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AI-Powered Prescription Decoder and Generic Medicine Recommender

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Abstract

Handwritten medical prescriptions are often difficult to interpret due to illegible handwriting, inconsistent formats, and the use of medical abbreviations. Misinterpretation of prescriptions can lead to medication errors, incorrect dosage, and serious health risks. Additionally, patients are often unaware of affordable generic alternatives to prescribed branded medicines, resulting in increased healthcare expenses. This project presents an AI-Powered Prescription Decoder and Generic Medicine Recommender, an intelligent system designed to automatically extract and interpret handwritten prescription information and provide cost-effective and safe medication alternatives. The system integrates deep learning-based OCR models such as CRAFT (Character Region Awareness for Text Detection) and CRNN (Convolutional Recurrent Neural Network) to detect and recognize handwritten text from prescription images. The extracted text is processed using NLP techniques to identify key medical entities such as medicine names, dosage, frequency, and duration. The system then maps recognized medicines to standardized drug databases such as RxNorm to recommend equivalent generic medicines. Additional features include price comparison between branded and generic drugs, side effect and drug interaction warnings using SIDER, and confidence score display to indicate OCR reliability.

Keywords: AI, Prescription Decoder, Handwritten Text Recognition, CRAFT, CRNN, LLM, Generic Medicine Recommendation, OCR, NLP, Drug Validation, Medical Data Processing.

1. Introduction

Medical prescriptions serve as a critical communication medium between healthcare providers and patients. They contain essential information such as medicine names, dosage, frequency, and duration of treatment. However, handwritten prescriptions often pose significant challenges due to poor handwriting, use of abbreviations, and lack of standardization. These issues can result in incorrect interpretation, leading to serious consequences for patient safety. In addition to readability issues, another major concern in healthcare is the high cost of branded medicines. Many patients are unaware that generic medicines with the same active ingredients are available at significantly lower prices. The lack of awareness and absence of automated recommendation systems contribute to unnecessary financial burden on patients. With advancements in Artificial Intelligence, particularly in Deep Learning and Natural Language Processing, it is possible to automate the interpretation of handwritten text and extract meaningful information. This project leverages these technologies to build an intelligent system that not only decodes prescriptions but also enhances them with additional features such as generic medicine recommendation, price comparison, and safety alerts.

1.1 Problem Definition

Handwritten prescriptions are prone to misinterpretation due to illegible handwriting, inconsistent terminology, and varying prescription formats. Manual transcription by pharmacists increases the chances of human error and delays in dispensing medications. Moreover, patients are often unaware of cheaper generic alternatives to prescribed branded drugs, leading to increased medical costs. Traditional OCR methods are insufficient for recognizing complex handwritten text and medical jargon, while manual validation and correction are time-consuming. There is a lack of an integrated system that can automatically read, process, and interpret prescriptions accurately while ensuring data integrity and recommending generic equivalents. Therefore, there is a need for an intelligent AI-driven system that can decode handwritten prescriptions accurately using advanced computer vision and deep learning techniques, process the extracted text semantically using natural language models, and suggest suitable generic medicines to ensure accuracy, affordability, and accessibility in healthcare services.

1.2 Existing Systems

Existing tools for prescription digitization and medicine recommendation have useful capabilities but also important limitations. General OCR tools like Google Lens can extract text from images, including some cursive handwriting, but they lack medical understanding and cannot interpret abbreviations or validate prescriptions. Healthcare platforms such as Practo and 1mg provide detailed drug information and online ordering services, but they require manual input of medicine names, making them less effective for unreadable prescriptions. Similarly, PharmEasy allows prescription uploads, but it depends on human pharmacists to read and verify prescriptions, leading to delays and reduced scalability. OCR solutions like Microsoft Read API and Tesseract OCR are strong in extracting printed text and partially handling handwriting, but they struggle with complex handwritten medical scripts and domain-specific language such as abbreviations. Overall, these systems either lack automation, medical intelligence, or scalability, highlighting the need for an AI-driven solution that integrates OCR with domain-specific understanding and recommendation capabilities.

1.3 Proposed System

AI-Powered Prescription Decoder and Generic Medicine Recommender is a fully automated system designed to decode handwritten prescriptions and suggest cost-effective generic medicines. The system combines computer vision, deep learning, and natural language processing to achieve accurate text recognition and intelligent data interpretation. The process begins with image preprocessing, where noise removal and grayscale conversion improve text clarity. The system then uses CRAFT to detect handwritten text regions. These regions are processed using CRNN to convert them into digital text. A LLM is applied to correct OCR errors and structure the extracted information. The system identifies key prescription details such as medicine name, dosage, and frequency. A validation layer cross-checks the extracted data with medical databases for accuracy. It then recommends generic medicines using sources like RxNorm or openFDA. The system ensures that recommended drugs have the same active ingredients as branded ones. Finally, an interactive user interface allows users to upload prescriptions and view structured outputs with generic alternatives.

2. Literature Survey

Application of Generative AI Models for Accurate Prescription Label Identification and Information Retrieval for the Elderly in Northern East of Thailand *by Parinya Thetbanthad, et al.* This study introduces a novel AI-driven approach to support elderly patients in Thailand with medication management, focusing on accurate drug label interpretation. Two model architectures were explored: a Two-Stage OCR and LLM pipeline combining EasyOCR with Qwen2-72b-instruct and a Uni-Stage Visual Question Answering (VQA) model using Qwen2-72b-VL. Both models operated in a zero-shot capacity, utilizing Retrieval-Augmented Generation (RAG) with DrugBank references to ensure contextual relevance and accuracy.

Pedi-Medi-Instructor: Pediatric Medicine Information and Instruction System *by G. Kaliyaperumal et al.* This study proposes a two-part system to enhance medication safety and user experience, especially for pediatric patients. The Data Acquisition System for Medicine Identification (DAMI) trains an AI model with comprehensive images of medications captured from various angles. The Medicine Identification and Instruction System (MIIS) leverages this model to identify medications and prescriptions, even with imperfect placement, and delivers audio instructions on usage.

Advancing Multilingual Handwritten Numeral Recognition With Attention-Driven Transfer Learning *by A. Fateh et al.* As deep learning continues to evolve, we have observed huge breakthroughs in the fields of medical imaging, video and frame generation, optical character recognition (OCR), and other domains. In the field of data analysis and document processing, the recognition of handwritten numerals plays a crucial role. This work has led to remarkable changes in OCR, historical handwritten document analysis, and postal automation.

Handwriting Enhancement: Recognition-Based and Recognition-Independent Approaches for On-Device Online Handwritten Text Alignment *by K. Korovai et al.* In this paper, we propose and analyze two approaches aimed at enhancing the legibility of handwriting by straightening the written content while maintaining the user's writing style. The first method is recognition-based and relies on the results of our online handwriting recognizer and heuristic rules of alignment designed for each character. The second method is recognition-independent and utilizes HRNN for handwriting alignment, applying it directly to input strokes without the need for recognition.

Image-Based Extraction of Prescription Information using OCR-Tesseract *by Mahesh Ponnurua et al.* The paper presents advancements in healthcare data capture through the application of image-based extraction techniques, which include sophisticated image processing techniques such as resizing and adaptive thresholding, for prescription information. This research explores the utilization of image processing and OCR methodologies to extract prescription information accurately. By converting prescription documents into image format and employing OCR algorithms, the text content is extracted and parsed for critical details such as medication names, dosages, and patient instructions.

Leveraging Deep Learning with Multi-Head Attention for Accurate Extraction of Medicine from Handwritten Prescriptions *by Usman Ali et al.* This paper presents a robust method for extracting medicine names using a combination of Mask R-CNN and TrOCR with Multi-Head Attention and Positional Embeddings. A novel dataset, featuring diverse handwritten prescriptions from various regions of Pakistan, was utilized to f ine-tune the model on different handwriting styles. The Mask R-CNN model segments the prescription images to focus on the medicinal sections, while the TrOCR model, enhanced by Multi-Head Attention and Positional Embeddings.

HTR-VT: Handwritten Text Recognition with Vision Transformer *by Yuting Li†a et al.* This study introduces a data-efficient ViT method that uses only the encoder of the standard transformer. We find that incorporating a Convolutional Neural Network (CNN) for feature extraction instead of the original patch embedding and employ Sharpness-Aware Minimization (SAM) optimizer to ensure that the model can converge towards flatter minima and yield notable enhancements. Furthermore, our introduction of the span mask technique, which masks interconnected features in the feature map, acts as an effective regularizer.

TrOCR: Transformer-Based Optical Character Recognition with Pre-trained Models *by Minghao Li et al.* In this paper, we propose an end-to-end text recognition approach with pre-trained image Transformer and text Transformer models, namely TrOCR, which leverages the Transformer architecture for both image understanding and wordpiece-level text generation. The TrOCR model is simple but effective, and can be pre-trained with large-scale synthetic data and fine-tuned with human-labeled datasets. Experiments show that the TrOCR model outperforms the current state-of-the-art models on the printed, handwritten and scene text recognition tasks.

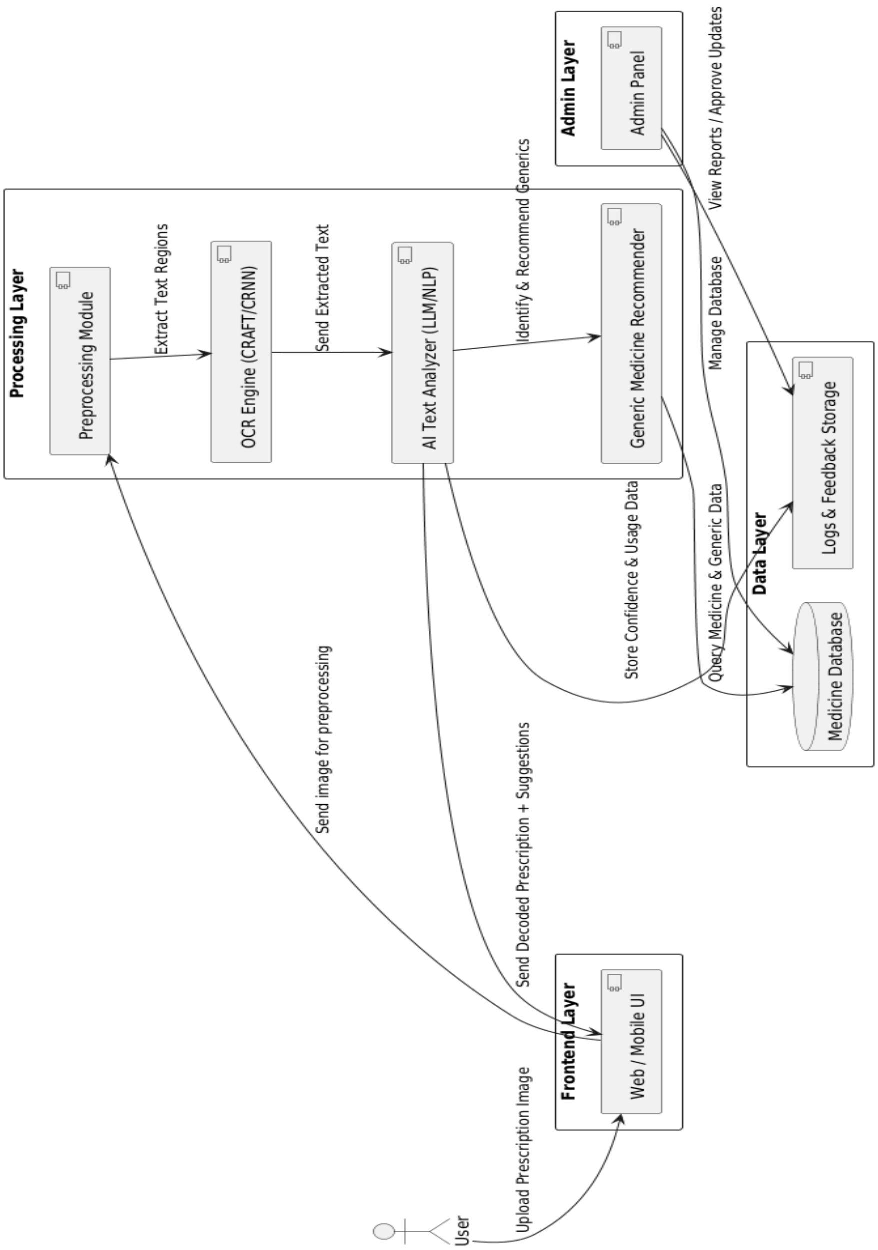
PHTI: Pashto Handwritten Text Image base for Deep Learning Applications *by IBRAR HUSSAIN et al.* Document Image Analysis(DIA) is one of the research areas of AI that converts document images into machine-readable codes. In DIA systems, OCR plays a key role in digitizing document images. The output of an OCR system is further used in many applications including, NLP, Sentiment Analysis, Speech Recognition, and Translation Services. However, standard datasets are an essential requirement for the development, evaluation and comparison of different text recognition techniques. Pashto is one of such low resource languages that lacks availability regarding standard dataset of handwritten text.

DeblurGAN-CNN: Effective Image Denoising and Recognition for Noisy Handwritten Characters *by SARAYUT GONWIRAT et al.* This research proposes a method that learns from the noisy handwritten character images and synthesizes clean character images using the robust deblur generative adversarial network (DeblurGAN). Second, we combine the DeblurGAN architecture with a CNN, called DeblurGAN-CNN. Subsequently, two state-of-the-art CNN architectures are combined with DeblurGAN, namely DeblurGAN-DenseNet121 and DeblurGAN-MobileNetV2, to address many noise problems and enhance the recognition performance of the handwritten character images. Finally, the DeblurGAN-CNN could transform the noisy characters to the new clean characters and recognize clean characters simultaneously.

3. Design Methodology of AI-Powered Prescription Decoder and Generic Medicine Recommender

3.1 System Architecture of AI-Powered Prescription Decoder and Generic Medicine Recommender

Figure 1: System Architecture diagram of AI-Powered Prescription Decoder and Generic Medicine Recommender



As shown in Figure 1:

1. Preprocessing Layer

- Noise Removal: Removes unwanted artifacts using Gaussian/median filtering.
- Grayscale Conversion: Simplifies the image to single-channel intensity for faster processing.

- Image Normalization: Standardizes image size and orientation for consistent input across models.

2. Text Detection and Recognition Layer

- CRAFT (Character Region Awareness for Text Detection): Detects and localizes handwritten text regions in the prescription image.
- CRNN (Convolutional Recurrent Neural Network): Recognizes the text within detected regions and converts it into digital, machine-readable text.

3. Language Processing Layer

- Error Correction: Fixes OCR-related spelling or syntax errors.
- Entity Extraction: Identifies important entities like drug name, dosage, frequency, and duration.
- Data Structuring: Formats the corrected output into a structured tabular representation for downstream modules.

4. User Interface Layer

- Prescription Upload Module: Allows users to upload prescription images (JPG/PNG/PDF).
- Result Display Module: Presents extracted text, corrected prescription data, and recommended generic medicines in an organized layout.

5. Validation and Recommendation Layer

- Medicine Validation: Matches detected medicines with verified entries in the medical database.
- Generic Recommendation: Identifies equivalent generic medicines based on active ingredients and therapeutic class.

6. Data Layer

- Prescription Database: Stores uploaded prescriptions, extracted text, and results.
- Drug Information Database: Contains verified brand and generic medicine data with mapping relationships.

3.2 Class Diagram of AI-Powered Prescription Decoder and Generic Medicine Recommender

Figure 2: Class diagram of AI-Powered Prescription Decoder and Generic Medicine Recommender

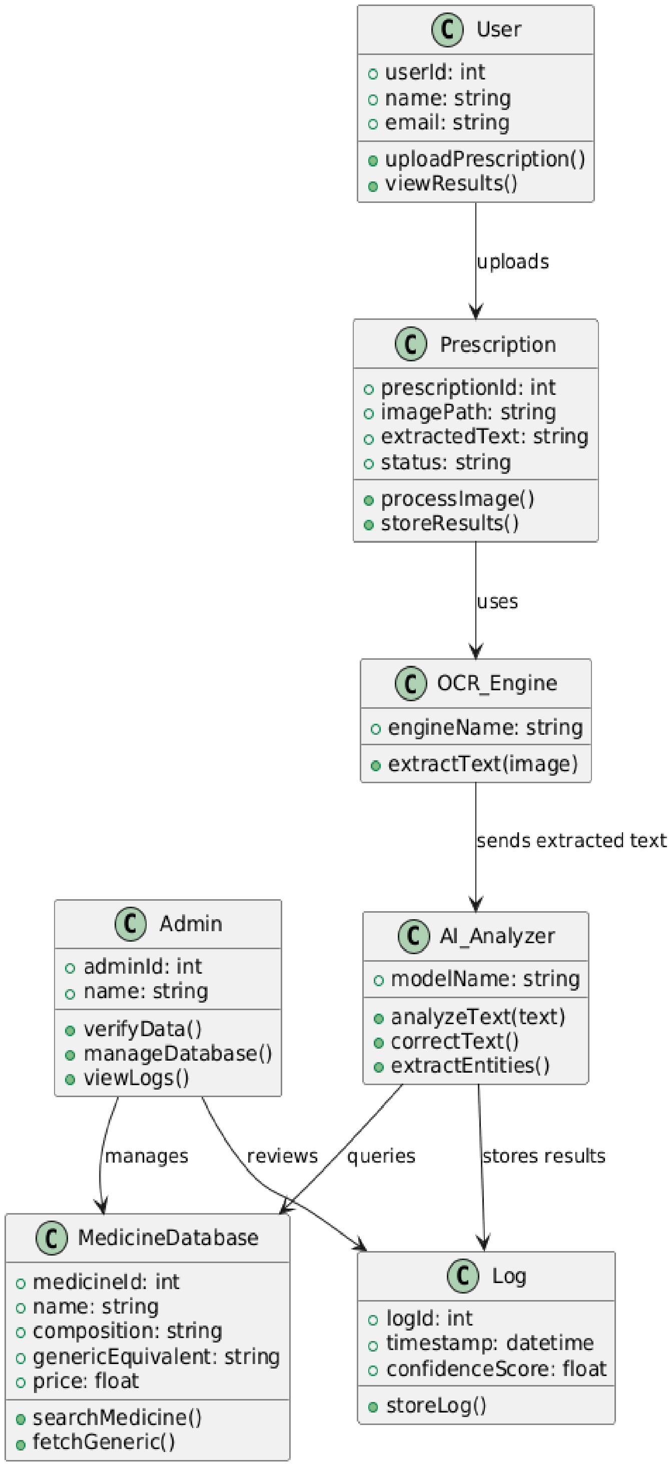


Figure 2 presents the class diagram of the AI-Powered Prescription Decoder and Generic Medicine Recommender system, showing the main classes, their functions, and relationships. The system revolves around the user uploading prescriptions, which are processed by an AI model to decode text and generate generic medicine suggestions. The User class manages registration, login, uploading prescriptions, and viewing decoded results and recommendations. The Admin class oversees system operations, verifies data, manages users, and updates the drug database. The Prescription class handles storing uploaded images and saving decoded text after processing. The core processing is performed by the AMLRuleEngine class, which decodes prescriptions using OCR, extracts drug details through NLP, and recommends generic alternatives. The DrugDatabase class acts as a repository for branded and generic medicine information and supports data updates. The Recommendation class generates reports and displays suggested medicines to users. Together, these classes form an integrated system that automates prescription decoding, ensures data accuracy, and provides cost-effective medicine recommendations.

3.3 Activity Diagram of AI-Powered Prescription Decoder and Generic Medicine Recommender

Figure 3: Activity diagram of AI-Powered Prescription Decoder and Generic Medicine Recommender

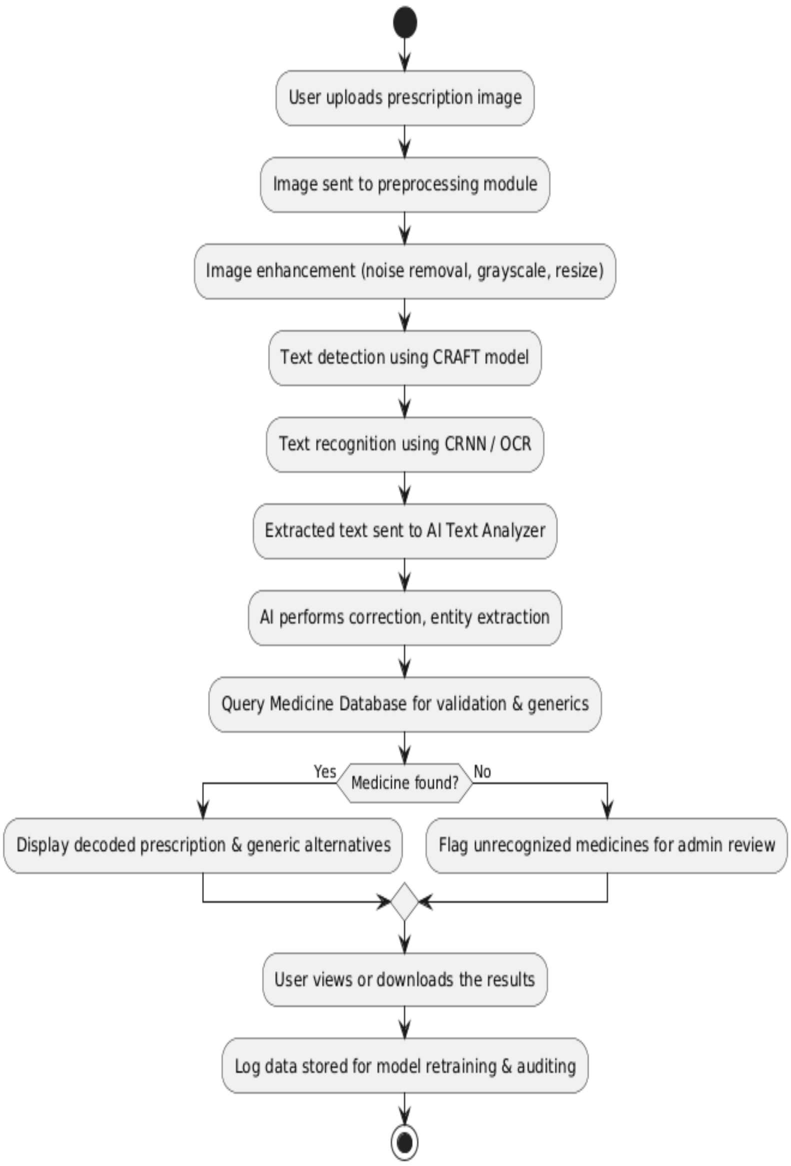


Figure 3 illustrates the end-to-end workflow of the AI-Powered Prescription Decoder and Generic Medicine Recommender system, starting from user interaction to final output generation. The process begins with the user uploading a prescription image or PDF, which is then preprocessed using techniques like noise removal, skew correction, and contrast enhancement to improve readability. If the image quality is poor, the system prompts the user to upload a clearer version. The preprocessed image is passed to the OCR engine, where text is extracted and forwarded to the NLP module to identify key medical entities such as drug names, dosage, frequency, and notes. The system then cross-references extracted medicines with drug databases like RxNorm or OpenFDA to find generic alternatives, composition, and pricing details. If a medicine is not recognized, it is flagged for manual review to avoid errors. A similarity matching algorithm ensures accurate mapping between branded and generic drugs. The results, including alternatives, cost comparison, and safety details, are displayed on the user dashboard. Finally, all extracted data and recommendations are securely stored, and a summary report is generated for future reference, ensuring transparency, traceability, and cost-effective healthcare decisions.

4. Implementation of AI-Powered Prescription Decoder and Generic Medicine Recommender

This chapter describes the practical implementation of the AI-Powered Prescription Decoder system. It explains how different software modules such as image processing, text detection, text recognition, and natural language processing work together to decode handwritten prescriptions and recommend generic medicines.

4.1 System Execution Overview

The core of the system is a Python-based backend application developed using Flask, which operates on a local server environment. When the application starts, it initializes all necessary libraries, including OpenCV for image processing, PyTorch-based deep learning models for OCR, and NLP components for text understanding. The system follows a pipeline-based architecture where each module is responsible for a specific task. The frontend interface allows users to upload prescription images, which are then processed by the backend system in a sequential manner. The application continuously executes the following high-level steps:

- Accept prescription image input from user interface,
- Perform image preprocessing to enhance quality,
- Detect text regions using deep learning models and Recognize handwritten text,
- Apply semantic correction and structuring using NLP,
- Validate medicines using a drug database,
- Generate generic medicine recommendations,
- Display structured output to the user

4.2 Prescription Image Processing and Text Extraction

This module detects obstacles in front of the user and announces what they are and how far away they are. A USB camera, accessed via OpenCV, streams live video to the Raspberry Pi; at startup, the program opens the camera, sets resolution and frame rate, then continuously captures frames and forwards them to the detection model in real time. A pre-trained YOLO model from Ultralytics is loaded once and reused for every frame, returning bounding boxes, class labels, and confidence scores. Only high-confidence detections are kept, and labels such as “person”, “chair”, or “vehicle” are used to generate meaningful spoken messages instead of generic “obstacle” alerts. An HC-SR04 ultrasonic sensor complements YOLO by providing accurate physical distance. The Raspberry Pi triggers the sensor with a short pulse and measures the echo time to compute distance in centimetres, updating this reading in parallel with the camera loop. In each cycle, the system fuses the YOLO result and ultrasonic distance: if at least one object is detected and the distance is below a safety threshold (for example, 75 cm), the most confident object is selected, a sentence like “Person ahead, 60 centimetres” is generated and spoken through earphones, and the vibration motor is driven with a pattern that depends on how close the obstacle is.

The prescription decoding module is responsible for extracting textual information from handwritten prescription images. The system first acquires images uploaded through the web interface and processes them using OpenCV to improve readability before passing them to deep learning models. Preprocessing plays a critical role in enhancing OCR performance and includes steps such as grayscale conversion to reduce computational complexity, noise removal using Gaussian blur to eliminate distortions, adaptive thresholding to improve contrast between text and background, and image resizing and normalization to match model input requirements. For text detection, the system uses CRAFT, which identifies individual character regions and links them to form meaningful text segments. The model generates heatmaps representing character probability and relationships between characters, producing bounding boxes around detected text regions. These regions are then passed to the recognition stage, where CRNN is used to convert image segments into digital text. CRNN combines convolutional layers for feature extraction, recurrent layers such as LSTM for sequence modeling, and a CTC layer for decoding, enabling recognition of variable-length handwritten text without explicit segmentation. Finally, the recognized text from different regions is aggregated and formatted into a structured form. This involves sorting text based on spatial alignment, merging fragmented words and lines, and preserving the layout of the prescription, resulting in a coherent textual representation.

4.3 Semantic Processing and Data Structuring

The semantic processing module enhances the quality and usability of the extracted text using Natural Language Processing techniques. Since OCR output may contain errors, a Large Language Model (LLM) is used to refine the extracted text by correcting spelling errors, expanding medical abbreviations, and removing noise introduced during OCR. This significantly improves the readability and accuracy of the decoded prescription. After correction, the system structures the text into meaningful fields such as medicine name, dosage, frequency, and duration. This structured format enables easier interpretation and further processing. Additionally, the system performs medical entity recognition using NLP techniques to identify important components such as drug names, dosage units, and instructions. This ensures that all relevant prescription details are accurately extracted and organized for downstream tasks.

4.4 Drug Validation and Generic Recommendation Module

This module ensures the correctness of extracted medicines and provides suitable generic alternatives. The extracted drug names are validated against a medical database using techniques such as exact string matching and fuzzy matching to handle spelling variations or OCR errors. Invalid or unrecognized entries are filtered out to maintain system reliability. Once validated, the system performs generic medicine mapping by identifying equivalent drugs with the same active ingredients and therapeutic effects. It retrieves information such as generic equivalents, active ingredients, and therapeutic class. Based on this mapping, the system generates recommendations that include the original medicine name, its generic alternative, and relevant usage details. This helps users identify cost-effective substitutes while maintaining treatment effectiveness.

4.5 System Integration and Execution Flow

The system integrates all modules into a seamless pipeline to ensure smooth data flow from input to output. The execution begins with the user uploading a prescription image, followed by preprocessing to enhance image quality. The processed image is then passed through text detection using CRAFT and text recognition using CRNN. The extracted text is refined using LLM-based processing and structured using NLP techniques. Subsequently, the validated data is used for generic medicine recommendation, and the final results are displayed to the user in a structured and user-friendly format. The complete workflow includes image upload, preprocessing, text detection, text recognition, semantic processing, validation, recommendation, and output display. This integrated approach ensures efficiency, accuracy, and reliability in decoding prescriptions and providing meaningful healthcare insights.

5. Testing and Results

This chapter summarizes how AI-Powered Prescription Decoder and Generic Medicine Recommender was tested using multiple prescription samples, including both handwritten and printed prescriptions, to evaluate its performance under different conditions. The testing focused on verifying the accuracy of text detection, text recognition, information extraction, and generic medicine recommendation. Different image qualities such as clear, blurred, and low-contrast images were used to analyze system robustness.

Figure 4: Prescription Upload Interface

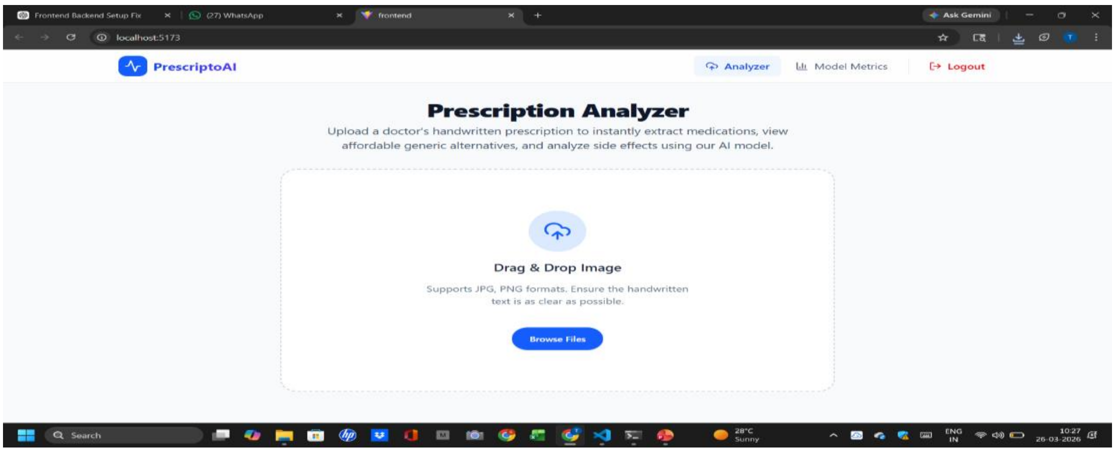


Figure 4 shows the frontend interface of the Prescription Analyzer system, which is developed using React.js. This interface allows users to upload handwritten prescription images through a drag-and-drop feature or by browsing files from their device. It is designed with a user-friendly layout to ensure easy interaction for all users. The interface supports multiple image formats such as JPG and PNG, making it flexible for different input types. Additionally, it provides a real-time preview of the uploaded image, helping users confirm their selection before processing. This module serves as the entry point of the system, initiating the entire prescription analysis pipeline.

Figure 5: Image Upload and Preview

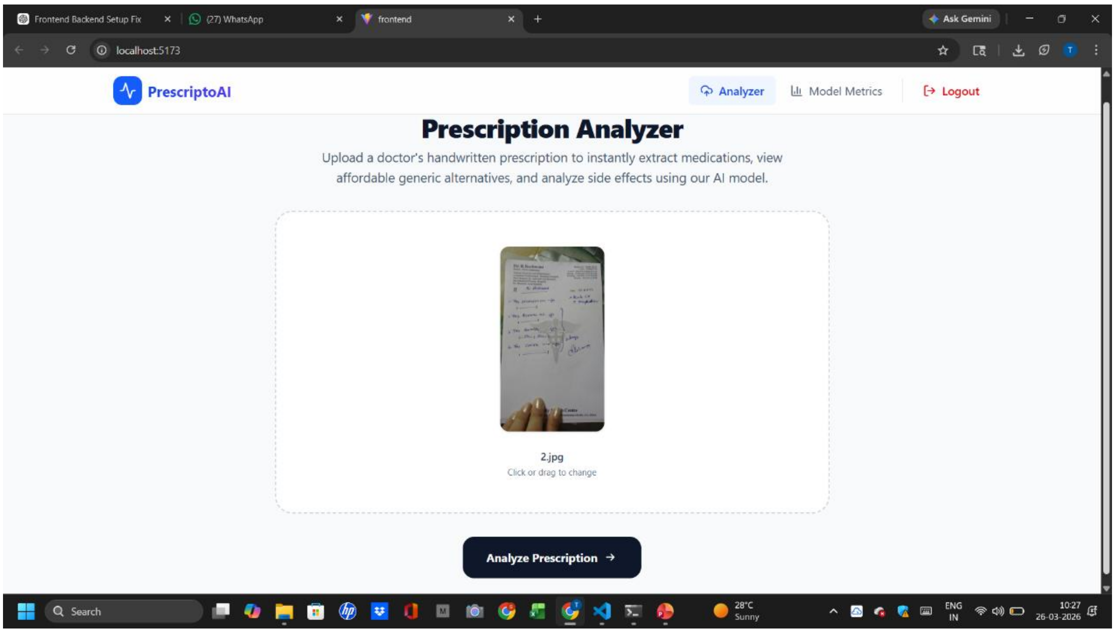


Figure 5 illustrates the image preview functionality after a prescription is uploaded. Once the user selects an image, the system immediately displays it on the screen, allowing the user to verify that the correct prescription has been chosen. This feature enhances usability by enabling users to re-upload or change the image if needed before proceeding with analysis. The preview also ensures that the image is clear and suitable for further processing. By validating the input at this stage, the system reduces the chances of incorrect analysis due to poor or unintended image uploads.

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Figure 6: Extracted Prescription Results and Recommendations

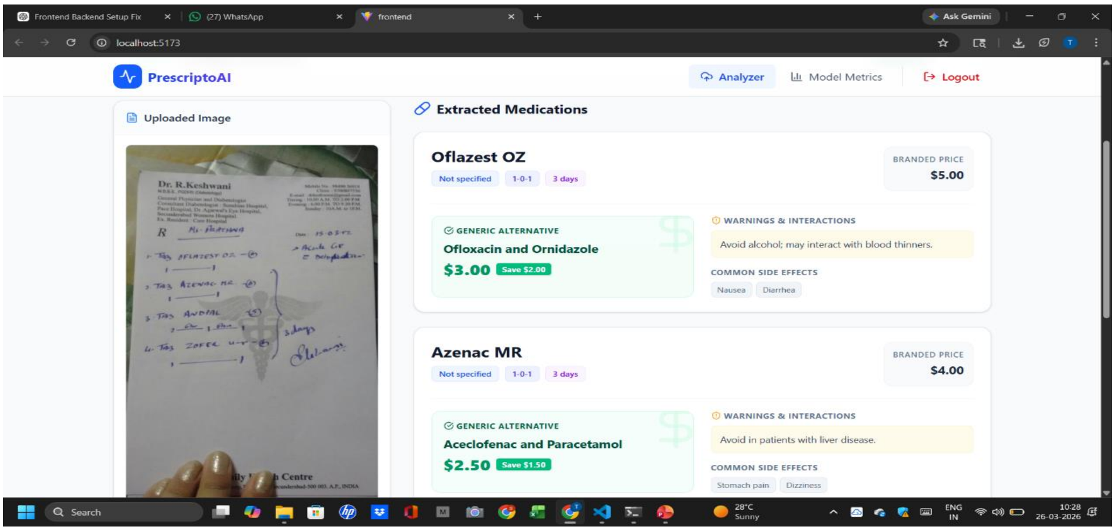

Figure 6 shows the output generated by the system after processing the uploaded prescription image. The backend analyzes the image using AI-based models and produces structured results. The system successfully extracts medicine names such as Oflazest OZ and Azenac MR, along with dosage details like frequency (e.g., 1-0-1) and duration of use. In addition to decoding the prescription, the system recommends generic alternatives for the identified medicines and provides a comparison of prices between branded and generic options. It also displays relevant side effects and safety warnings, ensuring that users receive comprehensive and informative results.

6. Conclusion

The AI-Powered Prescription Decoder and Generic Medicine Recommender successfully demonstrates the application of advanced artificial intelligence techniques in solving a critical real-world healthcare problem. The primary objective of the system was to automatically interpret handwritten medical prescriptions, which are often difficult to read and prone to misinterpretation, and to provide meaningful, structured outputs along with cost-effective generic medicine alternatives.

The system integrates multiple technologies including image processing, deep learning-based Optical Character Recognition (OCR), and Natural Language Processing (NLP) to achieve end-to-end automation. The use of preprocessing techniques enhances image quality, enabling more accurate detection and recognition of handwritten text. The text detection and recognition modules effectively extract relevant information from prescriptions, even when the handwriting is moderately complex. Furthermore, the integration of a Large Language Model (LLM) plays a crucial role in correcting errors, expanding abbreviations, and structuring the extracted data into a meaningful format. In conclusion, the project successfully fulfills its objectives by providing an efficient, reliable, and scalable solution for prescription decoding and generic medicine recommendation. It showcases the potential of combining computer vision and NLP techniques to improve healthcare accessibility, reduce costs, and enhance patient safety.

7. Future Scope

Although the current system provides an effective solution for prescription decoding, there are several opportunities for further improvement and enhancement. One key area is improving handwritten text recognition accuracy by integrating advanced models such as Transformer-based OCR systems. Training models on domain-specific medical datasets can further enhance performance, especially for complex handwriting. The system can also be extended to support multiple languages, making it more useful in regions where prescriptions are written in local languages. This would significantly increase accessibility and usability. Another important enhancement is the integration of real-time pharmacy APIs to provide information about medicine availability, pricing, and nearby pharmacies. This would make the system more practical for real-world usage. Deploying the system as a mobile application is also a valuable future direction. A mobile app would allow users to capture prescription images directly and receive instant analysis, improving convenience and accessibility.

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