

Advancements in Handwritten Text Recognition: A Survey of Methods, Challenges, and Future Directions

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Abstract—Handwritten Word Recognition (HWR), also referred as Handwritten Text Recognition (HTR), includes a computer's ability to acquire and comprehend understandable information written by hand, sourced from materials like paper documents, images, touch screens, and other devices. This technology is a subset of Intelligent Document Processing (IDP), which refers to the use of various technologies, including optical character recognition (OCR), natural language processing (NLP), and machine learning, to extract valuable information from documents. The primary goal of HWR is to interpret individual handwritten words, facilitating the digital conversion of handwritten text. Despite being a subject of study for over four centuries, certain key challenges in handwriting recognition remain unresolved. This survey paper aims to delve into these issues and give better understanding on the provided solutions. Additionally, the paper discusses various approaches in the field, such as offline and online handwriting recognition, providing a comprehensive exploration of methods to tackle the intricacies of handwriting recognition. The ultimate objective of the paper is to elucidate diverse strategies for resolving the challenges associated with handwriting recognition and provide future directions for the improvisations that can be made.

Index Terms— handwritten text recognition, deep learning, image processing, machine learning.

I. INTRODUCTION

The act of handwriting serves as a means to enhance and augment our limited biological memory by creating visually representational artificial marks that denote symbols in various languages [1]. Its primary purpose is to facilitate communication with others through the shared understanding of language symbols, encompassing characters and letters [2]. Despite the availability of numerous technological tools for writing, many individuals still opt for the traditional method of note-taking—using pen and paper. However, handwritten text poses challenges, as physical papers are not easily stored, accessed, searched, or shared efficiently with others. This issue is significant because valuable information may be overlooked or remain unexamined if documents are not digitally transferred. Recognizing this importance, the focus is on addressing this challenge, as managing digital text proves to be more convenient, enabling individuals to access, search, and exchange documents more effectively while still allowing them to employ their preferred writing method. Nevertheless, the fundamental mode of communication, namely handwriting and the straightforward recording of important information will likely continue to hold a prominent role until the transition to a paper-free society occurs. A hand written script is a set of graphic forms that defines a writing system, typically characterized by a specific set of characters. As

our reliance on information technology grows in our daily lives, we increasingly trust the digitization of routine services across various domains. Offline HTR is critical in unlocking the content of massive repositories of historical manuscripts housed in libraries. Although a lot of documents have been digitized, their availability is limited because they are only available as raw images. HTR systems are designed to transcribe these documents, converting their textual content into an accessible and searchable format [3, 4]. Because it cannot automatically isolate characters in handwritten text images found in historical documents, conventional Optical Character Recognition (OCR) is ineffective. Another application includes the use of image processing and HTR for automated bank cheque verification to improve the existing cheque truncation system and provide an alternative method for processing bank cheques with minimal human involvement. [5,6] OCR has been a longstanding area of research, but thus far, there is no creation of a versatile, multilingual, and robust system capable of accurately recognizing various scripts on a single page. While several OCRs have demonstrated efficiency in script recognition, many are limited to specific scripts. The current challenge lies in the recognition of scripts from multilingual documents where content is typically written in more than one script or language. The postal service is facing a significant challenge in sorting a large volume of letters and parcels. Many researchers have created various handwritten text recognition systems for languages such as English, Chinese, Arabic, Japanese, Bangla, Malayalam, Urdu and others.[7] Because of the distinctive features associated with individual writing styles – cursive, handwriting recognition presents a greater challenge than machine-printed text recognition. The difficulty stems primarily from the wide variation in handwriting between individuals. To address this issue, many HTR approaches include not only visually translating an image into a character sequence but also language models. By leveraging contextual and semantic information, these models play a critical role in mitigating the inherent ambiguity of handwritten characters. While we have made significant progress in character and isolated word recognition, creating high-performing recognition systems for unrestricted offline hand written texts is still a difficult task and we still haven't reached a satisfactory level. Following are some of the complicated data examples taken from the IAM Handwritten Forms Dataset that impose challenges in recognition.

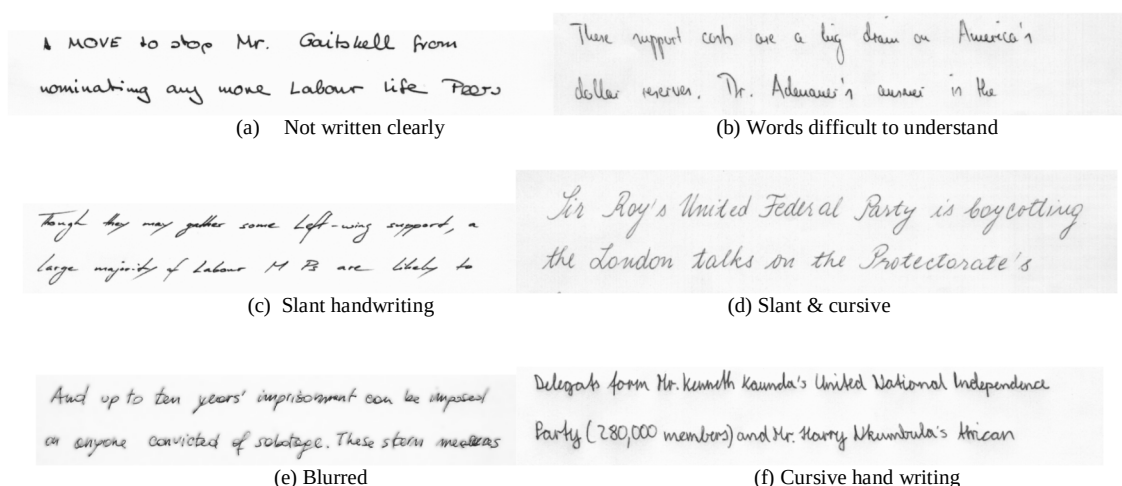


Figure 1: Example images of different handwriting styles that presents a greater challenge than machine-printed text

The emergence of modern communication channels, including social media, mobile apps, and digital marketing, has led to the generation of data that lacks a standardized format or predefined schema, unlike conventional data. This type of data, which includes text, audio, videos, emails, and images, is referred to as unstructured data. Unstructured data does not conform to a specific structure and lacks standardization, making tasks such as editing, searching, and analysis challenging for many organizations. The automatic identification of handwritten content found on various documents such as checks, envelopes, forms, and manuscripts hold significant practical and commercial value in sectors like banks [8], post offices, reservation counters, libraries, and publishing houses. Given the substantial volume of documents processed daily in these organizations, the implementation of automatic reading systems can substantially reduce workload, even if they are only able to correctly identify a small percentage of the documents.

A. Work Flow of HTR

Here's how the process of Handwritten Text Recognition and Intelligent Document Processing generally works:

1. Document Capture: The process begins with the capture of documents, which can be in various formats such as images or scanned pages. 2. Pre-processing: The captured documents often undergo pre-processing to enhance the quality of the images. This may involve tasks like image normalization, noise reduction, and skew correction. 3. Handwritten Text Recognition: This is the core component for handwritten documents. HTR systems use machine learning algorithms, particularly deep learning algorithms such as convolution neural networks (CNNs) and recurrent neural networks (RNNs), to recognize and transcribe handwritten text. Training these models requires large datasets of handwritten samples. 4. Intelligent Document Processing (IDP): Once the handwritten text is recognized, it's integrated into the broader Intelligent Document Processing workflow. This involves combining OCR for printed text, entity recognition for extracting specific information like names and dates, and NLP for understanding the context of the text. 5. Verification: Extracted information is often validated and verified against predefined rules or databases to ensure accuracy. 6. Data Integration: The recognized and validated data is then integrated into relevant systems or databases. This can include updating customer records, populating forms, or any other application-specific tasks. 7. Machine Learning: The system may leverage machine learning for continuous improvement. For example, feedback on the accuracy of the recognition system can be used to retrain the HTR model and enhance its performance over time. To sum up, Handwritten Text Recognition (HTR) is a field that combines the most recent technological developments with historical importance. The vast field of HTR is thoroughly explored in this overview study, which spans from the period of machine learning and artificial intelligence to centuries of handwritten text research. We want to explore the complexities of handwriting recognition, identify open problems, suggest machine learning approaches, and illuminate the developing tactics that will ultimately improve the precision and performance of HTR systems. Thus, we explore the intricacies of handwriting recognition, seeking to both comprehend its historical foundations and open the door for further advancements and discoveries.

II. BACKGROUND

In the past ten years, researchers have analyzed handwritten and printed documents and converted them to electronic formats using artificial intelligence and machine learning tools. In [9], discussed the practical applications of Optical Character Recognition (OCR) in converting various handwritten documents into analysable, editable, and searchable data. In [10], a three-layer Artificial Neural Network (ANN) with supervised learning approach is proposed to recognize the text. The proposed system achieves an impressive average accuracy of more than 95 percent on unseen test images, demonstrating its effectiveness in overcoming handwritten text recognition challenges in OCR. In [11], presents a neural network-based line recognition model without recurrent connections that achieves comparable accuracy to LSTM based models while improving parallelism. Script recognition from multilingual printed documents is also addressed in [12]. The issue to improve the recognition rate for author specific generic model via a writer adaptive recognition system and use Convolution Neural Networks (CNNs) to customize a structural representation is discussed in [13]. Recognizing cursive handwritten text is another challenge due to context sensitive character shapes, non-uniform spacing, complex dot and diacritic positioning, and low inter-class variation addressed in [14]. The digitizing historical documents into scanned images, the lack of digital text impedes efficient historical research, necessitating time-consuming manual transcription. Handwritten Text Recognition (HTR) aims to automate this process, but determining the best approach and dealing with challenges in historical datasets are difficult [15]. In [16], proposed Handwritten Text Recognition (HTR) system, built on Artificial Neural Networks (ANNs), that incorporates pre-processing techniques such as contrast normalization and data augmentation. It uses CNN layers for feature extraction and RNN layers for information propagation, along with an optional desalting algorithm for upright text. In [17], a hybrid HMM/ANN model for recognizing unconstrained offline handwritten texts that combines Markov chains for structural modelling and Multilayer Perception for emission probability estimation. It introduces supervised learning techniques for removing slope and slant, as well as normalizing text size, and achieves higher recognition rates in experiments on IAM database text lines than previous literature (almost 42 percent improved performance). Traditionally, paragraph text recognition involves two models: line segmentation and text line recognition. In [18], proposed a unified end-to-end model that utilizes hybrid attention to tackle this task. Line by line, paragraph images are processed iteratively by this model. Further, to investigate the impact of precision and detail levels in text line images transcribed by HTR systems with the goal to strike the right balance between ensuring accurate recognition and minimizing the amount of human effort required to correct errors [19], describes a study that tested three different techniques for text line segmentation, ranging from a simple rectangle to a perfectly fitted polygon around detected lines. The Straight-baseline method is also a viable option, providing a good balance of WER increase and low correction

time. The proposed approach in [20] addresses class imbalance by combining a deep convolution network with a recurrent Encoder-Decoder network that was trained end-to-end using Focal Loss. The model's decoding capacity is improved by the Beam Search algorithm. An approach to unconstrained online handwritten text recognition that combines path signature, a multi-spatial-context fully convolutional recurrent network (MC-FCRN), and an implicit language model (implicit LM) is presented in [21].

The work presented in [22] focuses on improving HTR systems by introducing simple yet effective modifications. A transfer learning (TL) approach is proposed in [23], to address the challenge of offline handwriting text recognition (HTR) with limited training data. There is also a need for a method that produces diverse and realistic handwritten text line images based on both visual appearance and textual content [24]. This method should address the style bias issue and provide an effective way to improve HTR performance without requiring extensive manual labelling. Thus, the proposed solution employs a generative method that is dependent on both visual appearance and textual content; the model efficiently produces diverse and realistic handwritten text-line images.

III. EXPLORING HANDWRITTEN TEXT RECOGNITION TECHNIQUES

A. Online vs Offline Script Recognition

Script recognition is divided into two types;

1. Online script recognition
2. Offline script recognition

Online script recognition [25] is an advanced technology that converts handwritten script into digital text in real-time. Utilizing specialized devices like stylus-enabled tablets, it captures dynamic information such as pen strokes, speed, and pressure. Employing features like velocity and acceleration, along with time-series analysis, the system interprets the sequence of pen movements. Neural networks, especially Recurrent Neural Networks (RNNs), play a key role in processing sequential handwriting data. Gesture recognition algorithms distinguish writing and non-writing gestures, contributing to accurate segmentation. Notable for real-time processing, online script recognition is seamlessly integrated into user interfaces for applications like note-taking and interactive whiteboards, fostering natural interactions with digital content. With continuous learning mechanisms, it adapts and improves over time, finding applications in education, business, and various domains where real-time transcription and interaction are essential. It involves the recognition of scripts on various online systems, such as Personal Digital Assistants (PDAs), graphics tablets, touch screen panels, and portable electronics like cell phones.

The complexity arises from the need for highly efficient algorithms to discern the script type, especially in cases where documents contain text in multiple scripts. Offline script [26] recognition is a sophisticated process that involves the recognition of written scripts from static images or scanned documents, distinguishing it from the real-time nature of online script recognition. In offline script recognition, the recognition of scripts occurs after the scanning of printed or handwritten documents. This process can be divided into two categories: Printed Script Identification (PSI) for printed documents and Handwritten Script Identification (HSI) for handwritten ones. Advances in machine learning and pattern recognition have significantly improved the accuracy and applicability of offline script recognition systems across various domains. In offline recognition, the Caliber of the documents being processed has a major impact on how well segments are performed. High-quality scanned documents facilitate a quicker and more effective recognition process. [27]. Conversely, lower-quality documents necessitate extensive pre-processing computations to accurately distinguish between the foreground and background elements.

B. Text Recognition Process

Text recognition can be achieved through conventional image processing methods that comprise four primary stages: preprocessing, segmentation, feature extraction, and classification [28]. Furthermore, to accomplish the overall task, a number of Machine Learning and Deep Learning techniques may be applied. Occasionally, language identification and script identification are combined. The handwritten text line recognition process presented by Ingle, R. Reeve, et al., is to generate a sequence of Unicode code points that correspond to the text in a single-line image, where x represents the line image and y represent the sequence of Unicode points in this context. They approach this by encapsulating the relationship between the image x and the sequence y in a probabilistic model denoted as $P(y|x)$. And tested these for LSTM-based and recurrence-free models. When switching from line to paragraph images, recognizing handwritten text becomes more difficult. The model must locate and order text regions while contending with issues such as varying region numbers, layout diversity, and

establishing a reading order. Current approaches use a two-step process that involves segmenting the document into text regions and then using Optical Character Recognition (OCR) to recognize the text. Regardless of individual success, combining these steps reveals three major drawbacks. This highlights the need for improved methods to address challenges and improve handwritten text recognition within paragraph images for more accurate and efficient processing of whole page documents. This section provides a brief overview of the general text recognition process, which is separated into two main classes: conventional image processing methods and contemporary deep learning approaches. The figure 1 presents a general workflow of any HTR system.

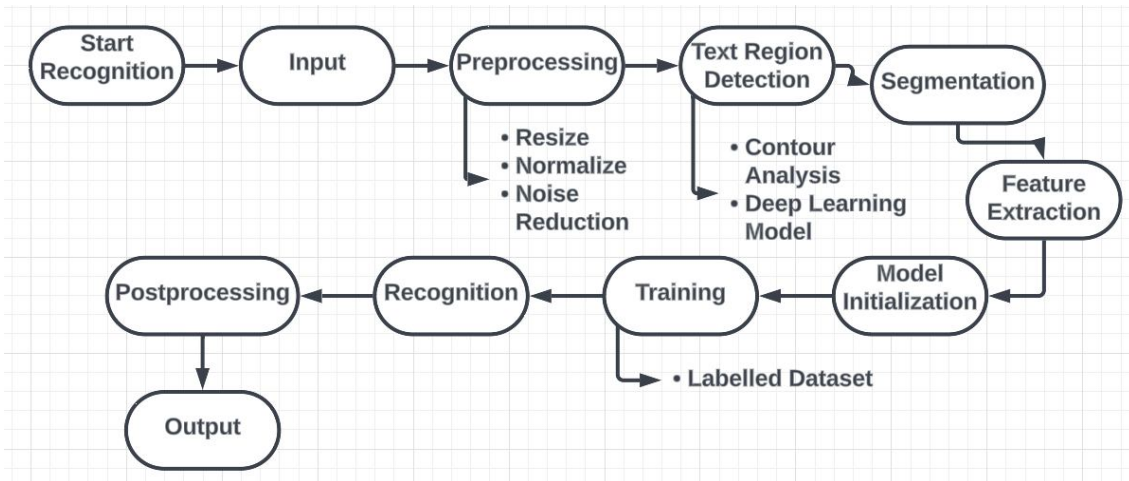


Figure 2. Workflow of HTR

C. Image Processing and Machine Learning

The method involves pre-processing of images that are scanned to remove noise (if any) and improve their quality. It is followed by segmentation, then feature extraction, and finally classification. The process of segmenting a larger image into multiple smaller segments for quick and effective computations is known as segmentation. Researchers have proposed a wide range of techniques for segmentation, including threshold-based segmentation, edge detection, pixel wise Support Vector Machine (SVM), region growing, and horizontal and vertical segmentation. However, rather than processing the entire image at once, feature extraction is required to extract the pertinent and necessary features. Researchers have proposed a variety of methods for extracting features, such as component-based features, wavelet-based features, topological features, curvature features, horizontal and vertical histograms, and more. Generally, machine learning techniques are used to assist in the classification process. Many classifiers have been developed to accomplish the task, similar to feature extraction. Support vector machines, K-Nearest Neighbours (k-NN), Multilayer Perceptions (MLP), Feed Forward Neural Networks, Hidden Markov Model (HMM), and others are a few well-known classifiers. The following subsections provide a summary of the process's four steps.

Preprocessing

In Handwritten Text Recognition (HTR), pre-processing is used to improve image rendering and prepare it for segmentation. Its primary goals include removing background noise, improving the region of interest, and separating the foreground and background. To achieve these goals, the input image is subjected to operations such as noise filtering, binary conversion, and smoothing. The goal is to improve image quality by effectively highlighting areas of interest and reducing unwanted background interference, thereby facilitating subsequent segmentation processes. Depending on the properties of the data and the demands of the recognition task, different preprocessing steps might be used. Nonetheless, the following preprocessing methods are frequently employed in HTR:

- **Image Rescaling and Normalization:** Rescale the input images to a standard size to ensure consistency across the dataset. Normalization is often applied to standardize pixel values, reducing the impact of variations in lighting conditions.
- **Noise Reduction:** Apply filters or techniques, such as Gaussian blurring or median filtering, to reduce noise in the images. Noise reduction helps improve the clarity of characters and reduces interference during recognition.

- **Binarization:** Convert colour or grayscale images to binary images by thresholding. Binarization simplifies the image, highlighting text regions and improving the contrast between foreground (text) and background.
- **Skew Correction:** Correct image skew caused by variations in writing angles. Skew correction ensures that the text is aligned horizontally, facilitating accurate character recognition.
- **Contrast Enhancement:** Adjust the contrast of the image to improve the visibility of characters. Contrast enhancement can be particularly useful for handling variations in writing styles and background conditions.

Segmentation

After the text images have undergone pre-processing, the image is divided into smaller sections, or segments. A more effective segmentation method leads to higher OCR accuracy. The research literature on segmentation has proposed a wide range of techniques, some of which are summarized;

- **Segmenting words and lines:** Prior to processing the entire page or document, the text must be broken down into text blocks, which are then further broken down into lines, words, and characters. The subdivision's concept is to count the black pixels in a row in order to locate the valleys. For the purposes of identifying words and text lines, respectively, the process continues in both horizontal and vertical directions.
- **Character Segmentation:** The process of determining final character boundaries starts after deciding on the text line and word boundaries. Labelling segmented parts, which are resized and normalized for feature extraction, yields the character count. Errors are compared to the average distance between points in the entire image to determine which segmentation points are valid. Valid segmentation points are found by finding minima or arcs between characters. To overcome the problem of ambiguity, in defining individual entities for segmentation, early approaches focused on character-level segmentation followed by classification. Following that, segmentation was extended to the word and line levels.

Feature Extraction

In order to enable efficient pattern recognition, feature extraction, a crucial preprocessing step in Handwritten Text Recognition (HTR), entails extracting and storing pertinent information from the input images. The selection of feature extraction techniques is frequently influenced by the particular specifications of the identification task and the attributes of dataset. The neural network's later layers use the extracted features as input, which helps the model learn hierarchical representations and efficiently distinguish between various handwriting patterns and styles during training. Many well-known features are used in feature extraction techniques, such as component-based features, Gabor features, features based on structural or shape characteristics, principal stroke features, Haar features, spatial characteristics, density distributions, features derived from the water reservoir principle, fractal-based features, Curvature Scale Space (CSS) features, the positioning of concavities, optical densities, and centre of gravity features, among others. The class of the character or word is then ascertained by feeding these extracted features into a trained classifier. Numerous techniques are used in text image recognition; these can be broadly divided into two categories: segmentation-based and segmentation-free techniques.

Classification

The process of categorizing inputs into distinct classes according to a variety of features is known as classification. It is referred to as the process's central component at times. Classifiers and features work together to determine the general script recognition process's accuracy and efficiency. A wide range of classifiers, including Support Vector Machine, Multilayer Perceptron, k-Nearest Neighbour, Naive Bayes, rule-based classifiers, tree-based classifiers (such as decision trees, Random Forest (RF), etc., cross-validation, hierarchical classifiers, Artificial Neural Network (ANN), etc., have been proposed in the research literature regarding classification problems.

D. Deep Learning

Handwritten Text Recognition (HTR) has seen tremendous advancements to deep learning, which has revolutionized the field and produced state-of-the-art outcomes. In deep learning for HTR, convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are frequently used architectures.

From the input images, convolutional layers extract pertinent features and capture spatial hierarchies. Further, there are various character recognition methods, word/line and multi-line recognition methods. Unlike traditional recurrent nets, which struggle with the vanishing gradient problem when modelling long-term dependencies,

TABLE I : SUMMARY OF ALGORITHMS USED

Ref. No.	Segmentation Scope	Algorithm Used	Dataset	Accuracy
[5]	SIFT method on these normalized images for feature extraction	Utilized Support Vector Machine (SVM) for classification and Scale Invariant Feature Transform (SIFT) for feature extraction in MATLAB	114 Images	99.94%
[13]	CNNs as a feature extractor	With respect to the input sequences, Multidimensional Recurrent Neural Networks (MDRNNs) are trained to compute the conditional probabilities for a list of possible labels directly	656 text lines of 18th Century	91.74%
[16]	Set of points/pixels and text of contours is used to find reference line of text and Skew -corrected lines and Multilayer Perceptron (MLP) are used for image cleaning	Hidden Markov Models (HMMs) and Artificial Neural Networks (ANNs)	1500 scanned forms of handwritten Text of different writers	95%
[17]	Soft attention mechanism and training using the standard Connectionist Temporal Classification (CTC) loss	Vertical Attention Network (VAN): A novel segmentation free encoder-decoder architecture with hybrid attention mechanisms is presented end-to-end. It can process images of different sizes for paragraphs. Using the RIMES, IAM, and READ 2016 datasets, the efficacy of VAN has been proven	100 Pages at paragraph, line and word levels	96.17
[23]		Used a novel modification of the variable length Frechet Inception Distance (vFID) metric to guide the choice of ideal hyper-parameters for variable length samples, like handwritten text images	The IAM offline dataset	82.4%
[27]	CNNs as a feature extractor	Multidimensional recurrent neural network (MDRRNs) CNNs as a feature extractor	42 names of different countries and cities, two tests were performed: with cursive word alignment and without alignment	83.85%
[29]	The text lines were detected in three different ways, polygon, Polybaseline, horizontal straight base line	1. Polygon, 2. Polybaseline, 3. Horizontal straight base line. Using the traditional embedded Baum-Welch algorithm, used the line images from the training segments to train the corresponding character HMM (Hidden Markov Model) models	40 pages hand written data	84.2%, 82.7%, 81.9%
[30]	Feature extraction CNN use convolution layer and pooling layer	Convolutional Neural Networks (CNNs) are utilized for the purpose of recognizing handwritten English characters and numbers	The MNIST dataset is a subset of NIST database. 70,000 handwritten digit images	98.94%

LSTMs effectively solve this problem. Temporal classification with connections (CTC): When used in conjunction with deep learning models, CTC is a potent technique for sequence-to-sequence tasks like HTR. It enables the model to pick up on the alignment between handwritten image input sequences and text transcription output sequences. The table 1 depicts the survey of various algorithms used by different authors till now along with their accuracy and datasets used.

E. Limitations and Future Scope

Handwritten text recognition systems have a number of drawbacks despite their advances. The quality and quantity of the labelled data that is being used has a major impact and are also the important factors that affect the system efficiency. Biased or small datasets lead to performance that is less than the ideal performance. Robust performance across a range of handwriting styles, languages, and historical scripts is hindered by

persistent generalization issues. Resource intensity poses a challenge specially where the computational power is limited. While using specialized fonts or terminologies, applications may encounter domain-specific problems. The future scope focuses on enhancing the support for a wide variety of languages and character sets to resolve issues brought about by the different handwriting styles [30]. Using the advanced transfer learning techniques may help to improve and make the models more adaptable to different datasets, be able to recognize the objects effectively and efficiently even if the training data available is less. Accuracy can also be increased by incorporating domain-specific knowledge like historical data or linguistic context. Further, areas like optimizing recognition in Realtime, consistently improving the pre-processing techniques, exhibiting resilience against diverse input sources etc., can be focused. Additionally, creating systems that support human-in-the-loop interactions could boost user participation and error correction, which would support iterative performance improvement.

IV. CONCLUSION

Finally, this survey delves deeply into the evolving field of Handwritten Text Recognition (HTR) systems, illuminating a range of approaches, developments, and difficulties that exist. It has been observed that Neural network-based methods, in particular recurrent neural networks (RNNs) and convolutional-recurrent architectures, are the focus of the current HTR literature. After finding success in natural language processing, methods like sequence-to-sequence models and Connectionist Temporal Classification (CTC) have been smoothly incorporated into HTR systems to enhance sequence alignment and recognition. The study also highlights the significance of preprocessing stages, like the critical classification stage, which is vital for separating text from complicated backgrounds. Though HTR has made promising progress, there are still issues that need to be resolved, like the requirement for large amounts of labelled training data and the vulnerability to handwriting style variations. The survey also highlights the importance of using industry standards for comparing and assessing HTR systems, like RIMES and IAM. More robust and effective HTR systems may be possible as the field develops and new methods, generative models, and artificial data augmentation are added. In summary, this survey offers a thorough assessment of the state of HTR today, illuminating current approaches, obstacles, and potential paths forward. As a result, it advances our knowledge of this dynamic field of research.

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