



## CNN-Powered Handwriting to Digital Text Converter

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**Abstract:** The technology has become a crucial component in the digital transformation of documents for banks, educational institutions, and other sectors. In this paper, we design a handwritten character-to-text converter using CNN, where the input is a handwritten character and it is converted into computerized text. You see, CNNs are pretty darn good at image processing, and basically, what we're doing in the input debugger is detecting individual characters from a wide range of horrible handwritten gibberish. The model is trained on a dataset of handwritten characters, and its hierarchical feature extractors are able to pick up patterns in how handwriting looks that we might not be consciously aware of. Results from experiments carried out demonstrate that CNNs are excellent at predicting accuracy well and an error rate less when it comes to handwritten text conversion, so using them in, say, real-time application takes the performance to the next level across industries.

**Keywords:** *Handwriting Recognition, Convolutional Neural Networks (CNN), Handwriting-to-Text, Image Processing, Document Digitization, Machine Learning, etc.*

### I. INTRODUCTION

The conversion of handwriting to text is a process that leads efficient conversion of handwriting into text allows handwritten notes to be used and managed in any situation with ease. This makes it crucial to save vital records and effortlessly provides access while simplifying data management. In an era of digital disruption, where more tasks are moving online under automation, the ability to convert handwritten notes or archival records into digital text can be game-changing. In the technological space, it has become a necessity to transform handwritten notes into digital text [1].

It also allows users to preserve their handwritten work, making it searchable across various platforms like email or shareable on social media. These tools include features such as automatic text recognition, integration with cloud services, and support for multiple languages, meeting the needs of all users, from students to professionals. Handwriting-to-text converters transform the personalization of handwritten notes into clean, readable formats that streamline workflows while retaining the warmth of handwritten content, making them invaluable in both educational and professional environments [2].

The most common method for this is optical character recognition (OCR). This technology allows the conversion of various documents, such as scanned paper, images, and PDFs, into editable or searchable text. In handwriting-to-text conversion via OCR, the key stages include the Preprocessing stage (which enhances image quality by correcting distortions, adjusting contrast, brightness, etc.), the Detection and Segmentation stage (which may use Kernels to detect edges, characters, or





features), and finally the Character Recognition stage, where the unique shapes and patterns of handwritten characters are analyzed [3].

Problems with OCR include print distortion, the quality of typed input, and poor resolution images, as well as difficulties reading stylized text in certain type settings. It also struggles with text recognition in scaled scans or low-quality images due to background contamination. Traditional OCR systems rely on rule-based algorithms, which can become inadequate when faced with complex character variations or noise in images, leading to text extraction errors. To address this, CNNs leverage deep learning to directly learn hierarchical features from data. CNNs excel at recognizing patterns and structures in images, making them more resilient to variations in text appearance. They are also adaptable to different contexts by training on large (and noisy) datasets, removing the need to write numerous ad-hoc rules for each domain. As a result, CNN-based OCR systems are better suited for recognizing difficult text and achieve superior performance across multiple applications [4].

## II. LITERATURE REVIEW

**Table 1:** List of Different Methods

Ref. No	Title	Year	Objective	Methodologies	Advantages	Future Scope
[5]	An Offline Handwritten Chinese Text Recognition Based on Fully CNN	2021	Based on fully CNN that aims to improve accuracy and efficiency.	The system employs attention gates and FCN for segmentation free recognition of hand-written text.	Achieves high accuracy, competitive performance, enhances feature extraction	Network optimization, broader dataset testing, enhanced accuracy techniques
[6]	End-to-End Historical Handwritten Ethiopic Text Recognition Using Deep Learning	2023	Aims to advance Ethiopic text recognition using deep learning enhancing feature extraction, and addressing data scarcity challenges.	Uses CNN layers for feature extraction, BLSTM layers for sequence learning, and attention mechanisms to enhance recognition.	Improved Accuracy Automatic Feature Extraction, Robustness Against Variations, Comprehensive Framework	Dataset Expansion, Exploring Alternative Architectures, Cross-Language Testing
[7]	Handwritten Amharic Word Recognition with Additive Attention Mechanism	2024	Develop a CNN-RNN model with additive attention for Amharic word recognition, enhance accuracy using CTC for sequence modeling.	CNNs for feature extraction, RNNs for sequence modeling, and additive attention to highlight features. Data augmentation expanded the dataset, CTC was used for alignment.	Greater Adaptability, Improved Interpretability, Effective Performance	Multilingual Word Recognition, Enhanced Robustness, Real-World Applicability





[8]	A Residual-Attention Offline Handwritten Chinese Text Recognition Based on Fully Convolutional Neural Networks.	2021	A residual-attention model using fully CNN to, enhancing accuracy and efficiency without explicit character segmentation.	Android camera captures image, followed by preprocessing, segmentation into lines, words, characters, and feature extraction for character classification.	Recurrent-Free Architecture, Smart Residual Attention Gate Block, Performance Analysis with Expansion Factor, Competitive Recognition Performance	Integration of Language Models, Exploration of Variants, Broader Applications, Improving Computational Efficiency
[9]	Handwriting to Text Converter Web Application	2023	Develop a user-friendly web application that converts handwritten text to digital using image processing and machine learning techniques.	The application uses OpenCV, NumPy, Tkinter, and Pillow for image processing and character recognition, with an OCR engine for text extraction.	User-Friendly Interface, Fast and Accurate Conversion, Supports Multiple Handwriting Styles, Editing and Formatting Tools, Accessibility, Image Quality Enhancement	Integration with Mobile Applications, Enhanced Recognition Algorithms, Multilingual Support Expansion, Collaboration Features, Integration with Cloud Services, AI-Powered Features
[10]	Automated Handwritten Text Recognition	2023	To develop a system that accurately recognizes and transcribes handwritten text into a digital format	Pre-processing, Model Training, System Architecture, Output Generation	Healthcare Application, Historical Document Preservation, Automated Data Entry	Enhanced Recognition, Broader Applications, Integration with Other Technologies
[11]	Two Decades of Bengali Handwritten Digit Recognition: A Survey	2022	To depict the progress of research in Bengali Handwritten Digit Recognition (BHDR) and provide useful directions for future research.	It investigates on BHDR, analyzing data preprocessing techniques, and summarizing methodologies used in machine learning and deep learning approaches.	It provides an in-depth analysis of existing BHDR works, identifying strengths and weaknesses, which can guide future research efforts.	It suggests broader applications of BHDR beyond conventional fields, including curating publicly available benchmark datasets and proposing robust models for various use cases.
[12]	Tulu Language Text Recognition and Translation	2024	To develop a neural machine translation system for English to	Utilized neural machine translation technology, achieving an accuracy of 89% for	High accuracy for simple translations and the potential for	Plans to enhance the model for complex sentences, improve dataset





			Indian language translation, specifically focusing on Tulu.	simple words and sentences. The model is currently being evaluated with individual sentences, with future assessments planned for phrases.	real-time application development with Tulu Unicode.	collection, and develop a more complex model for real-time applications.
[13]	Handwritten OCR: A Comprehensive SLR	2020	To provide a systematic literature review (SLR) of handwritten Optical Character Recognition (OCR) technologies, highlighting trends, gaps, and future research directions.	The review methodology includes the establishment of review protocols, criteria for inclusion and exclusion, search strategies, selection processes, and quality assessment criteria for the studies included in the review.	This systematic review serves as a reference for finding the latest trends in handwritten OCR and highlights research directions for further studies in this domain.	Identifies gaps in current research that require further investigation, suggesting that future studies could focus on improving methodologies and exploring under-researched languages and databases.
[14]	Multilingual Text & Handwritten Digit Recognition and Conversion of Regional Languages into Universal Language Using Neural Networks	2021	Utilize neuronal signals in literature. Reduce manpower needed for manually converting old literature into a digitized form. Serve as a reference for character identification. Enrich the digitized language library.	The paper focuses on text recognition of traditional languages, specifically Gujarati and Marathi, using neural networks for multilingual text and handwritten digit recognition.	Improved performance in recognizing characters that traditional OCR techniques may struggle with. Capability to utilize synthetically generated training data, reducing dependency on extensive manual data collection.	The methodology can be extended to include more languages and improve the accuracy and efficiency of OCR systems, particularly in recognizing diverse scripts and handwritten texts.
[15]	Handwritten Character Recognition to obtain Editable Text	2020	The objective of is to develop an Android application for character recognition that reads text from images, facilitating into editable text.	It uses OCR, which include pre-processing, segmentation, feature extraction, and post-processing by the OCR engine to convert the text.	The system achieves a recognition accuracy of 94.12% for handwritten text and 100% for printed text. It provides an easy method for users to edit and share recognized data.	It suggests that while the current system offers significant accuracy, further improvements can be made to enhance recognition capabilities, especially for





						diverse handwriting styles.
[16]	Handwritten Text Recognition using Machine Learning Techniques in Application of NLP	2019	It aims to develop a technique for computers to receive and interpret intelligible handwritten input from sources such as paper documents, touch screens, and photographs.	The paper discusses the adoption of HTR software, which categorizes or classifies data or objects efficiently..	The technology allows for easier storage and access of data that was traditionally stored, and it provides enhanced security for the data.	The paper suggests ongoing advancements in handwriting recognition technology and its applications in various fields.
[17]	Optical Character Recognition Based Webapp	2022	To create a portable solution that helps the specially-abled blind community by identifying and extracting text from product labels and currency notes using Optical Character Recognition (OCR).	It uses OCR methodology to recognize text. It deploys on a Raspberry Pi with a camera for image acquisition. Preprocessing and edge detection using the OpenCV library and conversion of extracted text into audio using the espeak library.	Provides an accessible tool for the blind community to interact with their environment by reading labels and currency, enhancing their independence.	Development of an ensemble model combining different OCR engines with advanced deep learning algorithms like Long Short Term Memory Networks (LSTMs) to improve accuracy and performance.

In this paper, they propose a new residual-attention and fully convolution dual pathway network for handwritten Chinese text recognition. It introduces a residual attention gate block that enhances the model's ability to focus more or less on important handwriting patterns while suppressing irrelevant background elements. Experiments on two benchmark datasets, CASIA-HWDB and ICDAR-2013, demonstrated competitive character error rates with and without a language model. The paper is structured as follows: Section 2 reviews related works, Section 3 outlines the proposed approach, and Section 4 presents experimental results and discusses future research directions [5].

The manuscript discusses a new and better model for the recognition of handwritten Amharic words via deep learning with an end-to-end additive attention mechanism. It begins with a survey of literature, illustrating the lack of studies on machine learning for Amharic script recognition. This work also introduces a new architecture and explains how they train their model. Experiments demonstrated the effectiveness of using this novel additive attention mechanism, which improves upon state-of-the-art models by reducing noise and writing-style differences between individuals,





helping focus on important parts of handwritten words. When 34,047 images were used for training with high-level preprocessing, performance metrics improved drastically. The authors also suggest that future research should focus on adding augmentation techniques and noise reduction to make the model more generalizable to real-world scenarios. This work is an important step forward in OCR for Amharic script and shows that the approach has great potential to improve handwritten word recognition performance [6].

The paper presents how document image retrieval methodologies can be combined to optimize access to multimedia and text content, with a focus on historical Indian languages like Gujarati and Marathi. The goal is to improve the digitization of antiquated writing, using neuronal signals. This is demonstrated through character recognition and further encourages the creation of new digital corpora for language, which can assist handicapped persons with speech disorders and other speakers. Overall, the paper underscores the importance of technology in conserving and providing access to cultural literature [7].

This paper aims to give an overview of Optical Character Recognition (OCR) technology, particularly focusing on handwritten characters. It describes the recent trend of digitizing handwritten documents for easier storage and updating. In OCR, this process involves steps like pre-processing, segmentation, feature extraction, and post-processing to convert handwritten text into an editable electronic format. The authors discuss challenges in identifying characters from various handwriting styles and introduce a mechanism that uses Android devices to scan handwritten documents. This system recognizes text and allows users to edit or save it as plain text or PDF files. The paper acknowledges the work of various researchers in this field and emphasizes the importance of developing efficient OCR systems for everyday use [8].

This paper addresses the issue of recognizing and converting handwritten documents into digital text, a key task for data entry, archiving, and accessibility services. The study emphasizes high-level machine learning, particularly deep learning algorithms, to improve handwritten text recognition. Their approach involves training a CNN on a large dataset of handwritten examples, allowing it to learn various handwriting styles. The experiments show that their proposed system achieves high accuracy in transcription compared to others. The authors note that this automated transcription system is not only convenient but can also be useful for transcribing historical documents and assisting people with disabilities. This research provides an effective solution to the challenge of handwritten text transcription in OCR [9].

A paper by E. Pavithra, R. Yadav et al. (2022) presents an innovative, low-cost mobile designed to help blind individuals navigate their surroundings with greater safety and independence. The device uses ultrasonic sensors to detect obstacles and provides audio feedback to inform users about the distance of objects, aiding in mobility and autonomy. This compact and affordable design has the potential to significantly improve the quality of life for a large portion of the visually impaired community [10].





In the paper "Handwritten Text Recognition and Translation with Audio" by Patibandla et al. (2022), a system is described that automatically converts handwritten text into a target language and produces an audio output of the translated text. The system effectively transforms written information into accessible content using OCR for digitization, machine translation (MTAA) for language conversion, and TTS technology for audio output, enabling users to independently access printed information. This innovative approach enhances ease of use and has the potential to significantly improve the quality of life for blind individuals [11].

The paper "Convolution Neural Networks for Text Recognition" by Sushmitha et al. (2021) discusses the use of convolutional neural networks (CNNs) in text recognition. CNNs, known for their ability to learn complex patterns and features, are effectively applied by the authors to process and recognize text within images. This research reveals that CNNs outperform traditional methods for both printed and handwritten text recognition. The results demonstrate that CNNs can enhance state-of-the-art text recognition frameworks, leading to robust and accurate word recognition systems for real-world applications [12].

The paper "Handwritten to Text Document Converter" by Deepthi et al. (2022) presents a system to convert scanned handwritten documents into digital text format. Handwritten text recognition faces challenges such as variations in writing styles and input image quality. To address these, the authors propose a solution using advanced image processing and machine learning algorithms to enhance text conversion accuracy. The study shows that their approach significantly improves recognition rates, enabling seamless digitization and easy access to written information [13].

The paper "Deep Learning-Aided OCR Techniques for Chinese Uppercase Characters in the Application of Internet of Things" by Yin et al. (2019) investigates the use of deep learning models to improve OCR for Chinese uppercase characters in an IoT setting. The authors discuss their model, which uses a convolution neural network (CNN) to significantly enhance character recognition. Experimental results show that the deep learning-based OCR method is not only more accurate than classical methods but also more robust to variances. This development has important implications for IoT use cases that rely on text recognition for processing and communication [14].

In the paper "Handwriting Recognition and Beautification Methodology" by Aayush Shah et al. (June 2023), the authors present a comprehensive machine learning approach to both handwriting recognition and beautification. The project is divided into two main parts: handwriting recognition and handwriting enhancement. They propose a new method for handwriting recognition using feature extraction and relative location matching via directed graphs. The goal is to develop a robust handwriting recognition system capable of handling unique writing styles. The beautification part modifies distorted documents while preserving the writer's handwriting, making it more legible. This process includes steps like creating a feature-graph database, noise reduction, slant correction, and character segmentation.





The authors claim that the system produces human-interpretable output, which could aid in improving the legibility of handwritten documents [15].

The paper "Improving Offline Handwritten Text Recognition with Hybrid HMM/ANN Models" by España-Boquera et al. (2011) focuses on improving offline handwritten text recognition by integrating hybrid models that combine Hidden Markov Models (HMMs) and Artificial Neural Networks (ANNs). The authors address the limitations of rule-based recognition systems and propose a new technique that enhances accuracy and robustness by leveraging both HMMs and ANNs. Experimental results show that their hybrid model significantly outperforms traditional methods, achieving higher recognition rates across various datasets. These findings suggest that combining these two methods can effectively overcome existing challenges in handwritten text recognition [16].

### III. MOTIVATION

In mainstream sectors like education, healthcare, and finance, which are increasingly digital, having a quick and accurate handwriting-to-text converter is essential. While digital documentation functions as expected, most business documentation isn't stored in digital format like PDFs. Handwritten documents can be scanned and transcribed into text, but this is often slow and prone to errors on a larger scale. Additionally, many systems face challenges with handwriting variations, as different people write in different ways. However, for handwritten text, where individual writing styles vary greatly, traditional optical character recognition (OCR) is not ideal. Components such as letter shape, spacing, slant, and even the writing medium contribute to a wide range of variations, making handwriting recognition complex.

This issue is further exacerbated by the fact that in many regions, especially in certain professions within developing areas, manual paper-based record-keeping is still prevalent. This project aims to address these issues by leveraging Convolutional Neural Networks (CNNs) to create a reliable handwriting recognition system. CNNs excel in handwriting recognition due to their ability to detect patterns in images. Their convolutional layers capture handwriting features, adapting to various writing styles or shapes. This technology could significantly advance bulk document digitization, swiftly and accurately converting handwritten content into digital form, while also ensuring the preservation of valuable handwritten records.

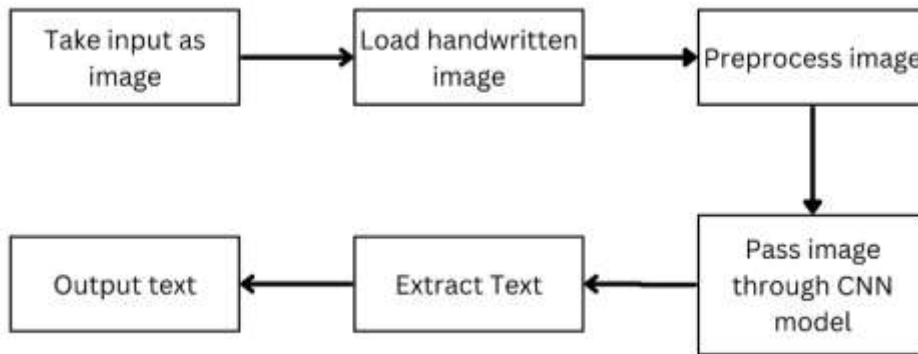
### IV. PROPOSED SYSTEM DESIGN

The following block diagram outlines a handwriting-to-text conversion system using a CNN. It begins with an input image, which is a scanned or captured handwritten text. Then image is to even this a little more in the preprocess steps by utilizing the image re-sizing, normalization or noise reduction, to impact quality and clarity modifications of this image that is loaded for further processing. After pre-processing the image, it is passed to a CNN model which will find patterns, shapes and features in that handwriting. Relevant features from the image are extracted and converted into text by CNN. The final results are the extracted text.

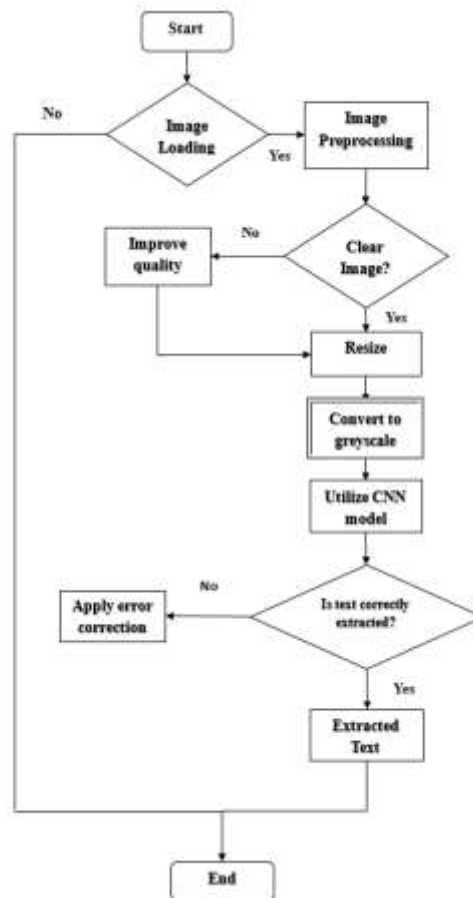




This System Purpose Automates Written Notes Which converts Into Machine readable text and it uses the power of deep learning has used CNN for feature definitive and recognition Text. This System Purpose Automates Written Notes Which converts Into Machine readable text and it uses the power of deep learning has used CNN for feature definitive and recognition Text.

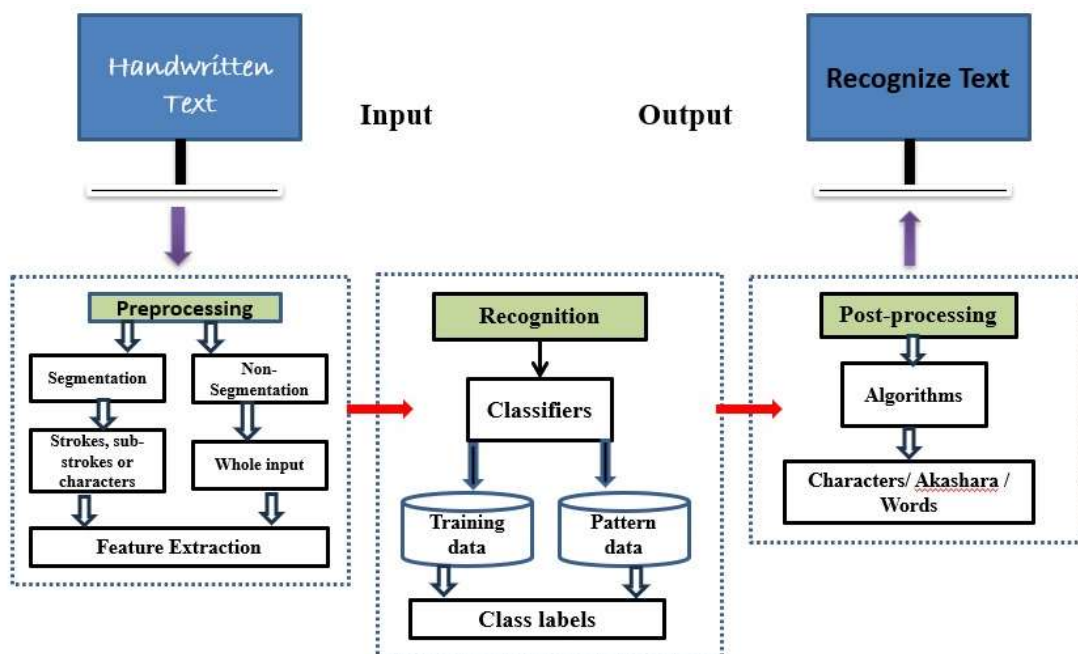


**Figure 1:** Proposed Block Diagram for Handwritten to Text Converter



**Figure 2:** Proposed Flowchart for Handwritten to Text Converter

The flowchart above represents the process of extracting text from handwriting using CNN, starting with the handwritten image load. After the image is successfully loaded, it goes through a series of preprocessing steps, where it is enhanced and cleaned from any noise or distortions. Next this image is checked to see if it is clear; if not, it goes back to the enhance stage for clarity of image and then the gray scale image is passed through a CNN model where feature extraction is done by the model to try to understand the text. After processing the image through CNN, we check that if this text was extracted properly. If any errors are discovered, a correction step fixes the output (possibly through methods like spell-checking or even language modeling). After the text is correctly extracted, it provides the final output. This pipeline ensures a consistent flow from raw image to accurate text conversion, validating processes at various stages, which in turn improves CNN performance.



**Figure 3:** Proposed System Architecture for Handwritten to Text Converter

The architecture diagram shows the process of handwritten-to-text recognition; Pre-process Input Text, which contains several modifications of human-like text, often is handwritten text on a device. Divide the input into strokes, sub-strokes, or characters/preprocess all at once in pre-processing. Next, apply feature extraction to identify features of the handwritten text.

Then, in the recognition phase, classifiers are used that match those features against a set of training data and pattern models. The system then assigns class labels (identifying characters or words) to these comparisons. Finally, in the post-processing stage, algorithms refine the recognized text in order to create actual characters, words or Aksharas (used by some scripts). This leads to the generation of the recognized text as output thus making machine-readable a handwritten input. It provides you with a dual stream of accuracy since it incorporates both well-defined feature extraction alongside the definitive classification technique.





## V. RESULT AND CONCLUSION

The objective of handwriting-to-text conversion is to design an efficient and highly performing system that can convert handwritten input into machine-readable text. Your CNN model should not only recognize different handwriting styles but also effectively extract relevant information from the image, regardless of character variations and noise. The preprocessing phase, such as image enhancement, resizing, and gray scaling, is expected to improve image recognition quality. By incorporating these techniques, the model can adapt to various writing styles and environments, increasing its overall versatility. The system should also maintain high accuracy with minimal errors through post-processing methods such as error correction. The model must be fast enough to process images in real-time or near real-time, making it practical for everyday use. Achieving this real-time capability would enable the system to be applied in various scenarios, such as instant digital documentation and live note-taking during business meetings or college lectures. We aim to produce clean, formatted extracted text that users can download, save, or further analyze using word processing tools. Overall, the system is designed to handle a variety of handwriting inputs while generating accurate, legible text. Its flexibility and robustness ensure that even highly stylized or sloppy handwriting is converted into clear, readable text, which is essential for handling diverse inputs in real-world scenarios

In conclusion, the handwriting-to-text conversion project using CNN automates the transformation of handwritten inputs into machine-readable or digitized formats for further analysis. The system enhances input quality through pre-processing, accurately identifies characters by focusing only on necessary features, and then processes them with the CNN model. Post-processing refines the output, minimizing errors and increasing precision. This project aims to handle various handwriting styles and conditions, ultimately creating a production-ready OCR solution. The system will offer fast text conversion, real-time or near real-time, and will be useful in digital documentation and for preserving traditional handwritten data.

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