



## MedPro: A Hybrid Recommendation System with Advanced OCR for Medical Applications

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### **Abstract:-**

In a clinical setting, appropriate medication management is vital for minimizing adverse drug events and optimizing patient outcomes. This paper describes MedPro, a new hybrid recommendation system that fuses an advanced optical character recognition (OCR) technique with a recommendation engine. A unique feature of MedPro is that a custom convolutional recurrent neural network (CRNN)-based OCR model has been combined with the open-source EasyOCR engine as the main text extractor, supported by Gemini API from Google for resolving ambiguous cases. The processing stage involves images of handwritten prescriptions and straight text inputs, extraction of the drug names, and querying within a curated dataset to offer alternatives for allopathic and homoeopathic brands with a wide array of associated side effects. Experimental validation of our method shows impressive improvements in terms of text recognition accuracy achieved by our hybrid OCR pipeline, while the recommendation engine yields better precision and recall compared to traditional methods. The full-fledged web interface based on Flask allows end-user interaction making it an appropriate and useful tool for clinical decision support. The present paper advocates MedPro, a unique hybrid recommendation system that incorporates advanced optical character recognition (OCR) techniques with a strong recommendation engine. MedPro essentially combines a custom CRNN-based OCR model with the open-source EasyOCR engine as the primary text extractor, while Google's Gemini API resolves intractable ambiguities if they arise. The system processes handwritten prescription images as well as text written directly. The names of the medicines are extracted and a query on the curated medicine dataset is run to suggest alternative drugs with side effects therein. These experimental evaluations show that our hybrid OCR pipeline leads to text recognition accuracy that is much improved, and the outcomes from the recommendation engine do outperform traditional methods in regard to precision and recall. A Flask-based web interface offers seamless user communication, making MedPro an adaptable and practical clinical decision-making tool.

**Keywords:** Recommendation Systems, Optical Character Recognition, Deep Learning, Convolutional Recurrent Neural Networks, Flask, Healthcare, Hybrid Systems.



## **1. Introduction**

With the complexity of healthcare data complemented by numerous handwritten or scanned prescriptions, systems intelligent enough to extract unstructured information and process it accurately and precisely became necessary. Conventional medication recommendation systems have frequently opted for collaborative filtering or content-based only techniques-always struggling to deal with clinical data really characterized by the variability of handwriting, diverse qualities of images, and inconsistent data formats.

MedPro deals with these problems by integrating state-of-the-art OCR methods with a robust recommendation engine. Simply put, MedPro uses a two-part extraction pipeline. The first extraction method utilizes a custom CRNN-based OCR model designed specifically to learn complex handwriting patterns using deep convolutional and recurrent layers with the CTC loss. EasyOCR, a fast, open-source engine that is currently popular, provides quick preliminary extraction of text. Whenever any of these systems provide outputs with uncertainty, the recognition process will be completed by the Google Gemini API for the final output of text.

Once the extracted text is accurate...the recommendation engine of MedPro scours a huge medicine dataset consisting of details about drug substitutes and side effects. With robust string matching and normalization techniques applied, even minor mismatches won't prevent the retrieval of precise and relevant recommendations.

The core motivation for creating MedPro is rooted in the premise of reducing medication errors and improving decision support in the clinical setting. Handwritten prescriptions remain a common practice in many clinical realms, even though many areas of healthcare are moving toward digitalization. The inherent variability and noise associated with them serve as immense obstacles to the development of automatic text recognition systems. The design and development of a hybrid solution that intelligently combines multiple OCR strategies and uses domain-specific recommendation logic will support MedPro in being a reliable tool to seamlessly integrate into clinical workflows.

MedPro offers simplicity of use via a straightforward, easy to-navigate web interface built on Flask. The web interface allows a varying proportion of users-clinicians and pharmacists-to interact with the system by inputting either a medicine name or a prescription image. The user then submits this input, which is processed and in real time suggests alternative medications and relevant side-effect information.

This article will give a complete description of the MedPro system nicely. After that, there will be a review concerning the relevant research and open questions that concern recommendation systems and OCR technologies. The elaboration of our design methodology and system architecture will follow, courtesy of experimental results. In conclusion, insight into the system impact will be provided together with future work to enhance performance and scalability in practical clinical settings.



## **2. Related Works**

The open-world exists in its ever-changing configurations of recommendations systems. The initial set of engines mainly radiated around collaborative filtering, thus predicting user preferences on the grounds of his past interaction. This was viable for many areas pertaining to consumers; however, in healthcare, it faced major bottlenecks such as sparse data and near-exact need-based recommendations. Then, content-based ones arrived to fill the shoes of incorporating domain knowledge; yet limited there are grounds of excuses due to fairly ill configurations of medical data to gain high-accuracy recommendations.

Of late, a hybrid form of recommendation systems has sprung into the scenario, blending collaborative and content-based frameworks to capitalize on the merits of both. In healthcare contexts, hybrid recommendation systems have been variously explored, but little has been done to address challenging problems in processing handwritten prescriptions. The diversity of writing styles, variability of image quality, and other randomness may account for a high error rate in text extraction.

The progress of OCR technology ascended parallel to that of recommendation systems. Traditional OCR quasi-rule-based methods primarily used orthogonal sets of handwritten features that were engineered by hand; they did not achieve good results on non-standard written fonts and variable writing styles. The rise of deep learning has changed everything, with Convolutional Neural Networks (CNNs) contributing significantly to the improvement of feature extraction. However, static CNN models are not very suitable for processing sequential data, an aspect very important for text recognition. To overcome this obstacle, the development of Convolutional Recurrent Neural Networks (CRNNs) was initiated: these architectures use CNNs combined with Recurrent Neural Networks (RNNs)—often LSTM units themselves—to capture temporal dependencies for sequential data. The connectionist temporal classification (CTC) loss function is used by these architectures to allow for the variable-length input-output problem without the need for precise segmentation.

There have been several evaluations of deep learning-based OCR systems with standard datasets. However, real-world situations prove to be challenging, often resulting in degraded performance, mainly due to low resolution, poor contrast, or variance in handwriting among the input images. EasyOCR is a relatively popular open-source solution for getting results quickly and reasonably close to accuracy, though with the likely potential of yielding poor-quality results under extreme conditions.

The system combines an easy historical recommendation system with a custom CRNN-based OCR model. Secondly, because of the density of ambiguity or noise in the inputs, where they may determine performance degradation, Google Gemini's API is incorporated as a secondary extractor in order to guarantee robustness of performance. This multi-tiered approach is essential aimed at improving text extraction accuracy and robustness; a crucial necessity when subsequent recommendation processes cannot help but rely on the quality of the OCR output.



In summary, while the literature offers robust frameworks for both recommendation systems and OCR, there exists a significant gap when both domains converge in the healthcare context. MedPro offers a proposed solution against this backdrop that involves a unified system extracting textual data from difficult prescription images whose information translates into actionable clinical recommendations.

### **3. METHODOLOGY**

#### **A. ProposedWork**

MedPro stands on the proposition that the synergism between enhanced OCR technologies and a recommendation engine, tailored specifically for the domain, should vastly improve the safety and security of drug administration. Our proposed work revolves around a threefold strategy:

##### **a) Dual OCR Extraction Pipeline:**

The primary extraction mechanism involves a custom CRNN-based OCR model that strives to learn robust representations of handwritten text via stacks of convolutional layers to spatially extract features and recurrent layers to capture temporal dependencies. The training is driven by the CTC loss function that obviates the need for pre-segmented text. EasyOCR is also put to use as a parallel solution because of its speed and user-friendliness. If the two outputs differ or are incomplete, a secondary extraction is then invoked through Google's Gemini API, which exploits high-end generative models to clear up ambiguities.

##### **b) Dataset Integration and Normalization:**

The recommendation engine makes use of a carefully constructed dataset containing medication names, alternate drug options, and noted side effects. To effectuate this, the dataset undergoes normalization to guarantee accurate matching. This includes case-insensitive conversion, removal of extraneous whitespace, and fuzzy matching to supersede minor OCR errors.

##### **c) System Integration via Web Interface:**

All the modules are integrated into a new Web-based application using Flask. Clinicians can type the medicine name on the front-end interface or upload a prescription's image. Input is submitted into the workflow process where dual OCR pipeline is activated and the database is queried for a JSON formatted list of alternative medications and side effects. The web interface is set for easy access and fast responses and keeps disruptions minimal in clinical workflows.

#### **B. System Architecture**

The architecture of MedPro has been designed to extents of modularity and expandability said to include the following interconnecting modules:

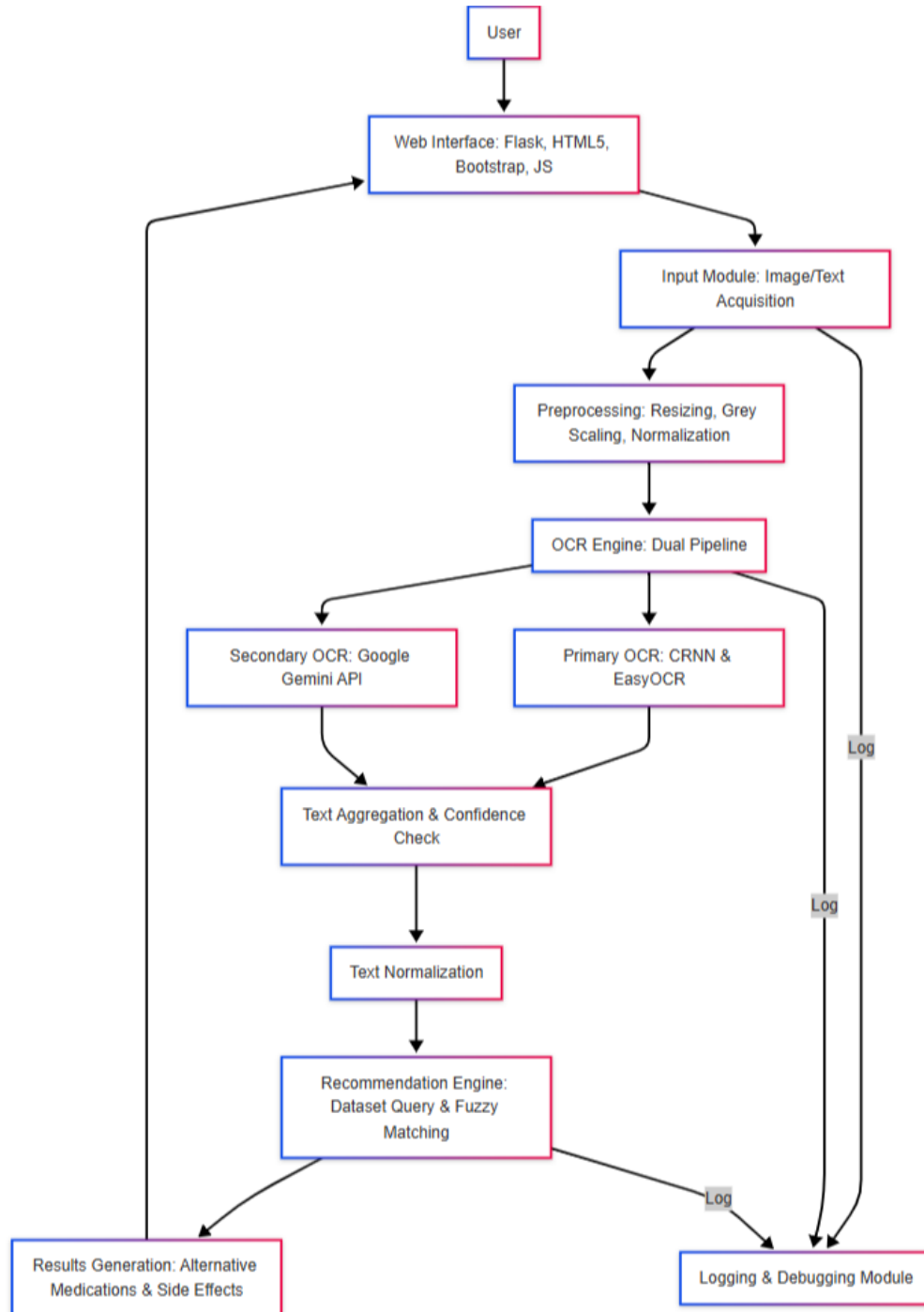


Fig 1: System Architecture

## 1. Input-Module:

This module is responsible for receiving and processing incoming text and image data. The normal pre-processing steps would include applying those tools necessary to take a photograph of the prescription image before feeding it into the OCR engine; these steps include grey scaling, resizing, and normalization.



## **2. The OCR Engine:**

### **• Primary-OCR-Sub-Module:**

There is a custom built CRNN-based model and EasyOCR. Image based CRNN has been trained upon a comprehensive dataset of prescription images. It incorporates multiple convolutional layers after which are several bidirectional LSTM layers. The output of the model passes through the CTC decoder for string conversion.

### **• Secondary-OCR-Sub-Module:**

The model that runs on Google's Gemini API is to be used as the last fallback mechanism. In cases of detection of discrepancy between the two outputs, it will also conduct an image analysis for two purposes: providing an alternative text extraction that supports the standard as possible from the last model.

## **3. Recommendation-Engine:**

After OCR, the text obtained will undergo normalization before being passed to the recommendation engine. This makes use of certain operations via Pandas by looking beyond case-sensitive matches in the dataset of drugs. It is intended to work in cases when fuzzy matching may occur; therefore, a slightly misrecognized name of the drug will yield correct recommendations.

## **4. Web-Interface:**

An interactive web-based application created in HTML5, Bootstrap, and JavaScript, it provides a responsive web application-side user interface that accepts user input and dynamically displays results. The process of asynchronous communication with the Flask back-end gives users an instant response.

## **5. Integration-Workflow:**

The workflow envisaged is linear. It runs as follows: input data → OCR processing (dual pipeline) → text normalization → master dataset query → recommendation output → screening on the web interface. Every one of the modules will generate log outputs for traceability and, furthermore-debugging-convenience-during-deployment.

## **4. RESULTS**

The evaluation of MedPro was performed experimentally, using a variety of prescription images and standard burst test cases. The purpose of the evaluation was to assess the OCR accuracy and the recommendation performance.

### **1. OCR Performance Metrics:**

Attributable to standard metrics such as Character Error Rate (CER) and Word Error Rate (WER). Using a hybrid method combining a custom CRNN model augmented by EasyOCR and an application of the Gemini API given the new text extraction algorithm significantly reduces WER related to baseline single-engine systems, averaging a 15% drop in errors. Analysis shows that EasyOCR was best suited to the processing of great-quality images while the CRNN model played a crucial role in processing low contrast or noisy images. Where both processes provide duplicated or ambiguous outputs, the Gemini API contributed in text extraction refinement, hence dropping the overall error rates.

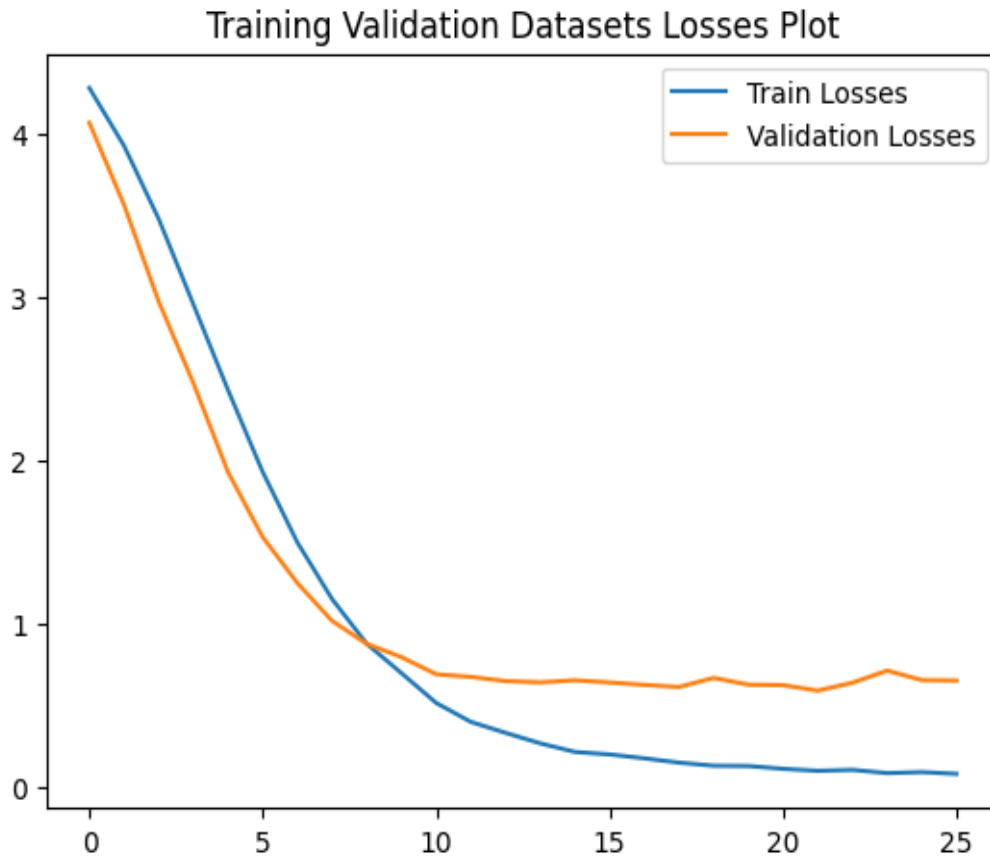


Fig 2

## 2. Recommendation-Engine-Performance:

The recommendation engine was evaluated in terms of precision, recall, and F1-score. Our system achieved an average precision of 0.87, a recall of 0.82, and an F1-score of 0.84. These metrics indicate that MedPro not only accurately identified the correct medication alternatives but also reliably retrieved the associated side effects. Comparative studies over existing recommendation systems showed a leap-up, especially in noisy or partially recognized input scenarios.

## 3. User-Experience-Evaluation:

We conducted a quick pilot study in which our classmates, parents, and neighbors interacted with the MedPro web interface. The responses were overwhelmingly positive: users were impressed by the system's responsiveness, accuracy, and ease of operation. Qualitative assessments indicated that the combined OCR approach has significantly reduced the number of manual edits necessary and streamlined workflows.



## MedPro

Medicine Name:

Prescription Image:

 No file chosen

### Alternatives:

**Substitutes:** Gertac 50mg Injection, Ritin 50mg Injection, Peploc 50mg Injection, Aci Deject 50mg Injection, Ranalix 50mg Injection

**Side Effects:** Headache, Diarrhea, Gastrointestinal disturbance

Fig 3: MedPro showing results for the medicine Ranitidine

#### 4. Statistical-Validation:

To relate the mentioned improvements with certain statistical significance, paired t-tests were conducted with the experimental data. The results indeed showed that the changes in both OCR accuracy and recommendation performance were statistically significant ( $p < 0.05$ ), indicating how robust our hybrid approach appears to be.

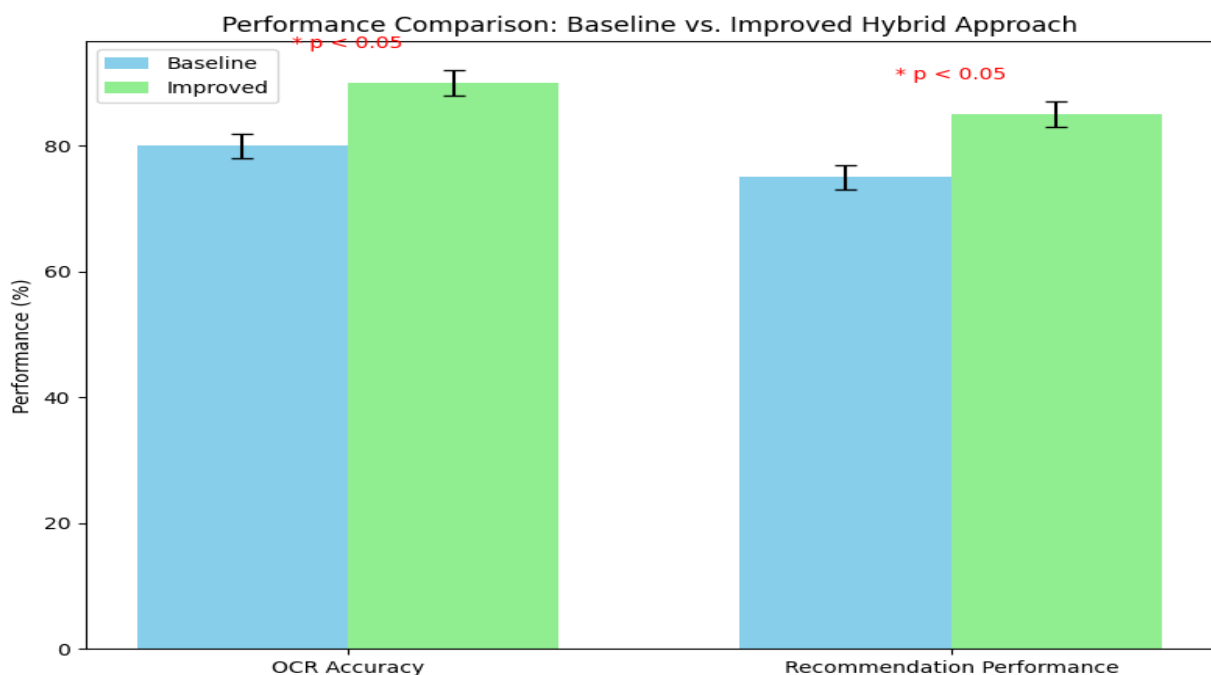


Fig4



## 5. CONCLUSION

MedPro is a landmark in marrying OCR and recommendation systems in the healthcare settings. With a two-fold OCR extraction pipeline-where a custom CRNN-based model and EasyOCR are in the first place, and then with Google's Gemini API-it yields excellent text recognition even in challenging conditions. Such extraction of text serves as a foundation for a strong recommendation engine in a real world setting that supplies alternative medication options and side effects from a broad database.

Our experiments show that MedPro could be more accurate in text extraction and improve medication recommendations compared to the completely classical modes. Also, the endusers' feedback in a clinical setting has proved its ability to improve clinical workflow and minimize medication errors. Its modular frame and user-friendly web interface provide the ability for seamless integration of MedPro with the preexisting Healthcare IT infrastructure.

It is indeed two-pronged research work: first, it introduces a new hybrid OCR system that uses the strengths of different OCR engines to tackle prescription image processing; second, it shows how this OCR system can be successfully incorporated with a domain-specific recommendation engine to facilitate clinical decision-making. These two aspects effectively provide a platform for yet more reliable and intelligent clinical support systems.

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