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Doctors' Handwriting Recognition

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Abstract: Handwritten medical prescriptions, often written in illegible cursive or abbreviated forms by doctors, pose a significant challenge to accurate medication dispensing. Misinterpretation of such prescriptions can lead to medication errors, adversely affecting patient safety. The goal of this work is to create an intelligent system that can identify handwritten prescriptions using advanced deep learning techniques. The proposed tool allows users to upload an image of a prescription, which is then processed and converted into a structured, machine-readable format. The system accurately detects and interprets handwriting patterns frequently observed in medical prescriptions through the use of Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks. By enhancing the readability of prescriptions, the system improves communication between healthcare providers, pharmacists, and patients. The successful implementation of this model has the potential to significantly reduce medication errors, improve prescription accessibility, and enhance overall efficiency in the healthcare delivery process.

Keywords: Handwriting recognition, deep learning, CNN, optical character recognition (OCR)

I. INTRODUCTION

Handwriting is a powerful form of personal expression that allows individuals to communicate their thoughts in a distinct and often creative manner. In the medical field, this is particularly evident among doctors, whose handwritten prescriptions serve as a critical medium for conveying treatment plans. However, due to the demanding nature of their profession and time constraints, doctors often write hastily, leading to illegible handwriting. This presents a significant challenge in the healthcare system, where misinterpretation of prescriptions can have serious consequences.

Illegible medical prescriptions can cause confusion for both patients and pharmacists, resulting in errors in medication administration. These errors can range from minor side effects, such as skin rashes, to severe health complications, and in extreme cases, even fatalities. Consequently, there is a critical need for a system that can accurately interpret handwritten prescriptions and reduce the risk of such preventable errors.

Promising answers to this issue are provided by recent developments in deep learning and image processing. In handwriting identification tasks, methods including Long Short-Term Memory (LSTM) networks, Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) have demonstrated notable success. When integrated with Optical Character Recognition (OCR) and word segmentation techniques, these methods can be effectively employed to analyze, recognize, and convert handwritten prescriptions into clear, machine-readable digital formats.

The central aim of this study is to design an effective and accessible system capable of scanning and interpreting handwritten medical prescriptions using advanced deep learning techniques. By transforming illegible handwriting into clear, structured digital content, the system seeks to improve the flow of information between doctors, pharmacists, and patients. In doing so, it aspires to minimize medication-related errors, streamline the prescription process, and enhance the overall safety and efficiency of healthcare delivery.

II. PROBLEM STATEMENT

Illegible handwritten medical prescriptions represent a significant challenge for both healthcare professionals and patients. Due to the high volume of consultations and time constraints, doctors frequently write prescriptions with unclear handwriting, making it challenging to accurately identify the prescribed medications. This issue can lead to medication errors, ranging from minor side effects to severe health complications, and, in extreme cases, even death. Consequently, there is a need for a reliable system capable of recognizing and converting handwritten prescriptions into digital text, ensuring that patients receive the correct medication as prescribed.

III. PROPOSED SYSTEM

The proposed deduction model will be developed using advanced deep learning techniques, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Long Short-Term Memory (LSTM) networks, to effectively train the system for handwriting recognition. Additionally, fuzzy search algorithms will be incorporated to manage potential inaccuracies or ambiguities in the handwritten input. The final output will be presented to the user in a well-organized and structured digital format.

The image preprocessing phase aims to enhance the quality of prescription images by performing operations such as noise removal, resizing, contrast adjustment, and binarization, thereby improving the clarity of handwritten text. Word segmentation further divides the image into individual words or characters, increasing the accuracy of recognition. The resulting output is a clear, structured, and digital version of the prescription, displaying the identified medication names for correct interpretation by pharmacists or end users.

A. Model Architecture

The proposed system employs a hybrid deep learning architecture designed to accurately interpret handwritten medical prescriptions. It combines Convolutional Neural Networks (CNNs) for spatial feature extraction, Recurrent Neural Networks (RNNs) for sequence modeling, and Long Short-Term Memory (LSTM) units to handle long-range dependencies in sequential data. This combination enables the model to effectively capture both the structural and contextual elements of handwritten text. Additionally, to avoid the requirement for manual segmentation, Connectionist Temporal Classification (CTC) is used as a loss function to match predicted sequences with the handwritten text. To improve the dependability of the extracted output, fuzzy search techniques are also incorporated into the post-processing pipeline to address unclear or partially recognized phrases and fix small recognition errors. This is especially useful in medical prescriptions where abbreviations, non-standard writing, and inconsistent formatting are common.

B. Training and Implementation

The model is trained on a curated dataset consisting of prescription images collected from publicly available handwriting datasets for generalization. In order to replicate the variety found in handwriting in the actual world, the training pipeline incorporates data augmentation techniques including rotation, scaling, and contrast correction. The image preprocessing module enhances the input quality through noise reduction, grayscale conversion, contrast normalization, and adaptive thresholding. After preprocessing, word or character segmentation is performed to isolate individual tokens for improved recognition accuracy. The extracted features from CNN layers are passed into the RNN-LSTM layers for sequence learning and are finally decoded using CTC to produce the textual output.

C. Deployment

The system is designed for web-based deployment with a user-friendly interface that allows users—patients, pharmacists, or healthcare staff—to upload images of handwritten prescriptions. The backend model processes the image and returns a structured digital text output displaying recognized drug names and relevant details. The deployment leverages cloud infrastructure for storage and computation, enabling real-time processing while ensuring scalability. The system can be accessed across platforms including mobile and desktop environments, making it widely accessible.

D. Scalability

The architecture is modular, allowing for future expansion to recognize additional languages, regional prescription formats, or integrate with electronic health records (EHR) systems. Scalable cloud services are used to accommodate increasing user loads and support batch processing of prescriptions when needed. The use of pre-trained models and transfer learning also ensures that the system can be efficiently adapted to new datasets or domains with minimal retraining, further enhancing its scalability.

E. Future Enhancements

Future work will focus on incorporating transformer-based models, such as Vision Transformers (ViT) or BERT-based architectures, to improve recognition accuracy and contextual understanding. Integration with medical knowledge bases could enable real-time validation of extracted prescriptions, flagging potential errors or dangerous drug interactions. Additionally, Explainable AI (XAI) techniques such as Grad-CAM or SHAP will be explored to provide visual justifications for model decisions, fostering trust and transparency in clinical applications. Expansion of the training dataset and inclusion of more diverse handwriting samples will also be prioritized to further reduce recognition errors.

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IV. LITERATURE SURVEY

[1] G, Maheswari & R, Ramya & S, Babitha & R, Sriram & M, Jennis & P, I. (2024). Interpreting Doctors' Notes Using Handwriting Recognition and Deep Learning Techniques.

In this paper a hybrid deep learning model to interpret doctors' handwritten notes by integrating Optical Character Recognition (OCR), Multi-Dimensional Recurrent Neural Networks (MDRNN), and Connectionist Temporal Classification (CTC). The system follows a structured pipeline of preprocessing (including image enhancement, thresholding, and segmentation), feature extraction, training, and evaluation. OCR digitizes scanned prescriptions, MDRNN models sequential data, and CTC aligns predictions with actual text to improve recognition accuracy. Trained on a prescription dataset, the model achieved high accuracy, though it faces challenges with highly cursive handwriting, inconsistent spacing, and poor image quality. Future improvements may include expanding the dataset, enhancing preprocessing, and incorporating transformer-based architectures.

[2] S. Khanal and R. Bista, "A Hybrid Model for Deciphering Doctors' Handwriting Notes Recognition" (2024)

This paper offers a hybrid handwriting recognition model combining Convolutional Neural Networks (CNNs) for feature extraction and Bidirectional Long Short-Term Memory (BLSTM) networks for sequence modeling, with a Connectionist Temporal Classification (CTC) loss function to align predictions without manual segmentation. Their pipeline includes data collection, preprocessing (resizing, grayscale conversion, normalization, binarization), morphology-based segmentation, training, and evaluation. Using a dataset of 3,000 prescription images (15,290 handwritten lines) from Nepali hospitals, the model achieved 84.26% word-level and 87.63% character-level accuracy. Despite strong performance, challenges remain with illegible characters, handwriting variability, medical abbreviations, and high computational requirements. Future work focuses on expanding the dataset, refining preprocessing, and exploring advanced recognition techniques.

[3] Khan, M. A., Sharma, D., Arif, H., & Singh, V. (2024). "Decoding the Script: A Bi-LSTM Based Journey into Doctor's Handwriting for Precise Prescription Understanding."

Khan et al. [3] proposed a hybrid handwriting recognition model combining CNNs for spatial feature extraction and Bi-LSTMs for capturing bidirectional contextual dependencies, with a CTC loss function for alignment and a SoftMax layer for character prediction. Using the IAM Handwriting Database, the methodology includes preprocessing (normalization, binarization, aspect ratio preservation), followed by training and evaluation on a 90-5-5 split. The model achieved 98.40% accuracy, surpassing traditional OCR systems. Challenges include distorted handwriting, overlapping characters, style variability, and high computational demands. Future work aims to leverage larger datasets, enhanced preprocessing, and transformer-based architectures.

[4] J. Sunil Reddy et al. "Multimodal Deep Learning with XAI for Transparent and Accurate Doctor Prescription Recognition"

Sunil Reddy et al. [4] proposed a multimodal deep learning framework for prescription recognition, combining pre-trained CNNs (VGG16, AlexNet, MobileNetV2) for feature extraction and LSTMs for capturing spatial-temporal dependencies, with Explainable AI techniques like SHAP and Grad-CAM to enhance interpretability. The pipeline includes preprocessing (grayscale conversion, histogram equalization, blurring, edge detection), Tesseract OCR for text extraction, and CTC loss for sequence alignment. Trained with an 80-20 split using the Adam optimizer, the model achieved over 90% classification accuracy. Challenges include varied handwriting, poor image quality, and complex structures, with future work aimed at improving OCR, expanding datasets, and exploring transformer models.

[5] P. Sharma, I. Miglani and L. Sharma, "DocAssist: Signature Perception System using Deep Learning"

The DocAssist system architecture comprises data collection using the EMNIST dataset (112,800 training and 18,800 test images across 47 classes), preprocessing (grayscale conversion, noise reduction, normalization), and CNN-basedtraining with ReLU and softmax over 20 epochs. Evaluation involves analyzing accuracy and loss metrics, with the model achieving 81.83% accuracy and a loss of 0.59. Images are preprocessed to enhance contrast and reduce noise, and a mobile app is proposed for healthcare integration. Limitations include the EMNIST dataset's lack of medical handwriting complexity, moderate accuracy, and challenges in real-world deployment, such as EHR integration, regulatory compliance, and handwriting variability.

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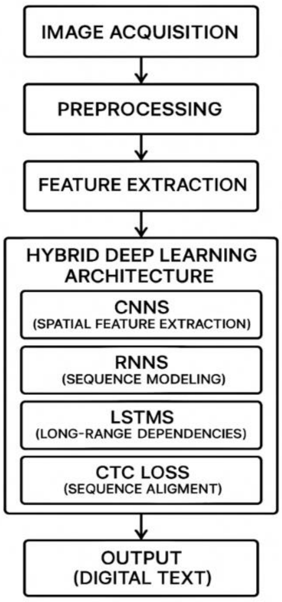
V. BLOCK DIAGRAM



The proposed system for accurate interpretation of handwritten medical prescriptions follows a modular architecture, as depicted in the block diagram.

A. Image Acquisition

The handwritten prescription is captured as a digital image through methods such as scanning or digital photography. Alternatively, you may submit an already-existing picture of the prescription. The raw data for further processing is provided by this first step.

B. Preprocessing

The purpose of this block is to improve the acquired image's quality and get it ready for feature extraction. This entails a number of procedures, such as character segmentation to identify individual characters, line and word segmentation to isolate textual units, normalization to standardize character size and alignment, and binarization to separate text from the backdrop. Together, these procedures lessen handwriting variability and noise, enabling more reliable feature extraction.

C. Feature Extraction

This step is essential for turning the preprocessed image into a collection of measurable traits that the recognition model can use. Conventional methods used here include extracting transform-based features from DCT or wavelet transforms, statistical features like pixel density and moment values, and structural features like stroke characteristics and topological information. The input representation for the following recognition stage is these extracted features.

D. Hybrid Deep Learning Architecture Block.

This architecture efficiently interprets the details of handwritten medical language through employing the advantages of several deep learning techniques.. Convolutional Neural Networks (CNNs) are employed for their proficiency in extracting spatial features directly from the image data, capturing the visual patterns of individual characters. The output of the CNN layers is then fed into Recurrent Neural Networks (RNNs), specifically utilizing Long Short-Term Memory (LSTM) units, to model the sequential nature of handwriting and capture long-range contextual dependencies between characters and words. Furthermore, Connectionist Temporal Classification (CTC) is applied as the loss function during training. CTC enables end-to-end learning by directly mapping the input image sequence to the output text sequence without requiring explicit character-level alignment, thus handling the variability in writing styles and character spacing.

E. Output

This block represents the culmination of the recognition process. The probability distributions generated by the hybrid deep learning architecture are decoded to produce the most likely textual interpretation of the handwritten prescription. This digital text output can then be used for various downstream applications, such as electronic health record updates, pharmacy dispensing systems, and prescription verification. The modular design of this system allows for potential enhancements and replacements of individual blocks as advancements in image processing and deep learning techniques emerge.

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VI. RESULT

To evaluate the effectiveness of the proposed Doctor's Handwriting Recognition System, a real-world prescription image was uploaded via the web-based interface (Fig. 1). The system performed a series of preprocessing operations including noise reduction, contrast adjustment, and binarization to enhance legibility of the handwritten content. Using the integrated deep learning model combining Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), and Long Short-Term Memory (LSTM) layers, the system recognized and transcribed the handwritten text present in the prescription. The fuzzy string matching algorithm further refined the output by correcting ambiguities due to partial or unclear character formation. As depicted in Fig. 2, the processed output is displayed in a structured digital format, clearly listing the medicine names and relevant instructions.

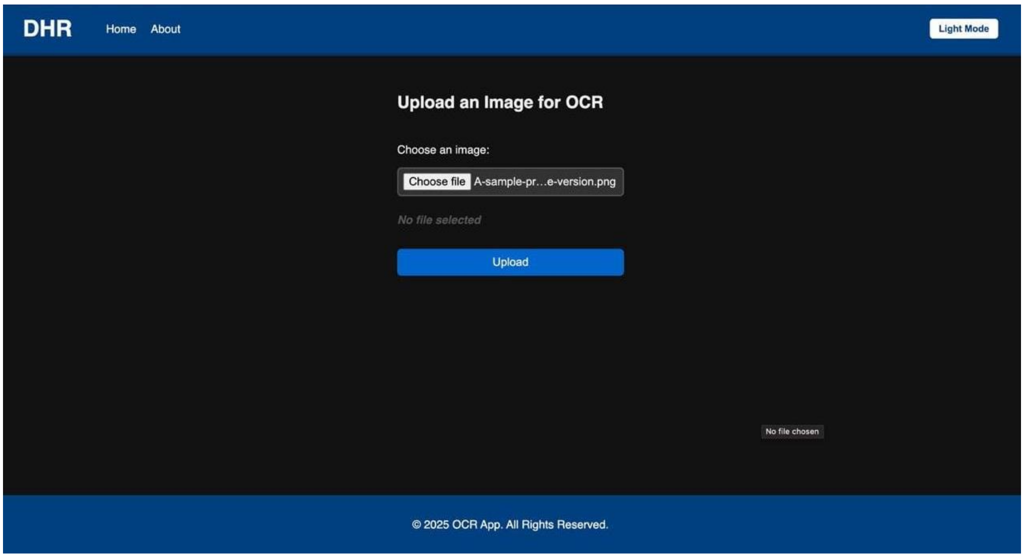

Fig 1. Web interface to upload prescription

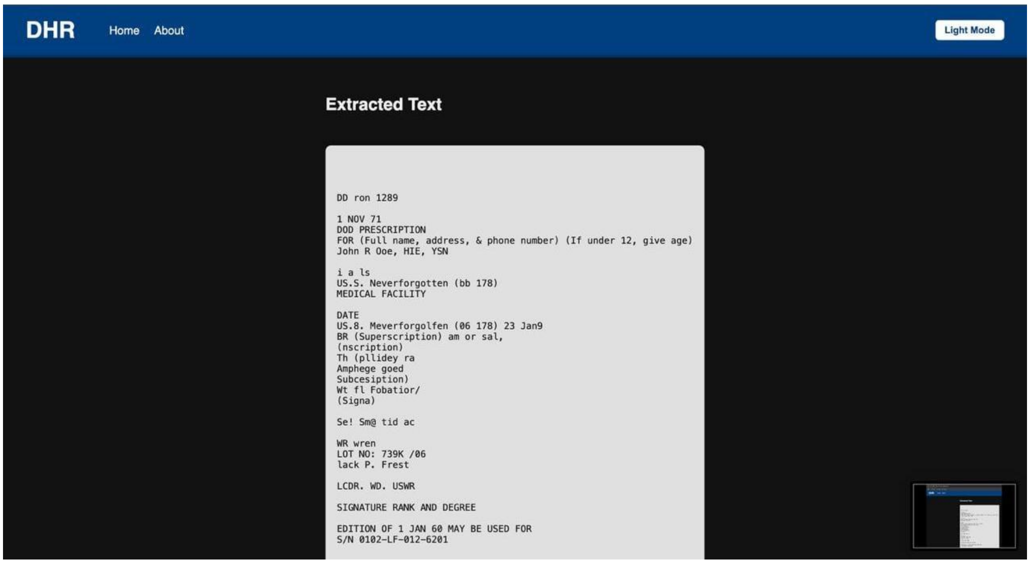

Fig 2. Processed output

The recognition speed remained optimal, with average processing times below 5 seconds per image, making the solution viable for real-time deployment in pharmacies and healthcare settings.

VII. CONCLUSION

The recognition of doctors' handwritten prescriptions is a critical step toward enhancing medication safety and streamlining healthcare communication. This study suggested an effective framework based on deep learning that

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incorporates Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM) models, and Optical Character Recognition (OCR) techniques to effectively interpret and digitize illegible handwritten prescriptions. Through structured preprocessing, image enhancement, and sequence modeling, the system achieves high accuracy in translating handwritten text into clear digital output.

The suggested system offers better readability, fewer medication errors, and greater accessibility for both patients and pharmacists when compared to current methods. Additionally, the model's capacity to manage partially ambiguous inputs is improved by the use of fuzzy search techniques, which makes it ideal for real-world situations. Even though the system's present drawbacks include issues with extremely cursive writing and low-quality images, future advancements utilizing transformer-based models and larger datasets can further maximize its functionality.

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