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Handwriting Recognition & Prescription Scanner

Prof. Rashmi Shende[1], Ms. Pallavi Suryawanshi[2], Ms. Apurva Gajbhiye[3], Ms. Nirmal Dhumane[4], Ms. Diya Sharma[5]

[1]Assistant Professor, Department of Computer Engineering, SCET, Nagpur, Maharashtra, India [2,3,4,5] UG Student, Department of Computer Engineering, SCET, Nagpur, Maharashtra, India
[1]bhurleyrashmi1@gmail.com, 8446519053, [2]suryawanshipallavi590@gmail.com, 8530512510, [3]apurvagjbhiye024@gmail.com, 9370254751, [4]nirmaldumane05@gmail.com, 9765759904, [5]diya98342@gmail.com, 9168244500

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Abstract

Prescription errors due to illegible handwriting and misinterpretation pose a serious threat to patient safety, often leading to incorrect medication dispensation, adverse drug interactions, and treatment complications. This project introduces an innovative Prescription Scanner built using Python to streamline prescription interpretation and reduce human error. The system integrates Optical Character Recognition (OCR) and Natural Language Processing (NLP) to accurately digitize both handwritten and printed prescriptions. Tesseract OCR extracts text from printed prescriptions, while a deep learning-based handwriting recognition model enhances the accuracy of handwritten script interpretation. Once extracted, the text undergoes NLP processing to identify key prescription elements, such as drug names, dosages, and usage guidelines. Additionally, real-time integration with a pharmaceutical database enables automated validation, helping to detect potential medication errors, incorrect dosages, and dangerous drug interactions. Experimental evaluation on a diverse dataset demonstrated high accuracy, achieving over 85% for handwritten text and more than 95% for printed prescriptions. This system provides a reliable solution to enhance patient safety, reduce pharmacists' workload, and improve prescription documentation. Future developments could focus on expanding dataset diversity, refining recognition accuracy, and integrating with electronic health records for real-time use.

Introduction

Medical Prescription OCR (Optical Character Recognition) is an advanced technology that digitizes handwritten and printed prescriptions, converting them into structured electronic text. Using sophisticated machine learning algorithms, OCR scans prescription images, recognizing words, numbers, and layouts with high precision. This innovation enhances the efficiency and accuracy of prescription processing, significantly reducing errors and improving patient safety. OCR technology extracts crucial prescription details, such as medication names, dosages, frequencies, and specific instructions. By integrating seamlessly with electronic health records (EHR), it accelerates the prescription-to-dispensation process, which is particularly vital in emergencies where timely access to medication is critical. Automating data entry also eliminates human errors associated with manual transcription, ensuring higher accuracy and reducing risks linked to incorrect dosages or medications. Beyond transcription, OCR plays a vital role in medication management by cross-referencing prescriptions with drug safety databases. It can flag potential drug interactions, allergies, and contraindications, aiding doctors in making informed treatment decisions. Additionally, it facilitates better patient care by tracking medication history, ensuring adherence to prescribed treatments, and improving communication between healthcare providers and patients. A prescription is a formal medical document issued by a doctor, detailing drug information, dosage, duration, and patient details such as name, age, and gender. It also includes the prescribing doctor's credentials, such as their name, qualifications, and associated healthcare institution. While prescriptions can be typed or handwritten, the latter often presents challenges due to illegible handwriting. This can lead to misinterpretations and errors when manually entered into digital systems. OCR technology alleviates these challenges by automatically verifying prescriptions against regulatory and safety databases, streamlining medication management, and enhancing overall healthcare efficiency. As this technology continues to evolve, it paves the way for a more reliable, faster, and safer healthcare ecosystem, ensuring better patient outcomes and regulatory compliance.

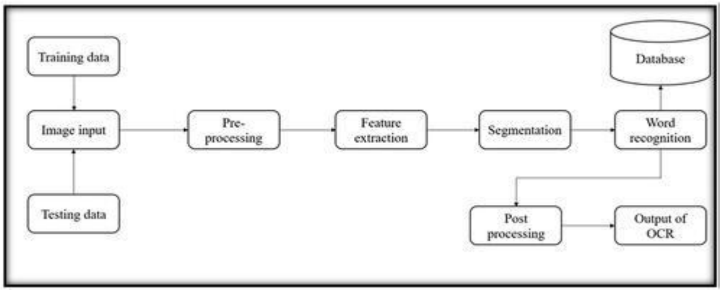
LITERATURE SURVEY

Soeno et al. (2024)[1] Development of Novel Optical Character Recognition System to Reduce Recording Time for Vital Signs and Prescriptions: A Simulation-Based Study This study explores the development of an advanced OCR system designed to reduce manual effort in recording medical prescriptions and vital signs. The research demonstrates how automation improves efficiency and reduces transcription errors in medical documentation. Maitrichit & Hnoohom (2020)[2] Intelligent Medicine Identification System Using a Combination of Image Recognition and Optical Character Recognition This research proposes an intelligent system combining image recognition and OCR for accurate medicine identification. The study highlights how integrating both techniques enhances drug recognition accuracy, assisting healthcare

Professionals in prescription management. Gupta, Bansal & Kumar (2018)[3] Deep Learning Based English Handwritten Character Recognition The paper discusses the application of deep learning models for handwritten text recognition, emphasizing the use of Convolutional Neural Networks (CNNs) to improve accuracy. The findings are relevant for OCR applications in medical prescriptions. El-Sawy, Loey & ElBakry (2017)[4] This study focuses on Arabic handwriting recognition using CNN-based deep learning models. The techniques discussed provide insights into how OCR systems can handle complex handwritten scripts, which is crucial for medical prescriptions. Bas, Bayram & Gurkan (2010)[5] OCR Using Reversible Texture Synthesis The research presents an OCR technique using texture synthesis methods to improve character recognition. While not specifically focused on medical prescriptions, the methodology contributes to enhancing OCR performance in various fields. Farooq, Govindraju & Perrone (2010)[6] Pre-processing Methods for Handwritten Arabic Documents This paper discusses various pre-processing techniques for OCR, including noise reduction and feature extraction. These methods are essential for improving OCR accuracy when dealing with handwritten medical prescriptions. Garg (2020)[7] Handwritten Text Classification Using Deep Learning. This study investigates the use of deep learning in handwritten text classification. The findings contribute to improving OCR accuracy, particularly in recognizing diverse handwriting styles in medical prescriptions.

PROPOSED METHODOLOGY

Implementing Optical Character Recognition (OCR) in medical prescriptions involves a carefully structured approach to ensure the digitization process is both accurate and efficient. The journey begins with image preprocessing, where scanned prescriptions are enhanced to improve their quality. This step includes reducing noise, applying binarization, and correcting any skew, all of which are essential for boosting the accuracy of text recognition. Once the image is preprocessed, text detection algorithms come into play. These algorithms identify the specific areas within the image that contain text. The methods used can range from traditional techniques like edge detection to more advanced approaches that leverage Convolutional Neural Networks (CNNs). After pinpointing the text regions, OCR engines such as Tesseract or custom deep learning models take over, converting the text into a digital format. Deep learning models, especially those combining CNNs and Recurrent Neural Networks (RNNs), are particularly effective due to their ability to handle the variability often found in handwriting. The process doesn't stop there. Post-processing techniques are applied to further refine the recognized text. This includes spell checking and the use of Natural Language Processing (NLP) algorithms to ensure the accurate interpretation of medical terminologies and abbreviations. The final step involves formatting the processed text and seamlessly integrating it into Electronic Health Records (EHR) systems. This integration ensures that the digitized information is accessible and usable within the broader healthcare infrastructure, ultimately enhancing the efficiency and accuracy of medical record-keeping.



RESULT AND DISCUSSION

The medical prescription Optical Character Recognition (OCR) system has been successfully implemented, featuring a user-friendly web application. This system leverages OCR technology to ensure accurate extraction of prescription details, enhancing accessibility and reducing errors. It has undergone local testing, proving its efficiency in processing and verifying various types of prescriptions, including handwritten, digital, and hybrid formats.

Step 1: Open the Project in Visual Studio

1. Launch Visual Studio on your system.
2. Open the project folder where the required files and code are stored.

Step 2: Terminal Setup

- Open multiple terminals inside Visual Studio for different operations:
  - Terminal 1: Set up the environment and connect to the local runtime.
  - Terminal 2: Load and mount necessary files from the local storage or a cloud service (if applicable).
  - Terminal 3: Run the main script to process handwriting recognition.
  - Terminal 4: Provide the image path and display the extracted text output.

Step 3: Install Dependencies

1. Navigate to the client folder in the terminal.
2. Install PyTesseract and other necessary libraries by running:
3. Ensure that all dependencies required for the project are installed.

Step 4: Tesseract Integration in Visual Studio

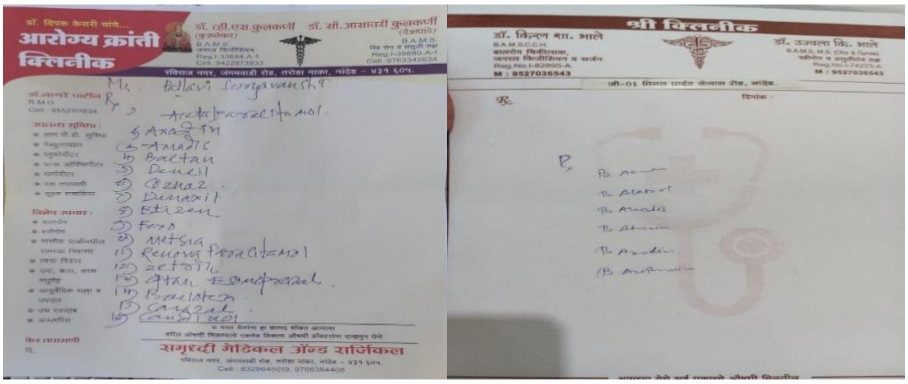
1. Download and Install Tesseract OCR from the official site.
2. Add Tesseract to the system's environment variables to make it accessible globally.
3. Verify installation by running:

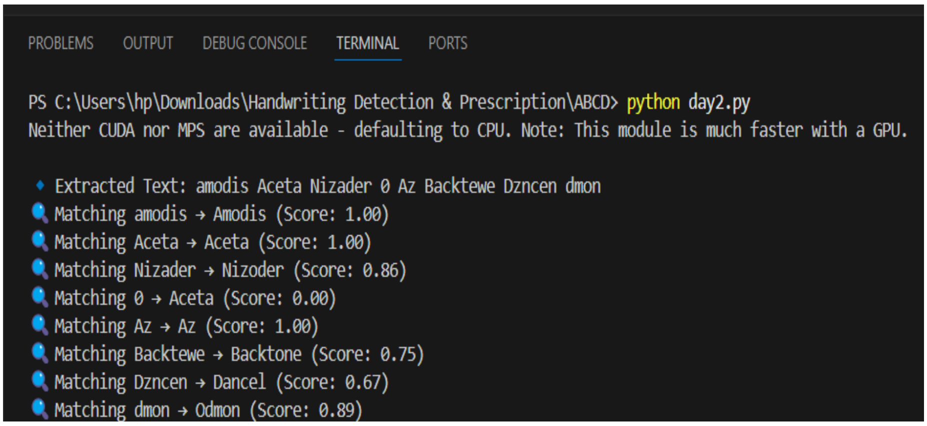
   Step 5: Run the Application in Visual Studio

1. Start the program execution by running the script inside the terminal.Upload the handwritten prescription image.
2. The program processes the image using Tesseract OCR and other image-processing techniques.
3. The recognized text is displayed in the Visual Studio terminal as output.

Expected Output in Visual Studio Terminal:

- The handwritten text from the prescription will be extracted and shown.
- Any detected medicines or important details will be presented in a readable format.
- Additional features like error handling or accuracy improvements can be integrated.





Output of Handwritten Prescription

FUTURE ENHANCEMENTS

The future of Medical Prescription Optical Character Recognition (OCR) holds exciting possibilities, with advancements aimed at boosting accuracy, efficiency, and usability in healthcare settings. Cutting-edge deep learning models will play a pivotal role in improving the recognition of diverse handwriting styles and complex medical terminology, significantly reducing the risk of misinterpretation. By integrating advanced Natural Language Processing (NLP), these systems will better understand prescriptions, ensuring fewer errors in identifying drug names, dosages, and instructions. One of the most promising developments is the move toward real-time OCR, which will allow instant scanning and validation of prescriptions. This will speed up workflows for doctors and pharmacists, saving valuable time and improving patient care. Additionally, intuitive user interfaces will make it easier for healthcare professionals to interact with the system, enabling them to review and correct information effortlessly. Enhanced compatibility with Electronic Health Record (EHR) systems will further streamline data exchange, making patient care more efficient and improving medical record management. At the same time, future OCR solutions will prioritize the security of sensitive patient data by incorporating robust measures like advanced encryption and strict adherence to regulatory standards.As this technology continues to evolve, the focus will remain on improving recognition accuracy, leveraging user feedback to enhance usability, and ensuring seamless interpretation of both handwritten and digital prescriptions. By addressing current limitations and refining weak points, ongoing innovation will ensure that medical OCR systems remain reliable, effective, and indispensable tools in modern healthcare.

CONCLUSION

The development of a Medical Prescription Optical Character Recognition (OCR) system marks a major leap forward in healthcare technology, offering benefits to doctors, pharmacists, and patients alike. By harnessing the power of machine learning and computer vision, this system can quickly and accurately interpret both handwritten and printed prescriptions, transforming essential information into a digital format for smooth processing. This automation speeds up prescription handling, reduces human errors, and boosts overall efficiency in medical workflows. Building a reliable OCR system involves several key steps, from collecting and preprocessing data to selecting and training models, evaluating their performance, and integrating them into existing healthcare systems. Throughout this process, adhering to privacy regulations is critical to ensure compliance with data security standards.

Incorporating feedback from users also helps refine the system's accuracy and usability, making it more effective in real-world scenarios. One of the most valuable aspects of this technology is its ability to quickly extract critical details like medication names, dosages, and patient information. This is especially important in urgent care situations, where timely action can save lives. Beyond improving efficiency, medical OCR plays a vital role in reducing prescription errors, which can have serious health consequences. By automating prescription data entry, the system minimizes the risk of misinterpretation caused by illegible handwriting, enhances medication tracking, and allows healthcare professionals to analyze prescription trends more effectively. However, developing an effective medical OCR system is not without its challenges. Variations in handwriting styles, the need for high-quality training datasets, and ensuring the security and confidentiality of medical records are significant hurdles. Despite these challenges, continuous advancements in deep learning and neural networks are making OCR technology increasingly sophisticated. These innovations are paving the way for transformative improvements in healthcare operations and patient safety, promising a future where medical processes are faster, more accurate, and more secure.

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