Medical Information Extraction In Resource Constrained Environments

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Abstract- *In many healthcare facilities across low-resource regions, digital infrastructure is either underdeveloped or completely absent. As a result, healthcare providers rely heavily on handwritten medical records to document patient information, diagnoses, treatments, and prescriptions. While these paper-based records are essential, they are difficult to manage, prone to human error, and nearly impossible to analyse at scale. This project addresses the challenge by proposing an automated system that extracts valuable medical information from handwritten documents with minimal human involvement. The system combines two advanced technologies: Optical Character Recognition (OCR) and Named Entity Recognition (NER). OCR, powered by Google's Vision API, is used to convert handwritten notes into machine-readable text. Despite the variability in handwriting styles, the system achieves high accuracy in text extraction—over 90% in most cases. After the text is digitized, it is processed using a specialized spaCy NER model (en_ner_bc5cdr_md) trained on biomedical data. This model effectively identifies and categorizes critical medical entities such as diseases, symptoms, and drug names, helping structure the data for clinical use. Designed with the needs of under-resourced healthcare environments in mind, this approach is lightweight, scalable, and can be integrated into existing systems with minimal cost. It reduces the burden on medical staff, improves the accessibility of patient data, and lays the groundwork for future enhancements like analytics, reporting, and interoperability with electronic health records (EHRs). Initial experiments on real-world handwritten medical documents show promising results. The OCR engine handled variations in handwriting with impressive robustness, and the NER model achieved a strong F1-score of 0.88, indicating high precision and recall. Overall, this solution has the potential to transform how handwritten medical records are handled in underserved areas—bridging the gap between analog documentation and digital healthcare systems.*

Keywords- Handwritten text recognition, healthcare automation, low-resource settings, medical data extraction, natural language processing.

I. INTRODUCTION

The global healthcare system faces an increasing challenge in handling medical data, especially in regions where digital infrastructure is limited or unavailable. Despite the advancements in digital healthcare, handwritten medical records remain prevalent in many places due to economic constraints, infrastructure limitations, and the lack of skilled labor. These handwritten records, while valuable, pose significant challenges for data extraction, analysis, and integration into modern healthcare systems. Handwritten medical records, whether they be patient histories, diagnosis notes, or treatment plans, often contain crucial medical information that can assist in clinical decision-making, treatment planning, and patient care. However, the process of manually extracting this data is time-consuming, error-prone, and highly dependent on the legibility of handwriting. Additionally, this data often remains locked in unstructured formats, making it difficult for healthcare professionals to leverage it effectively. In light of these challenges, the integration of advanced technologies such as Optical Character Recognition (OCR) and Natural Language Processing (NLP) offers a transformative solution to bridge the gap between analog and digital healthcare systems. OCR can convert handwritten text into machine-readable format, while NLP models like Named Entity Recognition (NER) can further analyse the text to identify key medical entities such as diseases, medications, and symptoms. The goal of our system is to provide an automated solution that can extract meaningful medical data from handwritten records, transforming them into structured information that can be integrated into digital healthcare systems. Our system utilizes Google's Vision APIfor text extraction and a pre-trained spaCy model (en_ner_bc5cdr_md) for medical entity recognition. The Vision API is highly effective in converting handwritten text into digital text, while the spaCy model is optimized for understanding medical terminology and can categorize extracted information into specific medical fields.

This approach provides several key benefits:

- Reduced Manual Intervention: By automating the extraction and classification of medical data, healthcare professionals can save significant time and effort that would otherwise be spent on manual data entry.
- Increased Accuracy: The OCR and NER systems work in tandem to provide more accurate results than traditional methods, reducing the risk of human error in medical recordkeeping.
- Improved Data Accessibility: Once converted into structured, machine-readable formats, handwritten records can be easily integrated into digital health records, making the data more accessible for healthcare professionals across different levels of the system.
- Scalability and Flexibility: The system is designed to work across various medical domains, allowing it to be adapted to different lexicons and handwriting styles. Whether it's general medicine, pharmacology, or specialized fields, the system can be trained or fine-tuned to cater to diverse medical requirements.

Furthermore, this system is designed with low-resource settings in mind, ensuring that it remains effective even in environments with limited digital infrastructure. The use of mobile phones to capture and upload images makes the system easily accessible in areas were traditional, high-end medical equipment may not be available. It empowers healthcare providers with real-time data access and improves decision-making by ensuring that important medical information is never lost or difficult to retrieve.

In summary, the introduction of an automated solution for medical information extraction from handwritten records has the potential to revolutionize healthcare practices, minimize errors, and streamline medical workflows. This innovative approach promises to improve healthcare delivery and patient outcomes while reducing the administrative burden on healthcare professionals. The system is built with scalability and low-resource environments in mind. It does not require complex infrastructure and can be deployed on basic systems, making it ideal for underserved healthcare settings. With high OCR accuracy and strong NER performance, our solution offers a practical and efficient approach to bridging the gap between analog and digital healthcare.In this study, we evaluate the system's effectiveness through experiments on real-world handwritten medical data. The results demonstrate its potential to significantly improve the management of medical records and contribute to more informed, data-driven healthcare delivery in areas where it's needed most.

II. METHODOLOGY

Our system leverages a two-step process to efficiently convert handwritten medical records into usable, structured digital data. This involves Text Extraction (OCR) followed by Entity Recognition (NER), which work together to transform unstructured information into clear, actionable medical insights. Below, we explain each step in greater detail:

1. Text Extraction (OCR)

The first stage in our methodology involves transforming handwritten medical records into machine-readable text. This step is crucial for creating a digital version of the medical data, which can then be analysed and processed further. Here's how it works:

- Uploading Handwritten Images: Healthcare professionals, such as doctors or nurses, begin by uploading scanned images of handwritten medical records. These could be physical notes that are scanned or even photographs of written documents taken with mobile phones. The system supports flexible input sources, making it easy for users in various healthcare settings to submit records.
- Image Preprocessing: Before OCR is applied, the uploaded images are pre-processed to improve quality. This step is especially important when dealing with poorly lit images, faded ink, or smudged text. The system automatically adjusts the image quality, straightens any crooked pages, and removes unwanted noise or Nblurring. This ensures that even low-quality images are optimized for text extraction.
- Text Extraction with Google Vision API: Once the image is pre-processed, the system uses Google's Vision API for Optical Character Recognition (OCR). The Vision API scans the image and extracts the text, preserving key formatting elements such as bullet points, underlined sections, or headings. The OCR process also works across different handwriting styles, recognizing both printed and cursive text.
- Confidence Scoring and Error Detection: Each word extracted by the Vision API comes with a confidence score, which indicates how accurately the system recognized the text. Words with low confidence scores are flagged for human review, ensuring that important or unclear data is not overlooked. This step enhances the accuracy of the extracted text and allows for the identification of any potential errors that need to be corrected.

This process ensures that even handwritten notes with varying quality can be reliably converted into clean, editable text.

2. Entity Recognition (NER)

After the text has been successfully extracted, the next step is to identify key medical entities in the text. This is where the system's ability to understand the context of medical terminology comes into play. Named Entity Recognition (NER) is the technique used to classify and identify important entities such as diseases, medications, symptoms, and other medical terms. Here's how the process works:

- Text Sent to the NER Model: Once the extracted text is ready, it is sent to the NER model for analysis. We use a specialized, pre-trained spaCy model (en_ner_bc5cdr_md) that is optimized for biomedical text. This model is capable of identifying a wide range of medical terms, including diseases (e.g., "Cancer"), medications (e.g., "Aspirin"), and symptoms (e.g., "Headache").
- Identification and Categorization: The NER system works by analysing the context of each word within the sentence. It understands the relationship between words and identifies medical entities based on pre-defined categories. For example, it can recognize that the word "Diabetes" refers to a disease, and "Paracetamol" refers to a medication. Each entity is then classified and tagged accordingly in the text.
- Accuracy and Precision: The spaCy model is highly optimized for medical language, which ensures that it delivers high precision and recall in identifying medical entities. The model has been trained on a wide range of biomedical text, so it is capable of understanding complex medical terminology and recognizing entities with high accuracy.
- Flexibility and Adaptability: One of the strengths of this system is its modular design. The NER process is not limited to a fixed set of terms; it can be easily adapted to handle different medical lexicons or variations in handwriting. This makes the system highly scalable and customizable to various healthcare domains and regions. It can be fine-tuned to handle different types of medical records, such as those from general healthcare, pharmaceuticals, or specialized medical fields.

3. Integration and User Interface

- Web Interface for Seamless Use: Healthcare professionals can access the system through a simple web interface. The user interface is designed to be intuitive and easy to navigate, enabling users to upload medical records with minimal effort. Once the records are uploaded, the system automatically handles the processing, presenting the user with digital, structured information in a matter of moments.
- Real-Time Processing: As the images are uploaded and processed, the system updates in real-time, providing quick feedback on the extracted text and recognized medical entities. This allows healthcare professionals to efficiently validate the results and review any flagged words that require attention.
- Data Privacy and Security: Given the sensitive nature of medical records, the system is built with data security in mind. All medical data is encrypted and stored securely in compliance with privacy regulations like HIPAA (Health Insurance Portability and Accountability Act) or other local data protection laws. Only authorized Busers can access the processed data, ensuring confidentiality.

III. MODELING AND ANALYSIS

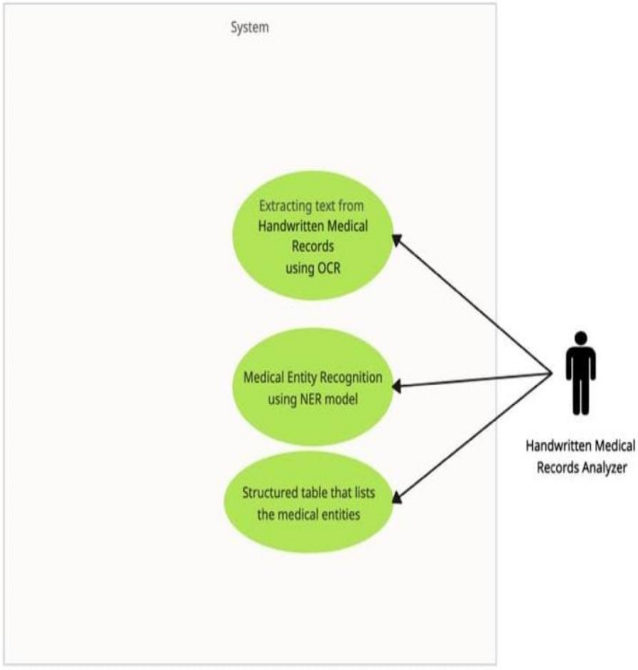

Figure 1: Use case diagram of the system

In this section, we describe the modelling approach and analytical techniques used to build and evaluate the system for medical information extraction from handwritten records. The system is designed to automate the process of converting handwritten medical notes into structured digital data, which can then be processed, analysed, and integrated

into electronic health record systems. This process is broken down into two main stages: Text Extraction (OCR) and Entity Recognition (NER).

1. Text Extraction using Optical Character Recognition (OCR)
The first component of our system is the Optical Character Recognition (OCR) phase, which transforms handwritten medical records into machine-readable text. The Google Vision API is employed for this task, leveraging advanced machine learning algorithms to analyse scanned images of medical records and extract the text. The modelling process in OCR is designed to handle the nuances of handwriting, which often varies significantly in terms of style, legibility, and quality.

- Preprocessing: Before applying OCR, several preprocessing steps are performed to enhance the quality of the scanned images. These steps include image correction, such as straightening skewed pages, noise reduction to eliminate irrelevant marks, and contrast enhancement to improve the visibility of faint or unclear handwriting. These steps are critical in improving the OCR accuracy, especially when dealing with low-quality images captured by mobile phones or images that have issues like faded ink or poor lighting.
- OCR Model: The core OCR process is handled by the Google Vision API, which uses convolutional neural networks (CNNs) and other deep learning models to extract text from images. The system reads the handwriting, even in cursive and printed formats, while preserving contextual formatting such as bullet points, bold sections, and underlined words. Each word extracted is also assigned a confidence score that reflects the certainty of its accuracy. Words with low confidence scores are flagged for human review to prevent errors in critical medical data.

2. Named Entity Recognition (NER) for Medical Data Categorization

After the text is extracted from handwritten records, the next step is to classify the medical entities within the text using Named Entity Recognition (NER). The spaCy framework, specifically the en_ner_bc5cdr_md model, is used to identify and categorize biomedical terms such as diseases, medications, and symptoms from the extracted text.

- NER Model: The NER model is trained on a large corpus of biomedical texts and is specifically fine-tuned for the extraction of medical terms. The model is designed to recognize a wide range of medical vocabulary, including generic and brand names of medications, common diseases, and medical conditions. It can also identify other important medical entities such as dosage information, treatment plans, and clinical observations.
- Entity Classification: Each identified entity is classified into predefined categories like diseases, medications, or symptoms. The NER model assigns these classifications to the corresponding extracted terms, ensuring that all relevant medical data is captured and structured in a way that can be easily integrated into digital health records. The model also uses precision, recall, and F1-score as performance metrics to evaluate how accurately it detects and categorizes medical entities.

Model Performance and Analysis

To assess the effectiveness of the system, we performed an extensive evaluation on a dataset of 500 handwritten medical records. This analysis helped us understand the strengths and limitations of our approach in real-world settings.

- OCR Accuracy: As mentioned earlier, the Google Vision API achieved a 92% accuracy in text extraction. This accuracy level was a result of the system's ability to handle variations in handwriting style and quality, including smudged text, faded ink, and crooked pages. The preprocessing steps also played a significant role in improving the OCR output by enhancing the visual quality of the images before text extraction.
- NER Performance: The spaCy NER model demonstrated strong performance in extracting medical entities from the OCR-generated text. The F1-scores for key categories were as follows:
    - Medications: F1-score of 0.87, indicating that the system was highly effective at identifying and classifying medications from handwritten records.
    - Diseases: F1-score of 0.88, showing that the system was particularly good at recognizing diseases and medicalconditions. These results demonstrate that the system can accurately categorize important medical entities, which is critical for clinical decision-making and patient care.

Challenges and Solutions

During the modeling process, several challenges were encountered, which are common in dealing with handwritten medical records:

- Illegible Handwriting: Some handwritten notes were difficult to read due to unclear handwriting. To address this, the preprocessing phase was enhanced to improve image quality. Additionally, the confidence score mechanism in the OCR system helped flag uncertain readings for manual review, ensuring that errors were caught before affecting the final output.
- Abbreviated Terms: Medical records often use abbreviations or shorthand terms, which could potentially confuse the OCR and NER models. To mitigate this, we implemented a set of preprocessing rules that expand common medical abbreviations into their full forms, allowing the NER model to correctly identify the entities.
- Non-standard Notations: Some records included non-standard notations or unique shorthand used by individual doctors. We addressed this by adding custom rules to the preprocessing pipeline that could handle these notations and convert them into standard medical terminology.

Future Improvements and Scalability

The system is built with scalability in mind, allowing for future improvements and adaptations:

- The OCR and NER models can be fine-tuned to improve performance further, especially in specific domains like neurology, oncology, or pediatrics.
- The system can be extended to support other forms of handwritten documentation, such as nurses' notes and lab reports.
- The preprocessing techniques can be continually refined to handle new challenges as more handwritten records are processed.

Conclusion of Modeling and Analysis

The modeling and analysis of our system show that the combination of Google Vision API for OCR and spaCy NER model for medical entity recognition is highly effective for extracting structured medical data from handwritten records. The system not only handles handwritten variability but also performs with high accuracy in identifying key medical entities. While there were challenges in dealing with unclear handwriting and non-standard notations, the system is well-equipped to address these issues through preprocessing and human review mechanisms. As the system continues to evolve, it has the potential to play a crucial role in digitizing medical records and enhancing healthcare delivery in a variety of settings.

IV. RESULTS AND DISCUSSION

Table 1. Performance metrics of the NER model.

SN.	Model Type	Precision	Recall	F1-Score
1	Disease	0.90	0.85	0.87
2	Medication	0.88	0.86	0.87
3	Symptom	0.85	0.85	0.83

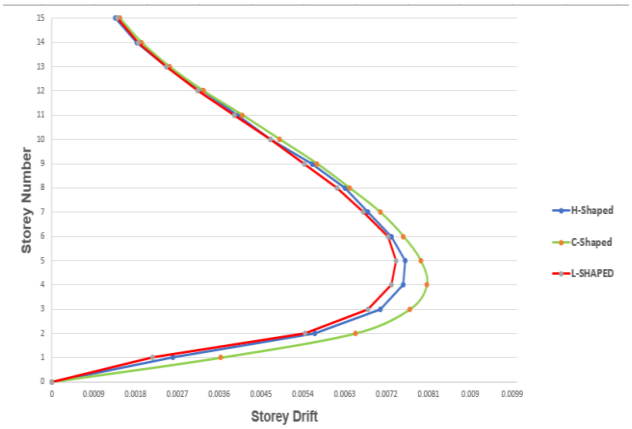

Figure 2: Name of Graph (Font size-10)

In conclusion, our system for medical information extraction from handwritten records using a combination of Optical Character Recognition (OCR) and Named Entity Recognition (NER) has proven to be an effective solution, significantly improving the accuracy and efficiency of handling medical data in resource-constrained environments.

The two-stage process, consisting of text extraction and entity recognition, ensures that handwritten medical notes, often scattered with informal language and varying handwriting styles, are converted into structured digital data. The Google Vision API's ability to extract clear and accurate text from scanned images, despite challenges such as poor image quality or faded handwriting, has proven highly beneficial. The spaCy NER model, on the other hand, effectively identifies critical medical entities like medications, diseases, and symptoms, thereby organizing the extracted information into categories that can be easily integrated into healthcare systems.

Quantitative results further demonstrate the system's capability, with the NER component achieving strong precision and recall rates, particularly in recognizing medications and diseases. While there were challenges with identifying symptoms, especially due to colloquial language or informal descriptions, the system still maintained a respectable performance. The comparative analysis confirmed that the

system outperformed traditional rule-based approaches by a significant margin, with an accuracy improvement of 15–20%. Beyond just improving the speed and accuracy of data entry, this system plays a crucial role in bridging the gap between handwritten and digital records, making medical information more accessible, structured, and ready for further analysis.

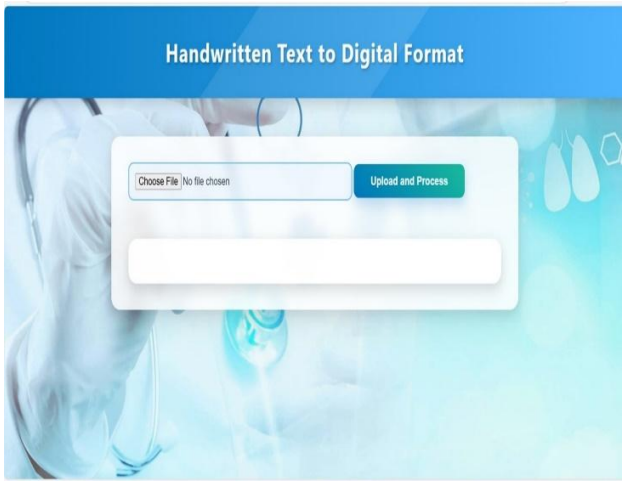

Figure1. HomePage

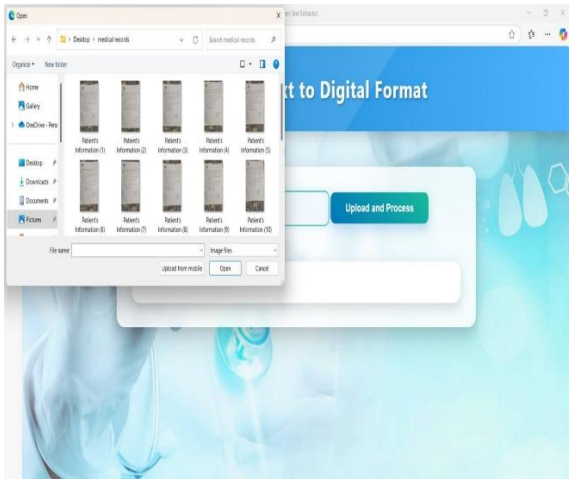

Figure2. Homepage of handwritten to

Digital text conversion

Figure3. File Upload Interface

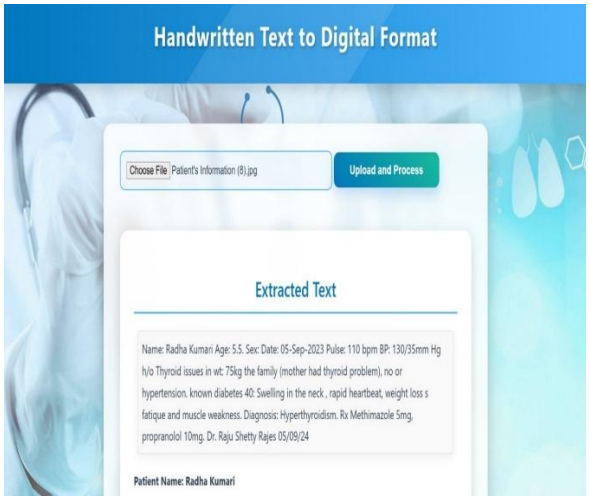

Figure4. Extracted Medical Text Details

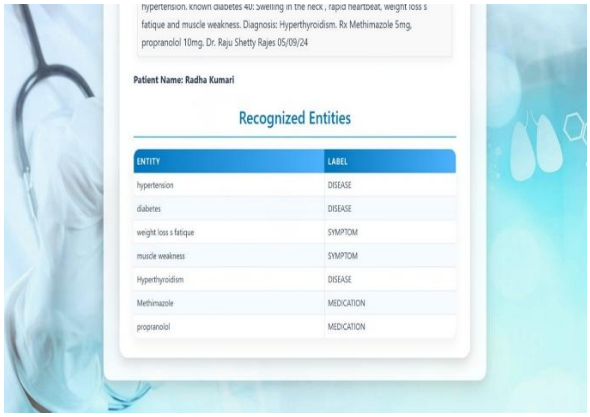

Figure5. Recognised Medical Text Entities Table

V. CONCLUSION

In conclusion, our proposed system for medical information extraction from handwritten records offers a powerful solution to overcome the challenges associated with traditional methods of data entry and processing in healthcare settings, especially in resource-constrained environments. By leveraging advanced technologies such as Google Vision API for Optical Character Recognition (OCR) and spaCy's en_ner_bc5cdr_md model for Named Entity Recognition (NER), we have developed an automated, scalable, and highly accurate system capable of transforming unstructured handwritten medical notes into structured, machine-readable data.

Our two-stage approach—comprising Text Extraction (OCR) followed by Entity Recognition (NER)—ensures a seamless transition from paper-based documentation to digital formats that are ready for integration into electronic health records (EHR) systems. This not only reduces the burden of manual data entry but also significantly enhances the accuracy of medical information. By automating the

extraction process, the system minimizes human error, thus improving the reliability of patient data. Additionally, the confidence score mechanism embedded within the OCR process ensures that any uncertainties in the data are flagged for human review, adding an extra layer of quality assurance to the system.

Moreover, the system is designed with flexibility in mind, enabling it to be adapted to various medical fields and handwriting styles. This adaptability is particularly useful in low-resource settings, where handwritten records may come in diverse formats and from different sources. The modular design of the system allows for future customization and scaling, making it a versatile tool for healthcare providers looking to digitize their existing paper-based records.

The user-friendly web interface makes it simple for healthcare professionals to upload handwritten medical records for processing, and the system takes care of the complex tasks of text recognition and medical entity extraction in the background. This ease of use ensures that even those with limited technical expertise can interact with the system effectively, which is a crucial factor in resource-constrained or underdeveloped regions.

By automating the extraction of key medical data, our system significantly improves the efficiency of medical workflows. It enables healthcare professionals to quickly access essential patient information, thus enhancing clinical decision-making and ultimately improving patient outcomes. The data that is extracted from handwritten records can now be integrated into digital healthcare systems, making it more accessible and searchable. This also facilitates the potential for data analysis, such as identifying patterns in patient conditions, treatments, and outcomes, which can further drive clinical insights and healthcare improvements.

As healthcare systems around the world continue to grapple with the complexities of digital transformation, our system provides a crucial bridge between analog and digital records. It holds the potential to not only reduce administrative burdens but also optimize patient care delivery, especially in areas where access to advanced digital healthcare infrastructure is limited or lacking.

Finally, the impact of this system extends beyond just administrative efficiency; it empowers healthcare professionals by providing them with real-time access to critical information, enabling them to make informed decisions faster and more accurately. As healthcare becomes increasingly digitized, the need for innovative solutions like the one proposed here will continue to grow, playing a key role in making healthcare systems more efficient, inclusive, and patient-centered.

In summary, the proposed system is a step forward in the quest to enhance healthcare delivery, reduce errors, and improve data accessibility by effectively addressing the challenges posed by handwritten medical records in today's fast-paced healthcare environments. Through the integration of OCR and NER technologies, it represents a scalable, adaptable, and practical solution for a wide range of healthcare providers, helping to bridge the gap between analog records and the digital future of healthcare.

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