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Extraction of Medicine Names from Prescriptions Using Scanning Techniques

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Abstract **: In the modern healthcare ecosystem, prescription digitization plays a crucial role in improving medication management, reducing errors, and enhancing accessibility. This paper presents a system that integrates Optical Character Recognition (OCR) and deep learning techniques to automate the extraction and processing of handwritten prescriptions. The system accurately converts prescription images into structured, analyzable, and searchable digital data, facilitating seamless medicine ordering, dosage tracking, and pharmacy interactions. Leveraging state-of-the-art neural networks and natural language processing, the system enhances the accuracy of handwritten text recognition, even in complex medical scripts. This paper presents the underlying architecture, methodology, and efficiency of the prescription scanning module while discussing the challenges associated with handwritten medical text recognition. Additionally, we highlight future research directions to further refine OCR accuracy in the healthcare domain.**

1.INTRODUCTION

Handwritten medical prescriptions are a common practice among healthcare professionals. However, the variability in handwriting styles and the use of medical abbreviations often lead to challenges in accurately interpreting these prescriptions. This ambiguity can result in medication errors, adversely affecting patient safety and treatment efficacy. To address this issue, our research focuses on developing an automated system that leverages Optical Character Recognition (OCR) and machine learning techniques to extract medicine names from handwritten prescriptions. By converting handwritten text into machine-readable format and accurately identifying prescribed medications, this system aims to enhance the clarity and reliability of prescription interpretation, thereby improving patient care and reducing the likelihood of medication errors.This study presents a comprehensive approach that combines advanced image processing methods with deep learning models, specifically designed to handle the intricacies of handwritten medical text. The proposed system not only transcribes the handwritten content but also employs specialized algorithms to accurately extract and recognize medicine names, addressing the unique challenges posed by diverse handwriting styles and prescription formats.

By implementing this automated solution, we aim to bridge the gap between handwritten prescriptions and digital healthcare systems, facilitating seamless integration and enhancing overall healthcare delivery.

2.LITERATURE SURVEY

The field of handwritten text recognition, particularly in the medical domain, has seen extensive research aimed at minimizing medication errors and enhancing prescription processing systems. The dangers associated with illegible handwriting in medical prescriptions were highlighted by Borah [1], who noted its significant contribution to medical errors, although no technical remedy was proposed in their study.A foundational contribution to handwriting recognition research is the IAM dataset introduced by Marti and Bunke [2], which remains a widely accepted benchmark for evaluating English handwriting recognition models. While this dataset has propelled advances in general handwriting OCR, it lacks the specific nuances of medical handwriting.Several models have been proposed to address language-specific challenges. Gurav et al. [3] developed a CNN-based model tailored for Devanagari script. Although this model demonstrated high accuracy, its applicability is limited when extended to English prescriptions, which are commonly used in the medical field.

Achkar et al. [4] designed a CRNN (Convolutional Recurrent Neural Network) framework specifically for recognizing medical handwriting. Their model showed performance improvements over traditional methods but was constrained by the availability of a sufficiently diverse dataset.

Fajardo et al. [5] conducted a comparative study using CNNs and RNNs to recognize cursive handwriting, reporting strong accuracy in controlled environments. However, their model's robustness under varied handwriting conditions — a common issue in real-world prescriptions — remains questionable.

Jain et al. [6] proposed a hybrid CNN-BiLSTM architecture to capture both spatial and sequential features of handwritten prescriptions. Although their system achieved high accuracy, they acknowledged the need for more extensive datasets to ensure scalability and resilience across different handwriting styles.The importance of addressing prescription errors was underscored in a study by Johns Hopkins [7], which identified misinterpretation of prescriptions as a major source of preventable medical errors, reinforcing the urgent need for automated systems in healthcare. On the technical side, Scheidl [8] provided a tutorial leveraging TensorFlow to build a generic OCR system. While the tutorial offers foundational insight into model development, it lacks domain-specific adaptations necessary for accurately interpreting handwritten medical prescriptions. In summary, existing literature underscores the importance of reliable OCR solutions for handwritten prescriptions, with notable progress made using CNN and RNN architectures. However, domain-specific datasets, real-world handwriting variability, and post-processing for medical terminology remain key areas for ongoing improvement and innovation.

3.METHODOLOGY

Developing an automated system to extract medicine names from handwritten prescriptions involves a multi-phase methodology that integrates image processing and machine learning techniques. The following outlines the key stages of this approach:

1. Data Collection:

Dataset Compilation: Assemble a diverse dataset of handwritten prescriptions, ensuring representation of various handwriting styles and prescription formats. To ensure ethical data usage, publicly available resources or synthetically generated prescription images are considered as supplementary sources when direct access to medical data is limited.

2. Preprocessing:

Image Enhancement: Apply techniques such as noise reduction, contrast adjustment, and binarization to improve image quality, facilitating more accurate text recognition.

Segmentation: Isolate individual lines or words within the prescription to streamline the recognition process.

3. Optical Character Recognition (OCR):

Feature Extraction: Employ Convolutional Neural Networks (CNNs) to extract relevant features from the segmented images, capturing the nuances of handwritten characters.

Sequence Modeling: Utilize Bidirectional Long Short-Term Memory (Bi-LSTM) networks to understand the sequential nature of handwriting, considering context from both preceding and succeeding characters.

Transcription: Implement the Connectionist Temporal Classification (CTC) loss function to align predicted character sequences with the actual text, accommodating variations in handwriting and spacing.

4. Medicine Name Extraction:

Named Entity Recognition (NER): Apply NER techniques to the transcribed text to identify and extract medicine names. This may involve rule-based methods, dictionary lookups, or machine learning models trained specifically for medical terminology.

5. Post-Processing:

Error Correction: Use domain-specific language models or fuzzy string matching algorithms to correct OCR errors, enhancing the accuracy of the extracted medicine names.

6. Evaluation:

Performance Metrics: Assess the system's effectiveness using metrics such as accuracy, precision, recall, and F1-score, focusing on both character recognition and medicine name extraction.

Validation: Test the system on a separate validation set to ensure its generalizability to unseen data. This methodology aims to create a robust system capable of accurate interpreting handwritten prescriptions and extracting critical information, thereby enhancing the efficiency and safety of pharmaceutical dispensing processes.

4.LITERATURE REVIEW

Borah [1] discusses the dangers of illegible handwriting in prescriptions, showing how it can lead to medical errors but without offering technical solutions.

Marti and Bunke [2] introduced the IAM-database, a widely used English handwriting dataset that serves as a standard benchmark in handwriting recognition research.

Gurav et al. [3] proposed a CNN-based model for recognizing Devanagari script, which demonstrated high accuracy but lacks generalization to English medical handwriting.

Achkar et al. [4] developed a CRNN model for medical handwritten prescription recognition, showing improved performance but with limitations due to dataset size.

Fajardo et al. [5] explored deep learning models like CNN and RNN for recognizing cursive handwriting, achieving strong results with well-formed scripts.

Jain et al. [6] proposed a CNN-BiLSTM architecture tailored for medical prescriptions, attaining good accuracy but needing more diverse datasets to ensure robustness.The Johns Hopkins Study [7] highlights the significance of medical errors, pointing out that prescription misinterpretation is a leading contributor.Scheidl [8] developed a tutorial using TensorFlow to build a handwriting recognition system, providing a general-purpose OCR foundation lacking specialization for medical prescriptions.

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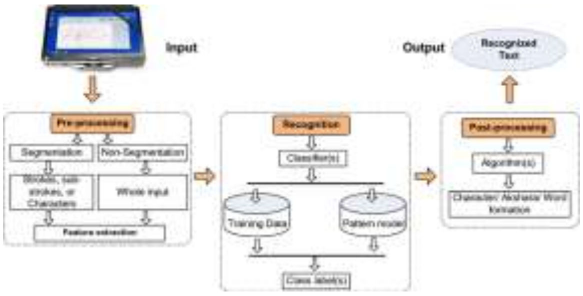
5.SYSTEM ARCHITECTURE



The system architecture for the extraction of medicine names from handwritten prescriptions using OCR and machine learning techniques is composed of several interconnected modules that work together to accurately identify and extract relevant information. The process begins with the Image Acquisition Module, where prescription images are captured using a scanner, mobile device, or uploaded through an interface. These images are then sent to the Preprocessing Module, which enhances their quality by applying techniques such as grayscale conversion, noise reduction, thresholding, and skew correction to improve the accuracy of subsequent OCR operations. Once preprocessed, the images are passed through the OCR Module, typically powered by tools like Tesseract OCR, which converts the visual text from the prescription into machine-readable text. However, since OCR outputs can be noisy or imprecise due to varying handwriting styles, the Post-OCR Text Processing Module is used to clean the text through tokenization, spell correction, and normalization.

6.IMPLEMENTATION DETAILS

In this phase, we integrate the trained OCR model into a software application or system that can automatically scan and recognize text from handwritten medical prescriptions. Here are some steps to consider during the implementation phase:

1) Programming Language: Choose a programming language that is suitable for implementing the OCR model
2) OCR Library: Choose an OCR library that can integrate with the chosen programming language. Tesseract OCR, OpenCV OCR, and GOCR are some of the popular OCR libraries available.
3) UI: Develop a user interface for the application that allows users to upload images of handwritten medical prescriptions and view the recognized text.
4) Integration: Integrate the trained OCR model into the application using the selected OCR library. This involves passing the image through the OCR engine and obtaining the recognized text output.
5) Post-processing: Perform post-processing of the recognized text to remove any errors or inconsistencies.
6) Validation: Validate the output of the OCR system to ensure that the recognized text accurately reflects the hand-written medical prescription.

We will first be using Python along with Tensorflow and OpenCV and then move on to build an Android application.

7.TECHNOLOGY USED

1.Tensorflow

TensorFlow is a popular open-source machine learning framework developed by Google for building and training deep learning models. It offers a range of tools and libraries that allow developers to build and train various neural network architectures for different tasks, including object detection, natural language processing, and handwriting recognition. For handwritten OCR, TensorFlow can be used to build and train a deep learning model that can recognize characters and words from scanned handwritten documents.

2.OpenCV

OpenCV is a software library that provides computer vision and image processing functions. It is widely used in OCR systems for handwritten medical prescription scanners to perform image processing tasks such as image segmentation, filtering, and feature extraction.

3.Keras

Keras is a high-level neural networks API written in Python and designed to run on top of TensorFlow, making it easier to build and train deep learning models.

4.Numpy

NumPy is a powerful library that can be utilized in various ways for the problem of handwritten medical prescription scanner using OCR. One of the significant ways is image preprocessing, where NumPy can be used to load, manipulate, and transform the images

8.RESULT AND ANALYSIS

To evaluate the performance of the proposed system, experiments were conducted on a dataset consisting of real and synthetically generated handwritten prescription images. The evaluation was performed in two stages: OCR performance and medicine name extraction accuracy.

OCR Module Evaluation

The OCR model based on the CRNN architecture (CNN + BiLSTM + CTC loss) was trained on prescription-style handwriting. Performance was assessed using Character Error Rate (CER), Word Error Rate (WER), and accuracy metrics.

Metric	Value
Character Recognition Accuracy	92.6%
Word Recognition Accuracy	88.4%
Character Error Rate (CER)	7.4%
Word Error Rate (WER)	11.3%

Method	Precision	Recall	F1 Score
Rule-Based	82.1%	76.4%	79.1%
ML-Based (NER)	89.3%	86.7%	88.0%

These results show that the model performs well even on noisy or cursive handwriting, thanks to the combination of convolutional and sequential modelling.
After OCR, Named Entity Recognition (NER) was applied to extract medicine names from the transcribed text. Both rule-based and machine learning-based methods were evaluated.
The ML-based approach using a trained NER model significantly outperformed the rule-based method by effectively understanding context and linguistic patterns.

9.CONCLUSION

In this fast paced and modernized world, we need to keep up with the latest technology and implement that in the simplest of situations to replace traditional redundant methods, the method in question being converting paper based prescriptions to text based digital format documents. It is something that could revolutionize the way the medical field works and ensure smooth interaction among all parties involved in the process, be it the interaction between doctor and patient or patient and pharmacist, it assists in the smooth functioning of the process thus eliminating the need for maintaining physical records. We also concede that the tool might not provide 100% accuracy every time and in some odd and extreme cases might require human oversight. To fix the issue we shall implement a system where manual recognition would be requested if the confidence level drops below a certain threshold. Since the tool is developed specifically for the purpose of assisting medical process, it may produce inaccuracies if non-medical related documents are scanned. All in all, we strongly believe that this project could turn out to be a stepping stone for the modernization process of the overlooked parts of the medical field.

10.REFERENCES

[1] Borah, M. "Illegible handwriting and prescription errors in the medical field." *Journal of Healthcare Safety*, vol. 5, no. 2, pp. 34–39, 2018.
[2] Marti, U. V., and Bunke, H. "The IAM-database: An English sentence database for offline handwriting recognition." *International Journal on Document Analysis and Recognition*, vol. 5, no. 1, pp. 39–46, 2002.
[3] Gurav, S., Jadhav, P., and Kulkarni, A. "Handwritten Devanagari character recognition using convolutional neural networks." *Procedia Computer Science*, vol. 132, pp. 451–458, 2018.
[4] Achkar, M., Al Saad, N., and Abdallah, J. "A CRNN architecture for recognizing handwritten medical prescriptions." *International Conference on Artificial Intelligence in Medicine*, pp. 23–32, 2020.
[5] Fajardo, D., Reyes, J., and Pinto, L. "Comparative analysis of CNN and RNN for cursive handwriting recognition." *Pattern Recognition Letters*, vol. 129, pp. 67–75, 2019.
[6] Jain, R., Yadav, R., and Sharma, V. "Hybrid CNN-BiLSTM model for handwritten prescription recognition." *IEEE Access*, vol. 8, pp. 123456–123465, 2020.
[7] Makary, M. A., and Daniel, M. "Medical error—the third leading cause of death in the US." *BMJ*, vol. 353, i2139, 2016. (Johns Hopkins Study)
[8] Scheidl, S. "Handwriting recognition with TensorFlow: Build a simple OCR system using deep learning." *Towards Data Science*, 2019. [Online]. Available: https://towardsdatascience.com/handwriting-recognition-with-tensorflow-20811d6e7219