten Recognition	Accurate segmentation	Character touching	Hybrid segmentation	Promising accuracy
Purohit et al., 2025 [23]	Multi	Writer ID	Style Variability	forensics	High accuracy	Data Dependency	Cross-language or Multilingual Expansion	98.78% IAM
Tadesse et al., 2023 [24]	Amharic	Word/Line	Complex script	Document digitization	CER reduced	Complex model	Improve generalization by using Larger dataset	CER: 9.17%
Al-Saqar et al., 2019 [25]	Arabic	Word	Script variability	Document digitization	Simple pipeline	Less scalable	Use DL models	Accuracy: 80–90%
Nurseitov et al., 2021 [26]	Kazakh/	Line	Lack of Cyrilli	Postal	Performed on large dataset	Data imbalance	Dataset expansion	Strong baseline

	Russian		Character dataset					Database HKR
Wróbel et al., 2021 [27]	Polish	Character	Stroke ambiguity	Archives Documents	Handles variation with flexibility	Low speed	Stroke ambiguity	Acceptable accuracy
Tsochatzidis et al., 2021 [28]	Greek	Line	Manuscript quality	Historical digitization	Good for old documents recognition	Noise sensitive	Handle noise	Competitive
Gharahbagh et al., 2018 [29]	Persian	Writer ID	Stroke similarity	Security, forensic analysis	Writer detection	Manual labelling and limited feature	Automation by making hybrid model	High accuracy
Pramanik et al., 2020 [30]	Indian	Word	Multi-script	Banking, Postal	Multi-script	Overfitting and complex	Larger data	Improved accuracy
Rexit et al., 2022 [31]	Multi	Signature	No dataset	Banking	High accuracy	Script dependent	Lightweight models	98.4%
Farooqui et al., 2020 [32]	Urdu	Word	Style variation	Document digitization	Data augmentation	High cost with complexity	Efficient GAN	98.96%+
Ren et al., 2024 [33]	Mongolian	Character	Lack of corpus	Cultural preservation	Improved accuracy	Training time and data dependency	More Cross-lingual dataset	90%+
Shin et al., 2024 [34]	Multi	Gender	Limited handwriting	Security	Accuracy achieved 90%+	Online only	Offline model	90.09%
Peng et al., 2023 [35]	Chinese	Text	Segmentation cost	Academic digitization (exam papers)	Complex process of recognition	Large vocab	Better context/ Language model	Higher than baseline model (90-96%)
Saidi et al., 2021 [36]	Arabic	Word	Limited Arabic works	Document digitization	Lightweight and feature simplicity	Dataset bias and limited accuracy	DL methods	80-90%
Ahmed et al., 2022 [37]	Urdu	Character	Dataset scarcity	Banking, Education	High performance	Alphabet recognition only	Word-level larger dataset	90-98%
Zhu et al., 2019 [38]	Chinese	Line	Exam noise	Education (exam papers)	Realistic data	Noise	Robust models development	86.28%
Khan et al., 2021 [10]	Pashto	Character	Dataset absence	Document digitization	First dataset	Limited samples and less focus on model	Deep models development	—
Zhou et al., 2026 [39]	Tibetan	Character	Low resource	Healthcare records	Very high accuracy	Data dependency	Cross-lingual models	99%+

**WER- Word Error Rate, CER- Character Error Rate

4.2 Some Essential Techniques / Platforms used in OHTR

Author / Year	Preprocessing	Feature Extraction	Classification	Platform
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Sousa Neto 2022 [7]	Z-score normalization	Gated CNN and PReLU	BGRU + CTC	Google Colab
Toiganbayeva 2022 [3]	GA segmentation	CNN	CTC	DL Framework Python
Hamdan 2023 [8]	Segmentation-free	ResNeSt50 CNN	Transformer	PyTorch
Singh 2021 [11]	Stroke Norm	CNN	Softmax	DL Framework Python
Dahbali 2024 [4]	Skew correction	CNN-CBAM	BLSTM+CTC	DL Framework Python
Yadav 2023 [5]	Image norm	CNN-BN	Softmax	DL Framework Python
Wang 2021 [12]	Seg-free	Residual CNN	CTC	DL Framework Python
Annanurov 2021 [13]	Resize	2+1 CNN	ANN	DL Framework Python
Lamtougui 2023 [14]	Augmentation	CNN	BLSTM	Python (TensorFlow /PyTorch)
Barreiro 2024 [15]	GAN Norm	Pix2Pix	DL	Python (PyTorch)
Momeni 2024 [16]	Resize	CNN	Transformer	DL Framework Python
Aradillas 2021 [17]	Augmentation	CNN	LSTM	DL Framework Python
Agduk 2022 [18]	Resize	TL DenseNet	RF	Python
Huang 2021 [20]	Zoning	HOG	KNN	DL Framework Python
Riaz et al., 2022 [21]	Normalization	CNN	Transformer	DL Framework Python
El Mamouni et al., 2019 [22]	Projection Histogram	Structural	Segmentation-based	MATLAB / Image Processing tools
Purohit et al., 2025 [23]	Normalization	Multi-CNN	BiLSTM	Python
Tadesse et al., 2023 [24]	Augmentation	Gated CNN	Self-Attention	DL Framework Python
Al-Saqqar et al., 2019 [25]	Skeletonization	PCA	SVM	MATLAB
Nurseitov et al., 2021 [26]	Segmentation	CNN	CTC	DL Framework Python
Wróbel et al., 2021 [27]	Stroke extraction	Fuzzy features	Fuzzy classifier	DL Framework Python
Tsochatzidis et al., 2021 [28]	Normalization	CNN	GRU	DL Framework Python
Gharahbagh et al., 2018 [29]	Segmentation	Gradient	KL distance	MATLAB
Pramanik et al., 2020 [30]	Skew correction	Statistical	CNN TL	DL Framework Python
Rexit et al., 2022 [31]	PCA	LOMO+HOG	kNN	DL Framework Python
Farooqui et al., 2020 [32]	GAN	HOG	LSTM	DL Framework Python
Ren et al., 2024 [33]	HWT	CRNN	Attention	DL Framework Python
Shin et al., 2024 [34]	SFFS	Statistical	GB/SVM	DL Framework Python
Peng et al., 2023 [35]	Weak supervision	FCN	CTC	DL Framework Python
Saidi et al., 2021 [36]	Skeleton	Structural	RBFNN	DL Framework Python
Ahmed et al., 2022 [37]	Diagonal	CNN	Softmax	DL Framework Python
Zhu et al., 2019 [38]	Normalization	CRNN	Attention	DL Framework Python

Khan et al., 2021 [10]	Normalization	ML features	ML	DL Framework Python
Zhou et al., 2026 [39]	Grid extraction	CRNN	Transfer	DL Framework Python

** DL- Deep Learning approach, CNN- Convolutional Neural Network, CBAM- Convolutional Block Attention Module, BLSTM- Bidirectional Long Short-Term, CTC- Connectionist Temporal Classification, PreLU- Parametric Rectified Linear Unit (PreLU)

4.3 Some Essential Datasets/Size/Sources used in OHTR

Author / Year	Dataset Name	Dataset Size	Dataset Source (Exact Location)
Ruiz-Parrado, 2022 [6]	Scopus Review DB	5389 Articles	https://www.scopus.com
Sousa Neto 2022 [7]	IAM, RIMES, Bentham, Washington, Saint Gall	1539 Pages, 13353 Lines, 115320 Words	https://fki.tic.heia-fr.ch/databases/iam-handwriting-database (fki.tic.heia-fr.ch)
Toiganbayeva 2022 [3]	KOHTD	3000 Papers, 140,335 Images, 922010 symbols	https://github.com/abdoelsayed2016/KOHTD
Hamdan 2023 [8]	IAM, RIMES, READ 2016	657 Writers, 1500 pages	https://fki.tic.heia-fr.ch/databases/iam-handwriting-database (fki.tic.heia-fr.ch)
Singh 2021 [11]	Self-created, OHGWD	~20,000 samples	Author generated
Dahbali 2024 [4]	KHATT	1000 Writers	http://khatt.ideas2it.com
Yadav 2023 [5]	DHCD	92,000 Samples	https://archive.ics.uci.edu/ml/datasets/Devanagari+Handwritten+Character+Dataset
Wang 2021 [12]	CASIA-HWDB	3.9M Samples	http://www.nlpr.ia.ac.cn/databases
Annanurov 2021 [13]	Khmer DB	10,000 Images	IAES repository
Lamtougui 2023 [14]	IFN/ENIT	26,459 Words	https://zenodo.org
Barreiro 2024 [15]	IAM	115,320 Words	https://fki.tic.heia-fr.ch/databases
Momeni 2024 [16]	KHATT	2000 Writers	http://khatt.ideas2it.com
Aradillas 2021 [17]	Washington	656 Pages	https://fki.tic.heia-fr.ch
Agduk 2022 [18]	Own Signature DB	3250 Images	Author dataset
El Khayati 2024 [19]	Review Paper	NA	Springer DB
Huang 2021 [20]	Own Pashto DB	11,352 Images	Author DB
Riaz et al., 2022 [21]	NUST-UHWR	10,000+ lines	NCAI NUST Islamabad Repository
El Mamouni et al., 2019 [22]	IFN/ENIT	26,459 words	http://ifnenit.com
Purohit et al., 2025 [23]	IAM/CVL	IAM-1539 pages	https://fki.tic.heia-fr.ch
Tadesse et al., 2023 [24]	HETD, HEWD	2800 lines	Collected at Debre Markos Univ.
Al-Saggar et al., 2019 [25]	IFN/ENIT v2	32,492 images	http://ifnenit.com
Nurseitov et [26] al., 2021	HKR	63,000 sentences	https://github.com/abdoelsayed2016/HKR_Dataset
Wróbel et al., 2021 [27]	Historical set	5000+ samples	Czestochowa archives
Tsochatzidis et al., 2021 [28]	IAM/RIMES	115,320 words	https://fki.tic.heia-fr.ch
Gharahbagh et al., 2018 [29]	Persian DB	300 writers	Semnan University
Pramanik et al., 2020 [30]	CMATERdb	15,000+	http://www.cmaterdb.com
Rexit et al., 2022 [31]	Custom (Multilingual signature)	12,000 samples	Xinjiang Univ
Farooqui et al., 2020 [32]	Custom Urdu Dataset	20,000 images	NUST Islamabad
Ren et al., 2024 [33]	Mongolian	8000+ chars	Inner Mongolia Univ
Shin et al., 2024 [34]	Self-collected Dataset	79 users	Kumamoto Univ
Peng et al., 2023 [35]	CASIA	3.9M chars	http://www.nlpr.ia.ac.cn
Saidi et al., 2021 [36]	Algerian DB	5000 words	Tahri Univ
Ahmed et al., 2022 [37]	UHDS	38,000 chars	Lahore Univ
Zhu et al., 2019 [38]	SCUT-EPT	50,000 lines	SCUT Guangzhou
Khan et al., 2021 [10]	HPCID	14,784 chars	Univ of Peshawar

Zhou et al., 2026 [39]	TibHCR	141,698 samples	https://huggingface.co/datasets/qixiao/TibHCR
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PHOG- Pyramid Histogram of Oriented Gradient, HMM- Hidden Markov Models, MAP- Mean Average Precision, IAM- RBN SADM - Residual Bidirectional Network-based Self-Adaptive Dwarf Mongoose, SER- Sequence Error Rate, CTC- connectionist temporal classification, HKR-Handwritten Kazakh and Russian Dataset)

5 Application Areas of Offline HTR

The handwritten text recognition proposed in this paper for an offline handwritten-to-digital text conversion system has numerous real-world applications across different areas. It has increased the accessibility, accuracy and efficiency in a number of areas, including this technology. Doctors are also beginning to digitize their handwritten notes, prescriptions and medical records in the healthcare sector, enhancing data management and reducing illegible handwriting errors. This enables better record-keeping and quicker patient treatment. In the business of finance and banking, technology does the same automating the interpretation of handwritten signatures, forms and checks, and reducing manual effort. Offline handwriting recognition can help the education industry to digitize tests and even tasks and evaluations of students. This will make it easier for schools to review student performance and keep data well organized. Logistics converts handwritten goods into goods to digital documents for inventory management and tracking. This technology is used by the government and legal entities to archive contracts, signed agreements and records, and to facilitate document management and retrieval.

In retail order forms and receipts can be dealt with in a timely manner in handwritten form, with support to the customer service and inventory management tasks. Moreover, the digitisation of old material preserves invaluable information and facilitates studies by offering digital copies of old manuscripts, letters and archival material. Taking claim forms and supporting documents and converting them to digital format assists insurance companies when it comes to claim processing and fraud detection. The research and techniques presented in the text are primarily in the context of Optical HTR and cover the following applications:

- Banking & Financial Services: Recognition of handwritten signatures/ checks/ forms for better processing & fraud detection. Today many banking forms, checks and loan applications are still handwritten. Recognizing this text digitally helps automate verification processes, speeds up data entry, and enhances security via signature verification.
- Postal Services: Automation of both sorting and processing of handwritten letters (addresses & postal codes).
- Document Digitization: Transforming handwritten paperwork into digital documents to be effortlessly stored, retrieved, and searched, especially in fields such as education and legal. In Retail, offline handwritten recognition helps to quickly digitize signed order forms, receipts and customer feedback so they can be easily archived, analysed and retrieved, aiding inventory decision making and customer service.
- Cultural Preservation: The digitization of historical and cultural artifacts, manuscripts and records, for the preservation of heritage and enhanced access for researchers. This technology is used to digitize old handwritten manuscripts, letters and archival materials, ensuring that valuable information is preserved and can be accessed for research.
- Healthcare: Digitalization of prescription and handwritten medical information for better patient care, data management and interoperability.
- Medical staff and doctors often have to write notes and prescriptions by hand. Offline handwritten text recognition aids in converting handwritten records into a digital form, which not only decreases the chance of data error due to illegible handwritten data but also enhances patient care by improving record management.
- Education: Handwritten exam papers and assignments are digitized for easier assessment and analysis, towards academic digitisation. The technology aids the digitization of handwritten exams, assignments and student records, making them easily stored, searchable and analyzable by teachers and institutions, which helps to streamline academic data management.
- Research and Development: Development of new deep learning techniques and algorithms for more accurate and efficient handwriting recognition in different languages and scripts.
- Data Augmentation and Prediction: Using generated data in model training, the data problem, and strong recognition systems.

- Handwritten shipping labels, invoices and delivery notes can be easily scanned to modernize package tracking, billing and inventory.
- Insurance: Insurance claim forms and corresponding documents, frequently handwritten, are digitized to speed up claims processing and also to prevent insurance fraud.

These regions serve as examples of the many uses and the potential benefits that handwriting recognition technologies could offer in terms of increased efficiency, accuracy, and accessibility in various fields.

In general, OWTWR technology is very important for converting handwritten data into searchable, editable text; aiding the digitization and automation process in numerous industries. The use of it cuts down on manual work, makes data more accurate and makes written information more accessible in various professional areas.

6 Research Queries and Inferences

RQ1: Which techniques and models have been observed as most frequently used in terms of higher accuracy in offline handwritten-text recognition in the last decade?

Response: The analysis of papers published over the past 10 years on the research question of the most widely used techniques and models for offline handwritten-text recognition reveals some interesting trends.

The most frequent method used in the data is Convolutional Neural Networks (CNN), with 19 publications as shown in figure 4. It is evident that it is widely used and has achieved high accuracy in handwritten text recognition problems. CNNs are especially suitable for image processing tasks because they can learn hierarchical features from raw pixel data.

While not as common as CNNs, other models were also a part of the handwriting recognition scene. The Connectionist Recurrent Neural Network (CRNN) was introduced in 3 papers, combining convolutional and recurrent networks, and has proven effective at modelling sequences of handwriting.

Furthermore, there were 2 papers for each of the traditional machine learning techniques – k-Nearest Neighbours (KNN) and Support Vector Machines (SVM). Furthermore, single papers were dedicated to the use of the structural method implemented in MATLAB and to fuzzy features, thus suggesting niche applications or focused research areas that address different aspects of the recognition problems.

Other approaches, including Pix2Pix, TL DenseNet, and Gradient+Segmentation, were also mentioned but do not appear to be widely used, possibly indicating new techniques or less popular methodologies in the field.

To summarize, CNNs are most common, and probably most accurate, offline handwritten-text recognition methods; others are a rich variety of methods in the area. Overall, the findings indicate that although traditional approaches may still be relevant, the focus of the conversation is on more advanced deep learning approaches for effective handwritten text recognition.

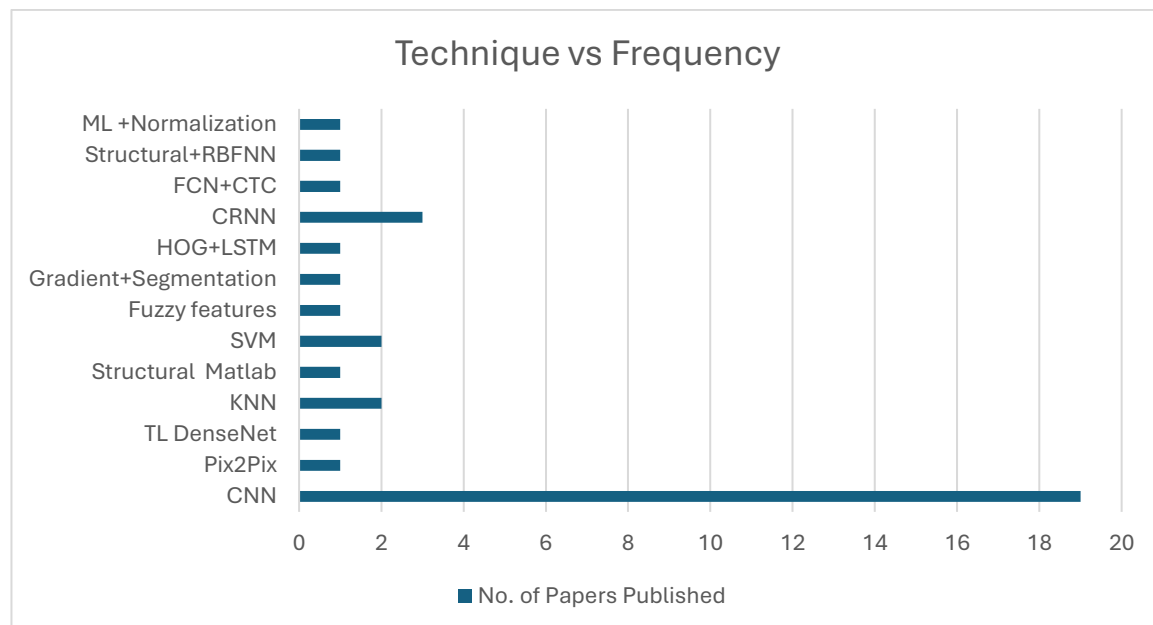


Figure 4 No of papers published using various techniques from 2016 to 2026

RQ2: Which evaluation metrics, such as CER, WER, accuracy, and F1-score, are most appropriate for evaluating offline handwritten text recognition across different scripts and writing styles?

Response: Accuracy is the most commonly used measure of performance used for offline handwritten text recognition as depicted in Figure 5, Evaluation of metrics utilized by various authors from 2016-26, and it was used 23 times. This indicates that, for evaluating the overall performance of recognition systems, different scripts and writing styles should be assessed separately. Also, a prominent measure for assessing recognition systems that only recognise individual characters rather than words is the Character Error Rate (CER), with 6 uses. This is a crucial metric in situations where character-level accuracy is crucial, particularly in multigraphic languages. Another important but used only twice metric, Word Error Rate (WER), will be used instead of the character error rate to account for correct word recognition. It is more appropriate for applications in which the meaning of the text is crucial, and could be especially useful when dealing with scripts that create coherent words more clearly. Finally, the other category (3 usages) shows that other, perhaps not as well-known, metrics are also at work but have not reached the level of popularity of the ones already mentioned. To conclude, for offline handwritten text recognition across different writing styles and scripts, Accuracy is the best overall metric, while CER is useful for character-level analysis, and WER is useful for word-level analysis. Ultimately, the type of metric used will depend on the evaluation's objectives, which can range from overall system performance to character precision or word accuracy.

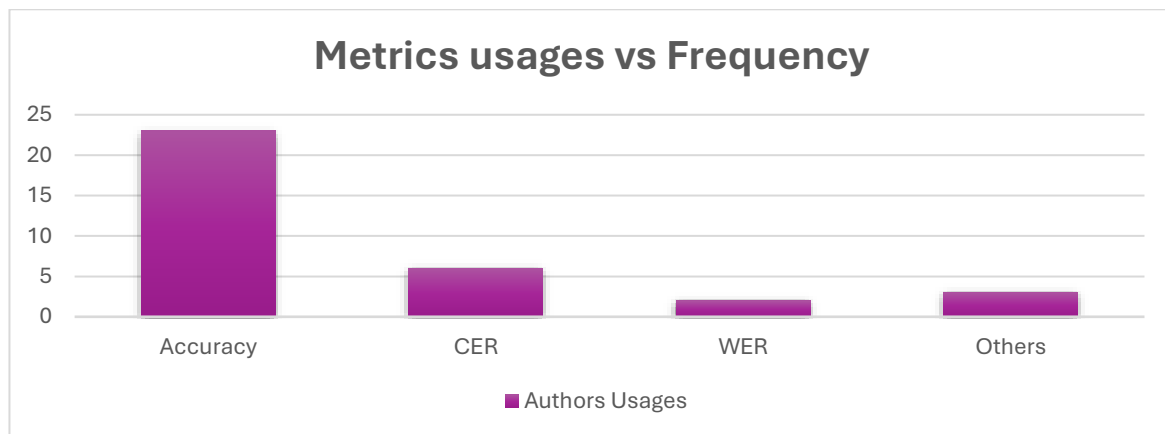


Figure 5 Evaluation of metrics utilized by various authors from 2016-26

RQ3: Which datasets and benchmark standards are frequently used in HTR research?

Response: There are several Handwritten Text Recognition (HTR) datasets that are widely used in the field as shown in Figure 6. The IAM dataset is the most widely used dataset, with 5 papers citing it, and is a standard used in many studies. The IFN/ENIT dataset is often cited after IAM, and was cited in 3 research efforts, indicating its importance in this topic area. The other interesting collections are RIMES and Washington, with value for 2 studies each, also contributing towards the development of HTR methodologies.

There are also several datasets that are less commonly used with a count of 1, but are specific in use, such as Bentham, Saint Gall, KOHTD and others, with language- or use-specific applications, showing the diversity and specialization in the field. All of these data sets complement the research work on handwriting recognition, serving as an important tool for training and testing handwriting recognition systems in various handwriting styles and languages.

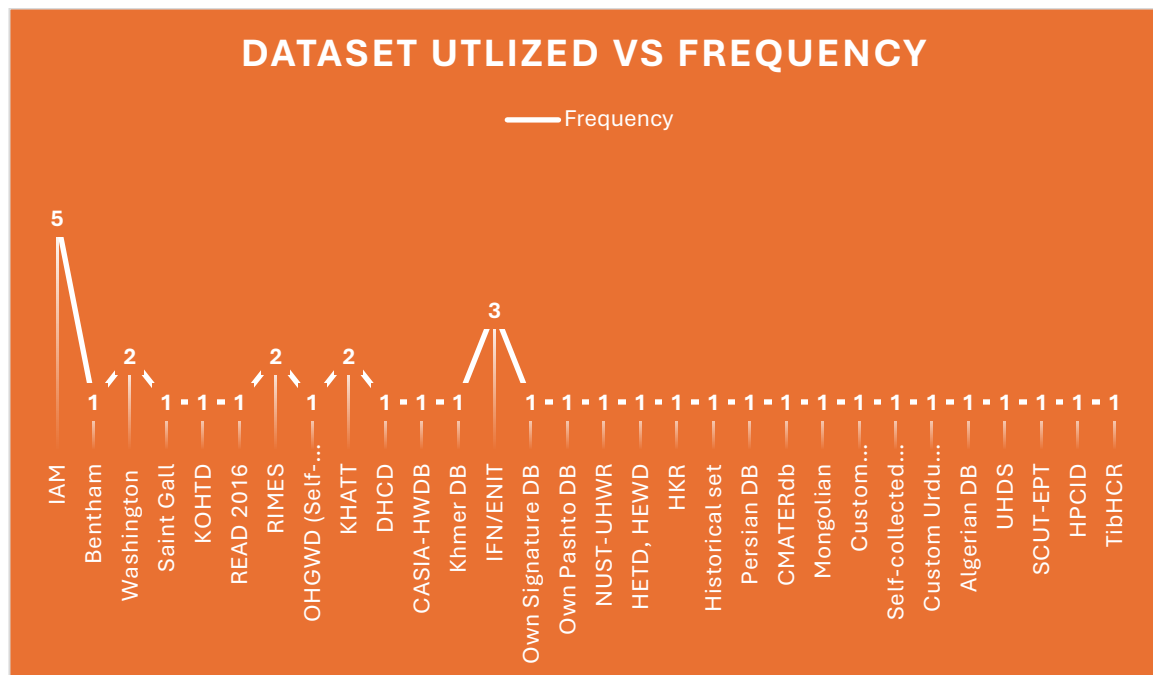


Figure 6 Evaluation of dataset usages by various authors from 2016-26

RQ4: What is the effectiveness of offline handwritten recognition systems in applications such as banking, postal services, healthcare (medical prescriptions), academic digitization, and document archiving?

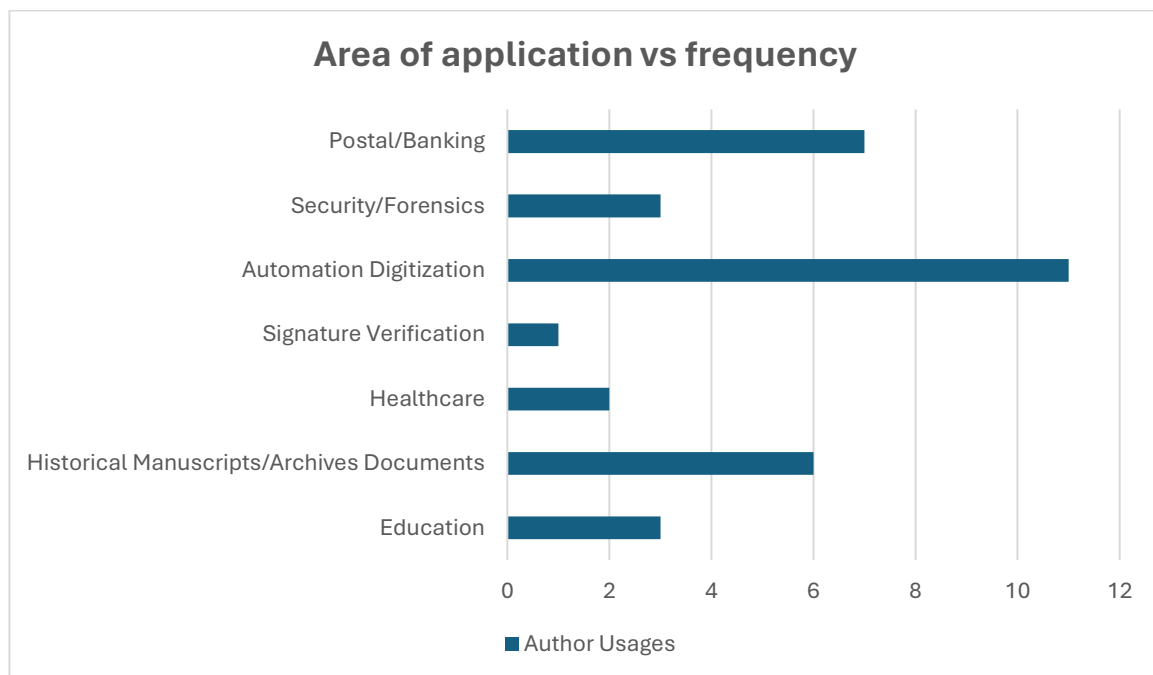


Figure 7 Areas of application by authors using from 2016 26

From the gathered data, the handwritten text recognition application area is large and has a wide variety of applications with an emphasis on automation and digitization as shown in Figure 7. Specifically, there are 3 usages in the education sector, indicating the need to convert handwritten materials into the assessment and organization of them. The top usage is for historical manuscripts and archival documents, emphasizing the importance of digitisation for preserving cultural heritage.

There are also 2 references in the health-care field, with more acknowledgements of the need to digitize handwritten medical records to enhance patient care. In contrast, signature verification is less effective with only 1 use, indicating that this may not be considered a top priority as much as others.

In addition, automation and digitization are the most frequently mentioned usages, indicating a general trend towards leveraging technology for efficiency and streamlined processes in different sectors. Three industries, postal and banking services (with 7 usages) show that they are still trying to modernize their operations by using tech solutions. Lastly, security and forensics have 3 usages, showcasing a commitment to data integrity and verification. All these insights demonstrate the wide range of potential applications and the growing significance of handwritten text recognition technologies across various contexts.

RQ5: Which script or language has shown the most promise in the past 10 years for offline handwritten-text recognition?

The improvement of offline handwritten-text recognition (OWHTR) in the last decade in different scripts and languages has been remarkable. Looking at the year-wise recognition data, we can note some differences for several scripts:

Recognition began with the Indic scripts (Hindi, Punjabi) in 2018. Latin scripts improved, with two languages (probably French, and another) being recognized by 2019 and Cyrillic script receiving one recognition point as shown in figure 8.

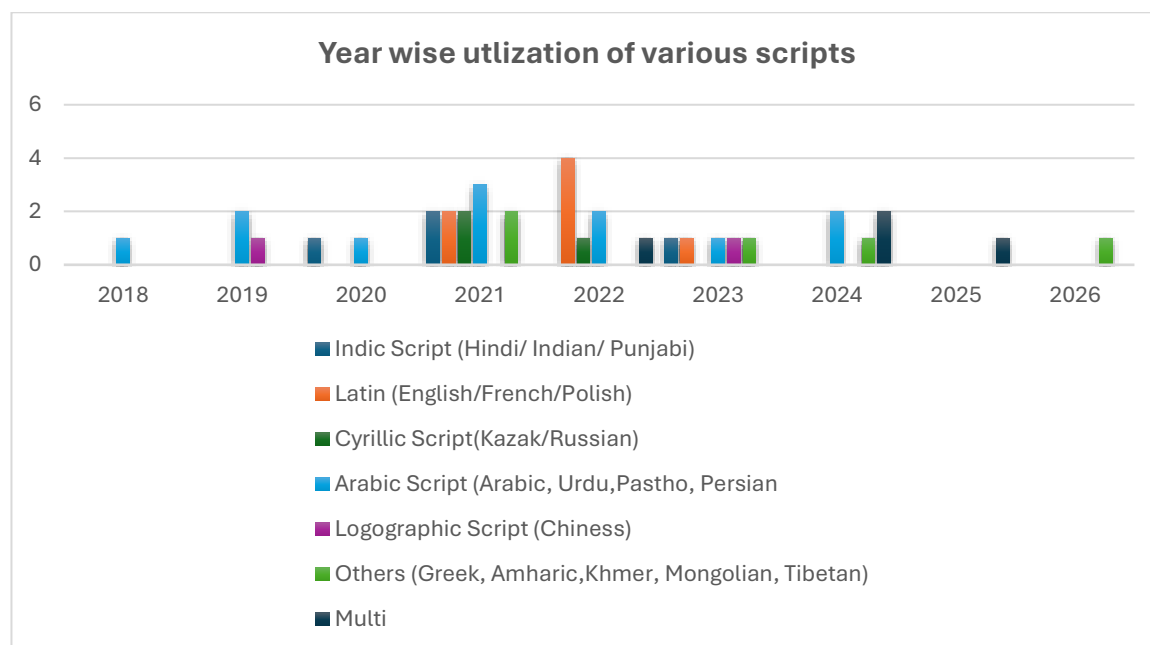


Figure 8 Script or language usages by various authors in the past 10 years

As 2020 began, Indic scripts held on to their lead with one, while we got our first sighting of the Cyrillic script's lead, with one recognition. In 2021, Indic scripts received two recognitions, Latin and Cyrillic scripts received two each, showing an increasing interest and ability in these scripts. Three recognitions were also won for Arabic script that year, which was an impressive feat. The 2022 data revealed massive progress, particularly with Latin scripts with 4 recognitions. There was also an increase in the visibility of Arabic and logographic scripts (such as Chinese) this year, along with several recognitions of languages. There was a slight shift in 2023, though some recognition of the multiple scripts emerged. There was one recognition given to Indic and Latin scripts, while Arabic and logographic scripts began to be recognized to a greater extent.

Longitudinal trends, projected into 2024, suggest continued development in technology for the recognition of handwritten text off the web, with a strong focus on Arabic and logographic scripts, both of which are seeing growth.

Overall, the data paint a dynamic picture of a landscape in which Indic, Latin, and Arabic scripts have all demonstrated strong growth over the last decade, and there is increasing interest in logographic and Cyrillic scripts as recognition technologies advance. This implies good prospects for the development of systems for multilingual handwritten-text recognition.

RQ6: Which recognition level (Character/word/line/paragraph/person/signature/writer ID/Gender) has been most effectively used in offline handwritten text recognition over the past decade?

Response: Studies of offline handwritten text recognition (HTW) have shown that different recognition levels have varying efficiency over the last decade, which can be seen from the trend in different years. Beginning in 2018, there was minimal progress with recognition primarily focused on lines. Starting from 2019, however, a wide range of recognition levels arose. Character recognition increased greatly in 2021, with five being the highest number used, and word and line recognition were also used. There was widespread use of word and line recognition in the following years (2022 and 2023), showing their effectiveness in capturing handwritten text. Interestingly, all levels of diversity were used in 2024 again, including character recognition, paragraph recognition and the new recognition factor of gender. Overall, character and word recognition produced consistent good results, but the different implementations of other recognition levels show a maturing of the offline handwritten text recognition (HWTR) techniques.

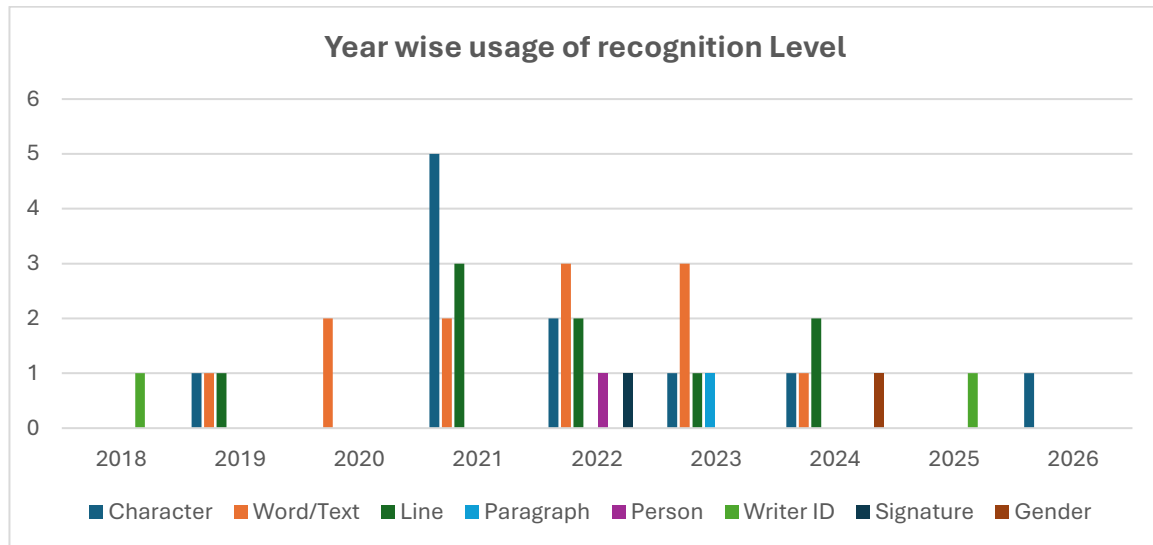


Figure 9 Recognition level (Character/word/line/paragraph/person/signature/writer ID/Gender) used in offline HTR over the past decade?

RQ7: Which Platform has been used most prominently in the past 10 years for offline handwritten-text recognition?

Response: Overall, the data show that Python, particularly the PyTorch deep learning framework, is the most widely used platform for offline handwritten-text recognition over the last 10 years. With a significant usage frequency of 30, Python/PyTorch stands out as the preferred choice among researchers and developers in this field. Google Colab, for cloud-based computation, was only used once, and Matlab had a very limited usage frequency of 3. It shows Python's leading position and its libraries in the development of technologies for handwritten text recognition.

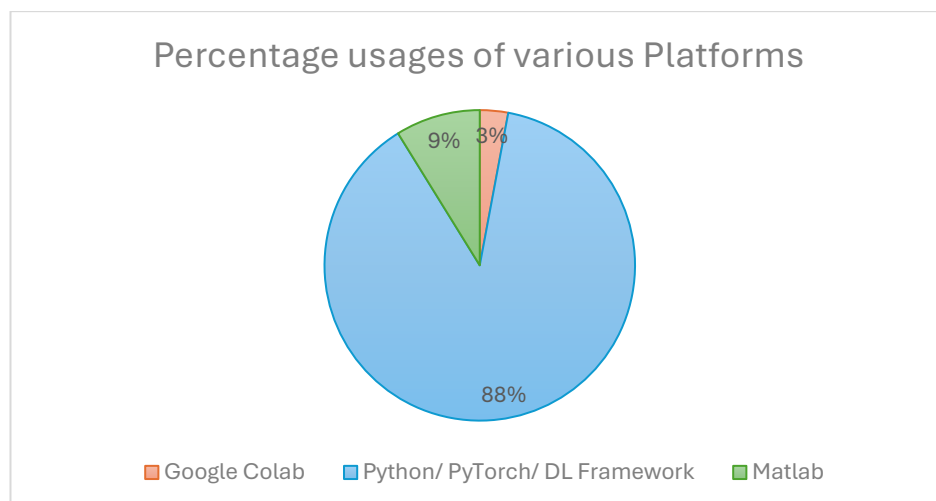


Figure 10 Percentage usages of various Platforms by different authors from 2016-2026

7 Results and Discussion

This decade-long study of handwritten offline text recognition has highlighted key insights into the most frequently used methods, assessment measures, datasets, the effectiveness of the applied methods, scripts, and research platforms.

Most crucially, CNNs are the most prominent machine learning technique and consistently superior to all others across a variety of applications! It is significant to note that the emphasis on accuracy as a major evaluation parameter underscores its importance in evaluating recognition systems. Other metrics, which can be applied but are not as frequently used, include Character Error Rate (CER) and Word Error Rate (WER), in addition to accuracy. The pattern indicates that practitioners working on handwritten text recognition tend to concentrate on metrics which are easily quantifiable, such as success. In terms of datasets, the most cited is the IAM dataset, which is considered as a standard dataset for the research of HTR, and has been cited 5 times. The IFN/ENIT data-set and RIMES also fall within this domain (3 and 2 citations, respectively). The growing number of such datasets highlights their valuable contribution to methodology development and to use in standard environments to check new algorithms. Off-line handwritten recognition system has been successful in the banking, postal administration, medical field, academic scanning and archiving field. The fact that these systems can be applied in practice and are significant in digitizing handwritten documents illustrates their applicability and significance. An analysis of the scripts and languages that have proven to be successful in OWT recognition shows that there are some characteristics of languages that are best suited to recognition technologies. The outcome of this result suggests the need to study the specific scripts to establish their characteristics that influence the recognition accuracy. Finally, Python's prominence in their design, particularly in the use of the PyTorch deep learning framework, highlights Python's contributions to the development of handwritten text recognition technologies. A significant number of developers and researchers use Python/PyTorch, using it 30% of the time. However other platforms like Google Colab and Matlab did not show much enthusiasm in helping to promote this and suggest that the Python library and community is an important factor in fostering innovation in the field. In summary, the results show the combination of efficient methods, powerful assessment measures, and useful datasets and the practical applications and state of the art tools for offline handwritten-text recognition research. Future opportunities can arise for the further development of methodology and/or capability of recognition systems in this area.

8 Conclusion

To summarise, the offline handwritten text recognition technology is an important component of various industries, contributing to increased efficiency, accuracy, and accessibility. From banking systems to healthcare, education, and logistics, it shows promise in these sectors, transforming data processing, reducing errors, and enhancing record management. The digitization of handwritten documents can help organizations to improve their workflows, customer services, and archival efforts. In conclusion, the progress of handwriting recognition technologies represents a positive trend in the digitalization process, providing the potential for more efficient handling of data and enhanced delivery of services in various sectors.

Conflict of Interest

The authors declare that they have no conflict of interest.

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