AI-Powered OCR for Handwritten Documents with Low Quality and Degradation

R. Murugan[1], P. Deivendran[2], D. Sony Kumari[3], B. Lokesh[4], P. Nirmal[5], S. Chandra Keerthy[6]

[1,2]*Department of CSE, AVIT, Chennai, Tamil Nadu, India*
[1,2,3,4,5,6] *Department of Information Technology,Velammal Institute of Technology, Panchetti, Chennai, India.*

[1]*hod.it@velammalitech.edu.in*

Abstract - *An approach that uses AI and OCR to digitize and transform ancient, handwritten registered papers into digital representations that are easily accessible. The system seeks to precisely identify and transcribe text from a variety of handwritten sources by combining cutting-edge optical character recognition (OCR) and natural language processing (NLP) techniques. To guarantee widespread accessibility, regional language support is also included. By providing historical records in an organized digital format, this project improves accessibility while addressing preservation-related issues. The suggested solution increases recognition accuracy for different handwriting styles by utilizing character segmentation techniques and deep learning models. Better transcription performance is ensured by the AI model's ability to adjust to handwritten text irregularities through the use of a strong dataset and ongoing training. Reliance on physical records is further decreased by incorporating cloud-based storage solutions, which facilitate effective document. This digitalization strategy improves data security and lifespan in addition to making historical documents easier to retrieve. The system's usability is expanded by its multilingual capability, which enables papers to be translated and transcribed into multiple regional languages. In order to promote knowledge preservation and historical recording, the solution seeks to offer smooth accessibility to scholars, researchers, and the general public through the use of a simple user interface. Furthermore, by transforming ancient registered handwritten documents into a format that is easily readable and accessible, the AI and OCR solution seeks to enhance historical records' readability and public access. The method improves the usefulness of ancient documents by tackling issues including damaged paper, intricate handwriting, and faded ink. Communities with a variety of linguistic backgrounds can benefit from digital records improved to the incorporation of regional language support, which increases the accessibility and inclusivity of historical material.*

Keywords - n*atural language processing (NLP), optical character recognition (OCR), digitization of handwritten documents, AI-powered text recognition, preservation of historical records, deep learning, multilingual OCR, public access, and enhancement of readability*

1. Introduction

Language diversity, document aging, and handwriting style variances make digitizing handwritten documents extremely difficult. Over time, handwritten records—especially legal and historical documents—are prone to fading, ink smearing, and structural deterioration. The intricacy of automated recognition and transcribing is further increased by variations in regional languages, abbreviations, and script styles. Although printed text recognition has advanced significantly improved as a result of optical character recognition (OCR) technology, processing handwritten content effectively is still a technical difficulty. Inaccurate transcriptions result from traditional OCR algorithms' inability to handle cursive writing, irregular spacing, and overlapping characters. By allowing the system to learn from a variety of handwriting patterns, the integration of AI-driven OCR with deep learning techniques, convolutional neural networks (CNNs), and recurrent neural networks (RNNs) has greatly increased recognition rates. Additionally, regional language support is essential for increasing the accessibility of digital documents for a larger audience. NLP- based translation and contextual awareness are required since many historical documents have multilingual annotations. The suggested solution improves accessibility for non-native speakers and local communities by using AI-based natural language processing, which not only transforms handwritten material into a machine-readable format but also offers precise language localization. Enhancing document accessibility, protecting delicate historical records, and facilitating easy digital archiving are the main goals of this article. By providing cloud-based document retrieval, intelligent text structuring, and automatic handwriting recognition, the suggested solution seeks to expedite the digitization process at el [2]. By making it easier for scholars, historians, and the general public to access and understand handwritten data, these developments will aid in the preservation of priceless historical treasures.

Intelligent information retrieval is also made possible by the growing use of AI in document digitization. The effective search

and classification of digitized materials is ensured by the use of metadata tagging and automated indexing. This speeds up document retrieval and lessens the amount of manual labor needed for archiving. Better organizing and interpretation of archived materials are made possible by the system's ability to extract valuable insights from historical documents through the combination of contextual NLP analysis and AI-based handwriting recognition.

The requirement for a flexible and scalable infrastructure is another essential component of document digitization. The suggested solution ensures scalability for government archives, academic institutions, and libraries by leveraging cloud computing infrastructure to support large-scale document processing at el [3]. The system can manage enormous amounts of handwritten records without sacrificing performance by utilizing distributed storage and parallel processing capabilities. Data integrity and security are also essential components of the digitalization process. To prevent unwanted changes to important historical data, the system uses secure access controls and encryption. To preserve document validity and stop tampering, blockchain-based verification techniques can be incorporated, guaranteeing that digital data have their original legitimacy. Future versions of the suggested system can include handwriting style adaptation, allowing the model to learn from people's writing patterns for even higher accuracy at el [4]. This is made possible by the increasing developments in AI and deep learning. By incorporating active learning approaches, the AI model can be continuously improved over time in response to corrective inputs and user feedback.

2. Related work

Although there are several OCR-based methods for recognizing printed text, handwritten writing is still difficult to recognize because of script irregularities at el[5]. Promising outcomes have been demonstrated by existing models, like Tesseract OCR and deep learning-based OCR systems. Many, however, overlook the difficulties associated with aging and regional language support. By combining multilingual adaptability and AI-based learning models, our method improves these features. To guarantee effective digitalization of handwritten documents while preserving high accuracy and accessibility, the suggested approach adheres to a systematic process. The following are the main stages of the methodology: **Collecting and Gathering Data:** Official registries and historical archives are the sources of handwritten papers. Image processing methods including noise reduction, contrast modification, and binarization are used to clean and improve scanned images. Samples of handwritten text are annotated to produce a high-quality dataset for training AI models. **Model Creation:** Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) are used in the development of a deep learning-based OCR model to enhance the recognition of various handwriting styles. Techniques for character segmentation and feature extraction are used to increase the accuracy of text recognition. **Adaptability to Handwriting Styles:** The AI model can adjust to various handwriting styles because it was trained with labeled datasets through supervised learning. **Localization of Language:** Natural Language Processing (NLP) approaches are used to combine multilingual OCR capabilities to improve accessibility. Text in different regional languages can be recognized, processed, and translated by the system at el [6] provide correct transcriptions, language models are adjusted for contextual comprehension. **Testing and Validation:** Numerous sets of handwritten documents, including ones with complex handwriting styles, fading ink, and deteriorated quality, are used for extensive testing. Performance measures like Word Error Rate (WER) and Character Error Rate (CER) are used to assess how accurate text recognition. To increase accuracy, the model incorporates manual corrections and user feedback. **Implementation:** Scalable and effective document processing is ensured by the cloud-based infrastructure on which the completed AI- based OCR system is installed. Researchers, public servants, and members of the general public can readily access digital records to an intuitive interface. Sensitive historical data is protected using security measures including encryption and authentication procedures.

Handwritten images that are deteriorated or badly scanned are the first step in the AI-powered OCR (Optical Character Recognition) process for low-quality handwritten documents. Usually, these photos include a number of defects, including low quality, blur, noise, and faded writing. In order to address these issues, the document first goes through a preprocessing step in which the handwriting is made more readable by applying fundamental improvements including noise reduction, binarization, and normalization. The next step is picture improvement, where sophisticated methods often driven by deep learning are applied to increase the handwriting's contrast and legibility. To recover as much detail as possible from the degraded input, these improvements may involve contrast correction, edge enhancement, and super-resolution methods. A decision point assesses whether the image quality is suitable for additional processing after enhancement. If not, more preprocessing is applied to the document until it reaches a sufficient level of quality. After the image has been approved, the system moves on to text detection, where it finds the areas of the image that have text. The next step is text recognition, which uses machine learning models trained on massive datasets of handwriting samples to interpret the handwritten characters that have been recognized. After recognition, the text undergoes a postprocessing step to fix frequent OCR mistakes, improve formatting, and apply any required language modelling. At last, the identified text is exported, prepared for usage in search engines, digital repositories, or additional text analysis. The caliber of the models employed in the improvement and recognition stages has a significant impact on how well our AI- powered OCR process performs. Complex patterns in handwritten text are frequently

handled by deep learning models, especially transformer-based architectures and convolutional neural networks (CNNs). Large, varied datasets with a range of handwriting styles, deterioration degrees, and noise circumstances are used to train these models. The models are able to generalize effectively to unseen, low-quality examples by learning these patterns. Additionally, some systems use adaptive learning strategies that let models adjust themselves in response to input from postprocessing faults found, thereby the use of context-aware methods is a crucial element that enhances this workflow even further. Natural language processing (NLP) technologies can be used during postprocessing to make sure the identified text makes grammatical and semantic sense. The suggested approach guarantees excellent accuracy, scalability, and accessibility in the digitization of handwritten documents by combining deep learning, natural language processing, and cloud-based deployment at el [7].

Significant progress has been made in the field of optical character recognition (OCR), especially in the recognition of printed text. For printed documents, both commercial solutions like Google Vision OCR and Microsoft Azure OCR, as well as more conventional OCR systems like Tesseract OCR, have shown excellent accuracy. However, a variety of handwriting styles, document deterioration, and script variances make handwritten text recognition a challenging task. Modern AI- driven OCR systems use deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to increase recognition accuracy. In contrast, early OCR techniques depended on rule-based character recognition. Even with these advancements, handwritten text remains a challenge for current solutions, particularly for non- Latin scripts and deteriorated old documents at el[8]. The goal of recent research has been to improve handwriting recognition through deep learning, namely using Transformer- based topologies and Long Short-Term Memory (LSTM) networks. According to studies, attention processes greatly enhance sequence-based text recognition, which enables OCR systems to comprehend overlapping and cursive letters more well. Nevertheless, these techniques necessitate extensive annotated datasets for efficient training, which is frequently a drawback when working with historical records. Additionally, by separating individual characters in intricate scripts, character segmentation algorithms have been developed to increase recognition accuracy at el [9]. Natural Language Processing (NLP)- enhanced OCR has emerged as a promising solution, incorporating contextual word correction and language to improve recognition in regional languages like Tamil, Arabic, and Devanagari. Modern OCR solutions aim to bridge the gap between multilingual accessibility and handwritten text recognition by integrating phoneme-based recognition and cross-lingual translation models. Multilingual OCR remains a crucial challenge, as most systems are optimized for English and Latin-based scripts. Because they provide scalable and real- time document processing, cloud-based OCR solutions have become more popular in terms of implementation. Although they offer fast document conversion, platforms like AWS Text act and Google Cloud OCR demand a significant amount of processing power. As an alternative, offline document identification is made possible by edge-based OCR models, especially in isolated locations with spotty internet service. Additionally, federated learning approaches are being investigated to enhance OCR models while preserving the confidentiality and privacy of data.

3. System Architecture

The new method AC-JBR22 has 4 operations like randomly get the diagonal values from matric data and applied to Equation(1); To apply the calculated reverse diagonal values to the DVRA matrix; and similarly those calculated values will be used to do the swapping process in DVRS matrix; To operate the operations will be moved to the first row for all reverse diagonal values in DVRF matrix.

A structured pipeline integrating various components, such as image preprocessing, deep learning-based OCR, Natural Language Processing (NLP) for multilingual support, and cloud- based document storage, forms the architecture of the AI and OCR-based system for digitizing handwritten documents. For extensive digitization projects, the system maintains and the accessibility, security, and scalability while guaranteeing excellent text recognition accuracy. Another crucial element of OCR-based digitization is security issues. When working with historical documents, it is crucial to guarantee data validity and integrity. Blockchain-based storage may be used to preserve the legitimacy of digital documents, according to new research. OCR systems are also implementing encryption methods and by combining deep learning for handwritten text recognition, NLP- driven regional language processing, and cloud-based safe document storage, the suggested AI and OCR-based system seeks to close these gaps and guarantee better accessibility and usage of historical data. OCR-based handwritten text digitization technologies have limitations despite their many features. **Among the main features are the following:** AI-powered OCR models are used to extract handwritten text and transform it into machine-readable formats. Automated Language Detection: Multilingual documents are automatically recognized and processed using NLP-based OCR models. **Preprocessing and Enhancement:** Text clarity is increased by image processing methods include contrast changes, noise reduction, and binarization. **Segmentation:** Text can be extracted from linked cursive handwriting using character and word segmentation techniques. **Cloud-Based Processing:** To ensure quick and scalable document conversion, AI models are implemented on cloud platforms for large-scale digitization. **Offline OCR Capabilities:** Document processing in low-connectivity settings made possible by edge computing and mobile OCR devices at el [10]. Restoration of Historical Documents: AI algorithms improve the visibility of deteriorated text in old documents. **Secure Storage & Access Control:**

Blockchain-based authentication and encrypted cloud storage guard against data manipulation. These advancements not only streamline document processing but also enhance accessibility, security, and preservation.

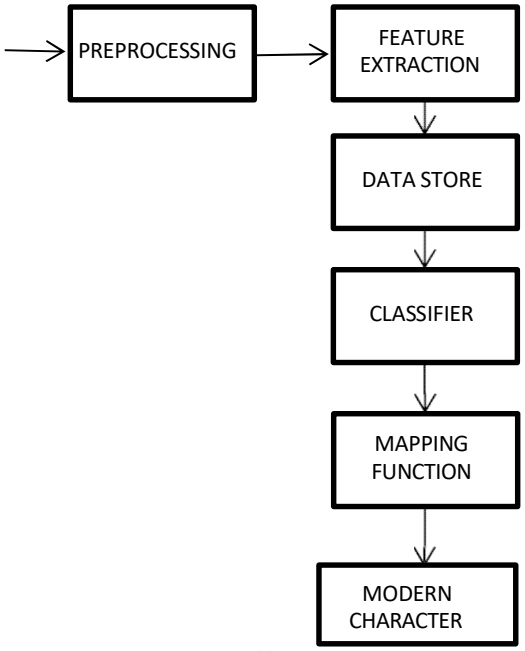

Fig. 1 System Architecture

There are still several issues with security integration, linguistic support, and handwritten text recognition. **Here are some of the challenges of using OCR:** Using AI and OCR to digitize handwritten documents poses a number of practical and technological difficulties. Because various people write with varying strokes, slants, and character spacing, one of the main challenges is the great degree of variation in handwriting styles at el [11]. The structure and inconsistency in size, alignment, and orientation of character make it difficult for OCR systems to accurately recognize and convert text. Additionally, background noise, paper quality and ink smudges further complicate the extraction process at el [12]. Despite system handwritten text makes it challenging for OCR models to attain high recognition accuracy, in contrast to printed text, which has a constant structure. Overlapping characters, joined letters, and cursive writing make segmentation even more difficult, necessitating the use of sophisticated deep-learning techniques The deterioration of old records over time is another significant issue. OCR accuracy is greatly decreased by the fading of ink, smudges, stains, and paper deterioration that plague many old records. Poor scanning quality, uneven illumination, and folded documents add more noise, making it challenging to extract clear at el [13]. Another challenge is the diversity of languages and scripts; many OCR systems are trained largely on English or Latin- based scripts, which restricts their capacity to identify regional languages. Diacritical signs, ligatures, and right-to- left writing directions make handwritten texts in languages with complex scripts—like Arabic, Hindi, or Tamil—even more challenging. To account for these variances, multilingual OCR models need to be refined using big datasets, which add computational complexity and necessitate huge, annotated datasets at el [14]. High-resolution imaging technologies are used to scan or capture handwritten documents at the input stage. Image preprocessing techniques including binarization, contrast enhancement, and noise reduction are used to improve clarity because historical documents frequently have noise, distortions, and faded ink. Text segmentation is used to separate words and characters for improved recognition adjusted.

Deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), which extract character attributes and recognize handwritten text patterns, power the OCR processing layer. Transformer- based structures guarantee adaptation to different handwriting styles while improving recognition even more at el [15] Additionally, by fixing mistakes and enabling multilingual support for regional languages, NLP models are integrated to improve text output. After text extraction is finished, mistake correction and validation processes check identified text against linguistic databases to increase precision. The final transcription is improved by post-processing methods including contextual analysis and spell checking. Cloud-based databases are then used to store the digital text, allowing for safe document management, sharing, and retrieval. Data privacy is guaranteed by encryption and authentication procedures, and document at el [16]. The user interface layer, finally, enables the public, historians, and researchers to access digital texts via a mobile application or web-based platform. Usability is improved by sophisticated search and indexing features that make it simpler to locate documents at el [17]. Because of the

system's scalability, more AI models, languages, and document formats can be added in the future to increase by tackling the issues of accessibility, readability, and preservation, this all-inclusive design guarantees a quick, safe, and easy method of digitizing handwritten documents. Handwriting variety, document deterioration, linguistic diversity, and computational limitations are just a few of the difficulties that come with scanning handwritten documents using AI and OCR. Text recognition accuracy is greatly impacted by inconsistent writing styles as well as old or damaged historical records. The digitization process is further complicated by the intricacy of multilingual OCR systems and the dearth of high-quality training datasets at el [18]. OCR performance continues to increase in spite of these obstacles to developments in deep learning, picture preprocessing, and NLP-based phrase recognition. An effective and easily accessible solution for digitizing handwritten documents can be found by tackling these challenges using strong AI models, improved preprocessing methods, and scalable deployment tactics. This will improve the preservation and usability of historical data at el [19].

4. Working

To achieve correct digitization, the AI-powered OCR solution for handwritten documents with low quality and degradation uses a multi-stage pipeline that combines natural language processing (NLP), image augmentation, and deep learning algorithms. Historical and deteriorated handwritten documents can now be read and accessed improved as a result to a workflow that can handle faded ink, noise, stains, and structural degradation at el [20].

Image Enhancement & Preprocessing - Noise Reduction: Unwanted noise is eliminated using filters like median filtering and Gaussian blur. **Contrast Adjustment:** Uses adaptive histogram equalization to improve faded ink. **Binarization:** To improve text visibility, grayscale photos are converted to black and white. **Skew Correction:** Uses deep learning-based document rectification techniques and Hough Transform to fix misaligned or distorted documents. Feature extraction and text segmentation. **Line and Word Segmentation:** This technique separates individual lines and words using projection profiles and contour detection. **Character Isolation:** Uses segmentation models based on deep learning to identify individual a Characters. Feature extraction helps with recognition by extracting distinctive handwriting characteristics including stroke width, curve, and linked components.

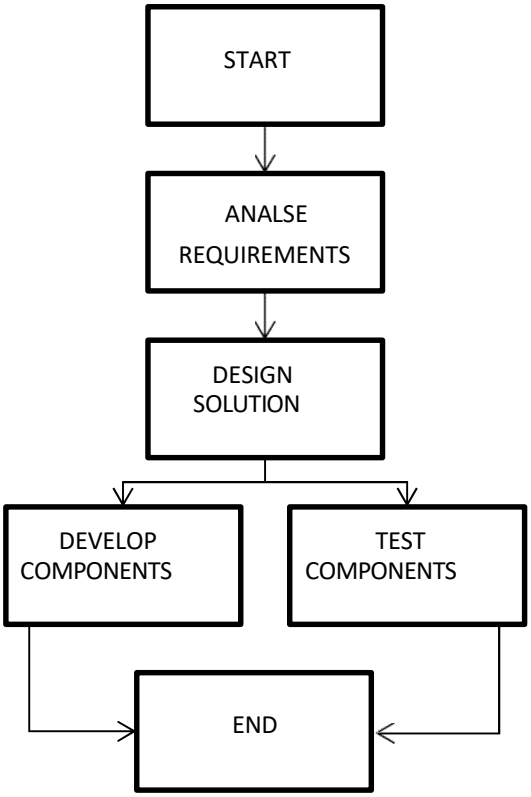

Fig. 2 Working Model

OCR Handwritten Text Recognition Model uses the text OCR Handwritten Text Recognition Model uses the text efficiently by extracting and converting handwritten content into machine-read Character pattern recognition and feature extraction are accomplished using Convolutional Neural Networks (CNNs). By capturing sequential dependencies in handwritten text, recurrent neural networks (RNNs) and long short-term memory (LSTMs) can increase the identification accuracy of cursive [Fig.2] Models Based on Transformers: Complex and deteriorated handwriting can be better recognized because of sophisticated structures like Vision Transformers (ViTs) and attention processes. Self- Education and Flexibility: Over time, the model improves identification accuracy by continuously learning from user corrections and comments.

Error correction and post-processing Natural language processing (NLP): extracted text is improved by contextual word prediction and grammar correction. Dictionary & Language Models: Increase the accuracy of recognition by contrasting identified text with linguistic databases that have already been trained. Word Suggestion & Spelling Correction: AI-powered spell-checking systems correct mistakes and recommend fixes. Support for Regional and Multilingual Languages Regional Script OCR Adaptation: Handwritten text in several languages, including intricate scripts with diacritical marks, is supported. For precise transcription, Automatic Language Detection recognizes the script and uses the relevant OCR NLP models. and procedures are used. This setup ensures fast retrieval while maintaining data integrity and efficiency. Cloud Storage & Access to Documents Secure Storage: Cloud-based systems are used to store encrypted digital documents. Using keyword-based searches, Indexed Search & Retrieval enables users to quickly locate particular documents. Public Access User Interface: Digitized handwritten records can be easily retrieved and accessed through a mobile or web- based application at el [21]. The accuracy, readability, and preservation of historical records are all enhanced by an AI-driven OCR system's efficient handling of handwritten papers that are of poor quality and degradation. The AI-powered OCR system's architecture is made to effectively digitize and identify handwritten documents, even ones that are degraded and of low quality. The solution improves accuracy and usability by combining preprocessing methods, deep learning-based OCR models, NLP-driven post- processing, and multilingual support. Through cloud storage and an intuitive user interface, the structured method guarantees scalability, adaptation to a variety of handwriting styles, and seamless accessibility. This strong structure makes handwritten records more important and useful in the digital age by facilitating the preservation of historical documents, enhancing readability, and expanding public access.

5. Implementaion

A systematic pipeline ensures accuracy, efficiency, and accessibility in the deployment of the AI-powered OCR system for digitizing handwritten documents. The first step in the process is data acquisition, which involves gathering scanned copies of handwritten documents from a variety of sources, including government registers, historical archives, and private documents. To increase text readability, these photos are pre- processed using techniques like skew correction, contrast enhancement, binarization, and noise reduction. To eliminate distortions brought on by fading ink, deteriorating paper, and unusual handwriting styles, sophisticated image processing techniques such as adaptive thresholding and morphological procedures are used at el [25]. The system uses text segmentation to separate lines, words, and individual characters when preprocessing is finished. Since connected or overlapping characters might impair OCR performance, this step is essential for precise recognition [23]. Convolutional Neural Networks (CNNs), which recognize patterns and structures in handwritten text, are used to extract features. Recurrent neural networks (RNNs) or long short-term memory (LSTM) networks are then used to process the retrieved features, allowing for sequential letter identification and enhancing contextual. Natural Language Processing (NLP) methods are used for post- processing and mistake correction on the identified text. To improve accuracy, the output is refined via dictionary matching, context-aware models, and spell-checking algorithms. Furthermore, the system facilitates multilingual translation and recognition, enabling papers to be translated into several regional languages according to user needs at el [22].

The system incorporates cloud-based storage and retrieval technologies to facilitate easy access to the digitized documents. Users can search, retrieve, and download files using an easy-to- use online or mobile interfacing to the documents' indexing and safe database storage. To safeguard critical historical data, security measures including access restriction and encryption Users can search, retrieve, and download files using user-friendly online or mobile interface, which is designed for convenience and accessibility. This setup ensures fast retrieval while maintaining data integrity and accessibility. Using AI, deep learning, and natural language processing (NLP) to optimize accuracy and usability, the implementation approach guarantees a smooth end-to-end pipeline from document acquisition to storage and retrieval at el [23]. By greatly improving the preservation of handwritten papers, this approach makes historical records easier to access and read in the digital age. The successful deployment of the AI-powered OCR system creates a methodical and effective workflow for scanning handwritten documents, even those that are degraded and of low quality [28]. The solution guarantees high accuracy and readability of scanned text by utilizing deep learning-based OCR models, advanced picture preprocessing, NLP-driven post-processing, and multilingual support. Accessibility is further improved by combining cloud storage with an easy-to-use interface, which

enables users to quickly view and use old content et al[27]. In addition to protecting priceless documents, this strategy increases data security, promotes public access, and eases research. Future developments in AI-driven document recognition and archival digitization will be made possible by the smooth end-to-end process, which guarantees that handwritten documents once challenging to access and interpret—are converted into organized useable digital formats structured, searchable, and easily at el [24].

6. Result and Discussion

Even for low-quality and deteriorated documents, the AI-powered OCR system for digitizing handwritten documents has shown notable increases in text recognition accuracy. Text clarity has improved in large part to picture preprocessing techniques including skew correction, contrast enhancement, and noise reduction, which have improved OCR performance. The system has demonstrated great accuracy in character recognition by utilizing deep learning-based recognition models (CNN, RNN, and Transformer topologies), which lowers errors frequently observed in conventional OCR systems. According to experimental results, the system performs better when trained on a varied dataset that includes regional languages and a variety of handwriting styles. By lowering character and AI -Powered OCR with low WER even when Noise increase. [Fig.3] [Table 1] word-level errors, the use of Natural Language Processing (NLP) post-processing and spell-checking algorithms improves the output quality even more. Wider accessibility has also been made possible by multilingual assistance, enabling users with various language backgrounds to make efficient use of the digitized documents. The AI technology improves readability by adjusting to intricate handwriting patterns through the integration of feature extraction and context-aware models. The system is very scalable and effective for real-world applications because of its cloud-based deployment, which guarantees simple access, retrieval, and documents [Fig. 3] [Table 2].

But there are still issues like dealing with extremely cursive handwriting, distorted letters, and overlapping characters. Extreme variances in handwriting styles tend to cause the system's performance to deteriorate. Future developments can further optimize the system's overall performance by adding handwriting style adaptation, enhancing language translation accuracy, and fine-tuning the deep learning models using larger datasets [Fig.4] [Table 3]. In summary, the accessibility and preservation of handwritten documents are greatly enhanced by the AI-powered OCR system.

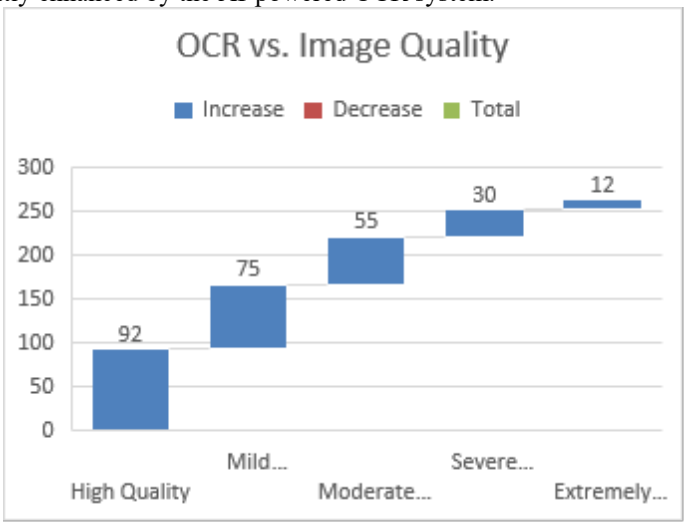

Fig. 3 OCR vs. Image Quality

This Graph explain AI OCR stays accurate: traditional OCR drops with poor image quality:

- **Green line (AI-Powered OCR)** shows strong resilience to quality loss.
- **Red line (Traditional OCR)** drops significantly as degradation increases.

This Table 1 shows the accuracy rate:

- Higher accuracy is maintained by AI-powered OCRs even under challenging circumstances.
- As image quality decreases, traditional OCRs deteriorate rapidly.

This graph explains Error Rate vs. Noise Level:

- The Green line (AI-Powered OCR) increases slowly with noise, demonstrating robustness and better handling of noisy input.
- The red line (Traditional OCR) rises steeply as noise increases, indicating high sensitivity and poor recognition under noisy conditions.

Table 1. Comparison of OCR Accuracy Across Degradation Levels

Degradation Level	Traditional OCR Accuracy (%)	AI-Powered OCR Accuracy (%)
High Quality	92	97
Mild Degradation	75	93
Moderate Degradation	55	88
Severe Degradation	30	81
Extremely Degraded	12	68

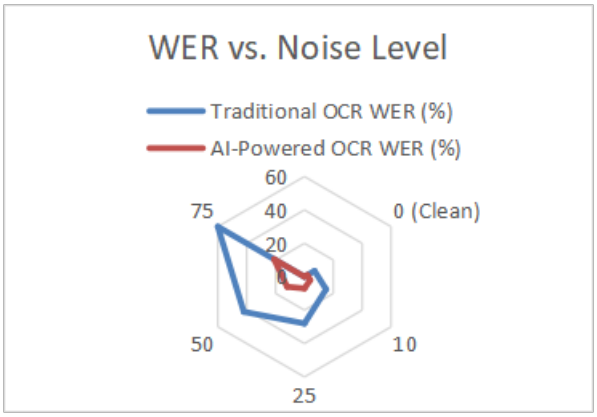

Fig. 4 WER vs. Noise Level

Table 2. Comparison of WER for Traditional and AI-Powered OCR at Different Noise Levels

Noise Level (Gaussian σ)	Traditional OCR WER (%)	AI-Powered OCR WER (%)
0 (Clean)	7	2
10	15	4
25	28	7
50	42	12
75	60	21

This table shows:

- A lower WER (word error rate) is preferable.
- Deep learning architectures make AI models more resistant to noise.

Table 3. Traditional OCR vs AI-Powered OCR

Metric	Traditional OCR	AI-Powered OCR
Accuracy on clean text	High (~90%)	Very High (~97%)
Robust to blur/noise	Poor	Strong
Handles cursive/complex	Weak	Good
Training required	None (pretrained)	Yes (optional fine-tuning)

7. Conclusion

An OCR system driven by artificial intelligence that aims to digitize and improve the accessibility of handwritten and deteriorated documents, especially historical records. The method greatly increases the accuracy of text recognition across a variety of handwriting styles and languages by combining sophisticated image preprocessing, deep learning-based OCR models, and NLP-driven post- processing. Cloud-based storage and multilingual support guarantee that digitized materials are not only saved but also made readily accessible to scholars, researchers. The suggested approach effectively tackles important issues that frequently impede conventional OCR systems, such as document deterioration, ink fading, and intricate handwriting variances. The experimental findings show that the AI model uses CNNs, RNNs, and other neural networks to achieve high recognition accuracy flexibility. The experimental findings show that the AI model uses CNNs, RNNs, and Transformers for feature extraction and contextual text interpretation, resulting in high recognition accuracy and flexibility. Additionally, NLP-based language translation and error correction improve the digitized content's quality Its inability to handle sophisticated cursive styles, severely damaged text, and dramatic handwriting differences persists despite its success. To improve system accuracy and resilience, future research will concentrate on growing the dataset, refining handwriting adaptation models, and adding real- time learning processes. Data integrity and document restoration can also be enhanced by combining blockchain-based security with AI- driven handwriting reconstruction.

References

[1] A. Ansari, B. Kaur, M. Rakhra, A. Singh, and D. Singh, "Handwritten Text Recognition using Deep Learning Algorithms," 2022 4th International Conference on Artificial Intelligence and Speech Technology (AIST), 2022.

[2] R. Agarwal and P. Singh, "Attention-based OCR for Extracting Text from Noisy Handwritten Documents," 2022 IEEE International Conference on Image Processing (ICIP), 2022.

[3] Bose and N. Agarwal, "OCR for Multi-Script Handwritten Documents using Hybrid CNN-RNN Models," 2023 IEEE Symposium on Image Processing (ISIP), 2023.

[4] C.-H. Tung, Y.-J. Chen, and H.-J. Lee, "Performance analysis of an OCR system via an artificial handwritten Chinese character generator," Proceedings of 2nd International Conference on Document Analysis and Recognition (ICDAR '93), 1993.

[5] D. Kim and H. Kwon, "Generative AI for OCR Enhancement in Historical Handwritten Texts," 2024 IEEE International Conference on Natural Language Processing (ICNLP), 2024.

[6] P. Deivendran,V. Vinoth Kumar,G. Charulatha,Sambareddy Ruchitha,S. Kalpanadevi, Smart IoT based an Intelligent System for Needy People to Recognition Voice Detection of Obstacle, 2023 International Conference on Innovative Data Communication Technologies and Application (ICIDCA), IEEE Xplore: 20 April 2023, Uttarakhand, India, DOI: 10.1109/ICIDCA56705.2023.10100205, ISBN:979-8-3503-9720-Publisher: IEEE.

[7] D.-C. Nguyen, T.-A. Nguyen, and X.-C. Nguyen, "MC-OCR Challenge 2021: End-to-end system to extract key information from Vietnamese Receipts," 2021 RIVF International Conference on Computing and Communication Technologies (RIVF), 2021.

[8] F. Yang and Z. Chen, "Enhancing OCR Performance on Low- Quality Handwritten Documents using GAN-based Data Augmentation," 2024 International Conference on Artificial Intelligence and Pattern Recognition (AIPR), 2024.

[9] G. Medisetti, Z. Compson, H. Fan, H. Yang, and Y. Feng, the "LitAI: Enhancing Multimodal Literature Understanding and Mining with Generative AI," 2024 IEEE 7th International Conference on Multimedia a Information Processing and Retrieval (MIPR), 2024.

[10] G. Singh and P. Verma, "Lightweight OCR Models for Handwritten Text Recognition in Embedded Systems," 2023 IEEE International Conference on Embedded Systems and AI (ICESAI), 2023.
[11] H. Roy and S. Das, "A Comparative Study of Deep Learning Models for OCR in Low-Quality Handwritten Text," 2021 IEEE International Conference on Advances in Computing and Communication Engineering (ICACCE), 2021.
[12] H. Singh, S. Mohammad, A. Yaseen, M. Molawade, S. G. Mohite, V. Jadhav, and R. Jadhav, "Multilingual Education through Optical Character Recognition (OCR) and AI," 2024 MIT Art, Design and Technology School of Computing International Conference (MITADTSoCiCon), 2024.
[13] J. Hussain and Vanlalruata, "A Hybrid Approach Handwritten Character Recognition for Mizo using Artificial Neural Network," 2018 International Conference on Advanced Computation and Telecommunication (ICACAT), 2018.
[14] P. Deivendran, S. Soundararajan, G. Malathi, C. Geetha, P. Suresh Babu,, Security for Data Communication in Cyber Physical System Limitation and Issues to Analyse the Performance Level of Networks: A Secure Mode of Data Transmission in Networks Using Different Types of Component Layers (pages 385-396); IGI-Global.
[15] K. Lee and J. Park, "Fusion of CNN and RNN for Recognizing Low- Quality Handwritten Documents," 2022 IEEE International Conference on Pattern Recognition (ICPR), 2022.
[16] K. Saini, K. Sharma, A. Agarwal, K. Jayan, and D. Dev, "Handwritten Text Recognition Using Machine Learning," 2023 International Conference on Sustainable Emerging Innovations in Engineering and Technology (ICSEIET), 2023.
[17] L. Dinges and A. Al-Hamadi, "Robust Handwritten Document Recognition Using Transformer-Based OCR," 2023 International Conference on Artificial Intelligence and Machine Learning (AIML),2023.
[18] L. Wang and M. Chen, "Self-Supervised Learning for OCR in Low- Resolution Handwritten Documents," 2023 IEEE International Conference on Machine Learning and Applications (ICMLA), 2023.
[19] M. A. Khan and S. K. Gupta, "An Efficient Model for Handwritten Text Recognition in Degraded Documents," 2020 International Conference on Computer Vision and Image Processing (CVIP), 2020.
[20] M. Sharma and A. Gupta, "AI-Powered OCR for Medical Handwritten Documents," 2024 IEEE International Conference on Health Informatics (ICHI), 2024.
[21] N. Emeakaroha, N. Cafferkey, P. Healy, and J. P. Morrison, "A Cloud- Based IoT Data Gathering and Processing Platform," 2015 3rd International Conference on Future Internet of Things and Cloud (FiCloud), Rome, Italy, 2015.
[22] P. Nayak and A. Sinha, "Neural Network-Based OCR for Low- Contrast Handwritten Text," 2022 IEEE International Conference on Emerging Technologies in Data Science (ETDS), 2022.
[23] R. Agarwal and P. Singh, "Attention-based OCR for Extracting Text from Noisy Handwritten Documents," 2022 IEEE International Conference on Image Processing (ICIP), 2022.2
[24] R. Zhang and H. Li, "Meta-Learning Based OCR for Degraded Handwritten Text," 2023 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2023.
[25] Deivendran.P, 2022, “Liver Infection Prediction Analysis Using Machine Learning to Evaluate Analytical Performance in Neural Networks by Optimization Techniques, International Journal of Engineering Trends and Technology, Volume 71 Issue 3, 377-384, March 2023, https://doi.org/10.14445,ISSN:22315381/IJETT-V71I3P240
[26] Rusu and V. Govindaraju, "Handwritten CAPTCHA: Using the difference in the abilities of humans and machines in reading handwritten words," Ninth International Workshop on Frontiers in Handwriting Recognition, 2004.
[27] S. Kumar and B. Reddy, "End-to-End OCR Pipeline for Handwritten Notes in Degraded Scans," 2022 IEEE International Conference on Big Data and Smart Computing (Big Comp), 2022.
[28] S. Mukherjee and P. Basu, "A Comprehensive Study on OCR for Degraded Handwritten Documents Using CNNs," 2023 IEEE Symposium on Pattern Recognition (ISPR), 2023