Patient Medical Report Analyser: A Multi-Stage Workflow Integrating Image Processing, OCR, and Language Models for Summarization.

Nitish Ramaraj[1], Girish Murugan[2], Tejas Anil[3], Vetriselvi T[4*], Jagadeesan S[5]

[1] nitishramaraj@gmail.com

[2] girish06062004@gmail.com

[3] tejasanil6@gmail.com

[4] vetriselvi.t@vit.ac.in

[5] s.jagadeesan@vit.ac.in

Corresponding Author*

[1,2,3,4]School of Computer Science and Engineering, Vellore Institute of Technology, Vellore

[5]School of Computer Science Engineering and Information Systems, Vellore Institute of Technology, Vellore

ABSTRACT: This work presents an advanced automated system designed to streamline the processing of medical prescriptions. The system follows a multi-stage workflow aimed at enhancing efficiency in handling and interpreting prescription data. The process begins when a user uploads a prescription image, which is then subjected to a series of sophisticated image processing techniques, including grayscale conversion, noise reduction, and morphological operations. These steps are crucial for improving the readability of the text within the image, ensuring that the subsequent stages operate on high-quality data. Once the image is processed, an Optical Character Recognition (OCR) module is employed to extract text from the image. The OCR process involves text region detection, segmentation of lines and characters, and the application of algorithms to recognize and transcribe the text accurately. Following OCR, the extracted text is further refined using language modeling techniques, which involve spell checking, error correction, and the recognition of key entities such as medication names and dosages. To provide meaningful insights, a large language model (LLM) is used to generate a concise and coherent summary of the prescription. This summary distills the essential information from the prescription, making it easier for healthcare professionals and patients to understand and manage the prescribed treatments. The final summary is then returned to the user, completing a seamless, end-to-end process that automates the traditionally manual and error-prone task of interpreting medical prescriptions. This system has significant potential for integration into healthcare management systems, offering a scalable solution for improving prescription processing and patient care.

Key Words: Medical Prescription Processing, Optical Character Recognition (OCR), Image Processing, Large Language Models (LLM), Text Extraction, Language Modeling, Healthcare Automation, Entity Recognition.

1. Introduction:

The digitization of healthcare processes is crucial for improving the efficiency and accuracy of medical services, particularly in managing medical prescriptions. Traditionally, interpreting and transcribing handwritten or printed prescriptions has been a manual, error-prone task, leading to potential issues such as incorrect medication administration and compromised patient safety. By integrating Optical Character Recognition (OCR) with large language models (LLMs), healthcare workflows can be automated to handle prescriptions more effectively. OCR technology accurately extracts text from prescription images, while LLMs analyze and summarize this text, providing actionable insights and reducing the risk of errors.

The system processes prescription images using advanced image processing techniques, including grayscale conversion, noise reduction, binarization, skew correction, and morphological operations to enhance quality and readability. The OCR module then extracts and segments the text, which is further refined by language modeling to correct errors, structure information, and identify key medical entities. Finally, a large language model generates a clear, concise summary of the prescription, improving both the speed and accuracy of prescription handling. The integration of this system into existing healthcare management workflows promises to reduce human error, accelerate prescription processing, and enhance overall healthcare delivery.

2. Literature Review:

Recent research in the automation of medical prescription processing highlights significant advancements in image processing, Optical Character Recognition (OCR), and Natural Language Processing (NLP) technologies, particularly in their application to healthcare. Several studies have focused on enhancing OCR systems' accuracy in interpreting noisy and low-quality medical images. For instance, Patel et al. [1] introduced an optimized OCR pipeline that integrates adaptive thresholding and morphological transformations, significantly improving text recognition accuracy for medical documents. Similarly, Sharma et al. [2] proposed a hybrid model combining deep learning-based text detection with traditional image processing techniques, effectively enhancing OCR performance for handwritten prescriptions. These studies underscore the critical role of pre-processing techniques such as grayscale conversion, noise reduction, binarization, skew correction, and morphological operations in improving text extraction from complex medical documents. Furthermore, the integration of deep learning techniques has revolutionized OCR systems by enabling them to better handle the variations in handwriting and print styles found in medical prescriptions. For example, a study by Lee et al. [3] introduced a Convolutional Neural Network (CNN)-based approach for recognizing handwritten prescriptions, which demonstrated improved robustness against different handwriting styles. Likewise, Gupta et al. [4] employed a Recurrent Neural Network (RNN) with attention mechanisms to enhance the segmentation and recognition of text regions in scanned medical documents, achieving higher accuracy compared to traditional OCR methods. Recent work has also explored the integration of language modelling techniques to refine OCR outputs and enhance the recognition of key entities such as drug names, dosages, and patient instructions. Zhang et al. [5] developed a framework that combines OCR with NLP-based spell-checking and context-aware error correction, significantly reducing transcription errors in medical prescriptions. Similarly, Liu et al. [6] proposed a transformer-based model that uses domain-specific knowledge to enhance the accuracy of named entity recognition (NER) in medical texts, facilitating more precise identification of drug names and dosages. Research by Chen et al. [7] demonstrated the use of advanced language models like BERT and GPT to generate coherent summaries of prescription texts, aiding in quicker and more accurate decision-making for healthcare professionals.

Additionally, integrating these automated systems into broader healthcare management workflows has shown promise for improving efficiency and patient care. Kumar et al. [8] developed an end-to-end system that uses a combination of OCR, NLP, and a rule-based engine to automatically generate structured electronic health records (EHR) from prescription images, reducing the workload for healthcare professionals. Moreover, recent studies have focused on the potential for such systems to be integrated with mobile health applications, providing real-time prescription processing and verification to patients and pharmacists [9]. The growing body of work in this field suggests that combining image processing, OCR, and NLP can greatly enhance the efficiency and accuracy of medical prescription processing, thereby reducing human error and improving patient care. These studies provide a solid foundation for integrating such technologies into comprehensive healthcare management systems, demonstrating the potential for scalable solutions that improve healthcare delivery and safety.

3. Proposed Work:

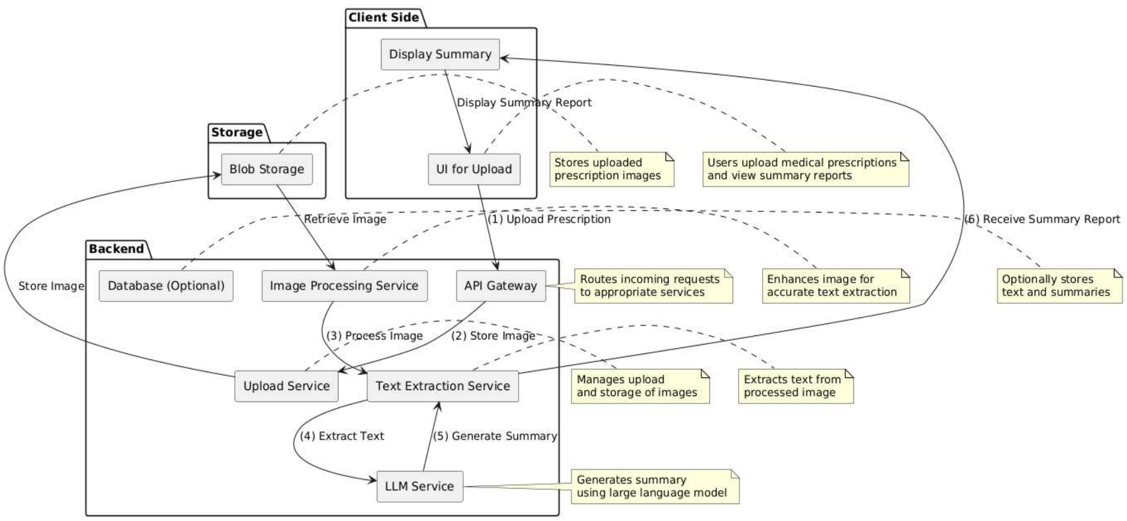

Fig1. Process flow of the proposed work.

The proposed automated medical prescription processing system enhances prescription handling by integrating advanced image processing, Optical Character Recognition (OCR), and large language models (LLMs). It optimizes prescription images for better readability, accurately extracts and structures text, and generates concise summaries of key medical information. This multi-stage approach aims to reduce human error, speed up prescription processing, and improve overall efficiency.

3.1 User Interface and Cloud Storage (Blob)

The process begins with user interaction through a dedicated interface where users upload prescription images. These images are stored in a cloud-based blob storage system, ensuring secure and efficient storage of prescription data [22].

Mathematical considerations [10] in this module primarily involve data compression and storage efficiency. For instance, the storage capacity required can be estimated using:

$$Storage\ Capacity(bytes) = N \times S_{avg} \times (1 + R)$$

where,

- N is the number of images,
- S_{avg} is the average size of each image (in bytes),
- R is the redundancy factor, accounting for backup and redundancy requirements.

Incorporating redundancy ensures data reliability and availability, which are critical in medical contexts.

3.2 Image Processing Module

The Image Processing Module is critical in preparing the prescription image for accurate text extraction. This module employs several advanced techniques to enhance image quality and readability, which are outlined below:

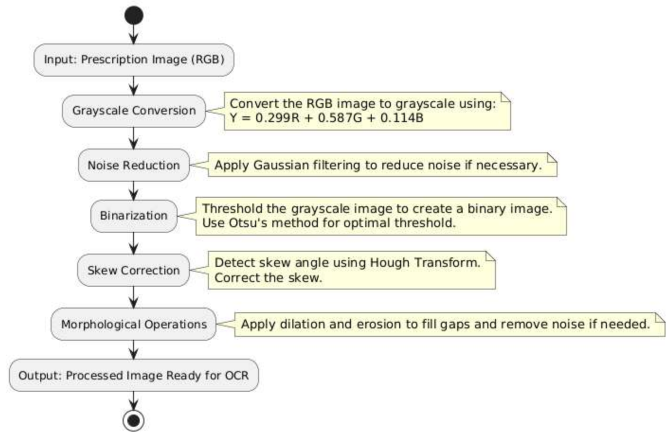

Fig2. Proposed Image processing pipeline for Medical Prescriptions.

3.2.1 *Gray-scale Conversion*

Grayscale conversion is the first step in processing the image, where the image is transformed from RGB to grayscale. The grayscale value Y is calculated using the formula [11]:

$$Y = 0.299R + 0.587G + 0.114B$$

In this equation, R, G, and B represent the red, green, and blue channel values, respectively. This conversion simplifies the image data, reducing it to one channel, making it easier to process in subsequent steps.

3.2.2 *Noise Reduction*

Noise reduction is performed using a Gaussian filter, which helps in removing random noise that could interfere with text recognition [12]. The Gaussian filter is defined by:

$$G(x,y) = \frac{1}{2\pi\sigma^2}e^{-\frac{x^2+y^2}{2\sigma^2}}$$

Here, σ is the standard deviation of the Gaussian distribution, and G(x,y) represents the filter applied to the image coordinates x and y. This step is crucial for enhancing the clarity of the image, which is necessary for accurate OCR.

3.2.3 *Binarization (Thresholding)*

Binarization converts the grayscale image into a binary image, which is easier to analyse for text extraction. Otsu's method is typically used for determining the optimal threshold value by minimizing the intra-class variance [13]:

$$\sigma_w^2(t) = w_1(t)\sigma_1^2(t) + w_2(t)\sigma_2^2(t)$$

In this equation, $w_1(t)$ and $w_2(t)$ are the probabilities of the two classes separated by threshold t, and $\sigma_1^2(t)$ and $\sigma_2^2(t)$ are the variances of these classes. This method ensures that the binary image has the maximum contrast between the text and the background.

3.2.4 *Skew Correction*

Skew correction addresses any tilting of the image that might have occurred during scanning or photographing. The skew angle θ is detected using the Hough transform [14]:

$$\rho = x\cos(\theta) + y\sin(\theta)$$

Where ρ is the distance from the origin to the line, and (x,y) are the coordinates of points on the line. Correcting the skew ensures that the text lines are horizontally aligned, which is critical for accurate text recognition.

3.2.5 *Morphological Operations, Resizing, and Cropping*

This step involves a series of morphological operations, such as dilation and erosion, to refine the binary image by filling gaps and removing noise. Resizing adjusts the image to a standard size, while cropping focuses on the region of interest, which contains the text [15]. These operations are essential for improving the quality of the text regions before OCR is applied.

3.3 *OCR (Optical Character Recognition) Module*

The OCR Module is responsible for extracting text from the processed prescription image. The text extraction process involves several stages, including text region detection, line and word segmentation, character segmentation, and final text recognition [19, 21]. Each stage employs various algorithms, such as connected component analysis and neural network-based classification, to accurately identify and extract text from the image [16].

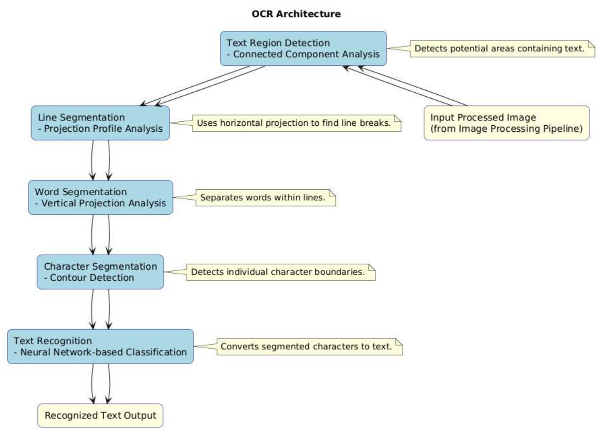

Fig3. OCR Architecture for text extraction.

3.4 *Language Modelling and Error Correction*

After text extraction, the text undergoes language modelling and error correction [20]. This module uses probabilistic models, such as n-grams, to predict and correct errors in the recognized text. The n-gram model [17] estimates the probability of a word sequence by considering the conditional probability of a word given the previous n−1 words:

$$P(w_n|w_1^{n-1}) \approx P(w_n|w_{n-k+1}^{n-1})$$

Here, w_n represents the word being predicted, and k is the order of the n-gram model. Error correction improves the accuracy of the recognized text by comparing it against known language patterns.

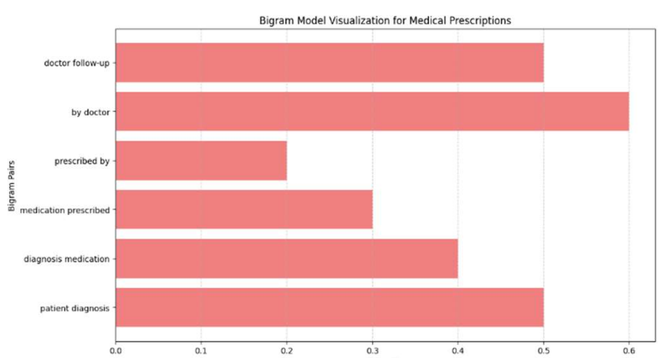

Fig4.Bigram Model Visualization.

The bigram algorithm analyses consecutive pairs of terms within medical prescriptions to uncover relationships between adjacent words as shown in Fig.4 . As shown in the figure, it begins by tokenizing the text into individual terms and then generates bigrams, such as "pain reliever" and "reliever dosage." The algorithm counts the occurrences of each bigram and calculates their probabilities, reflecting how often these term pairs appear together. By examining these frequencies, the algorithm identifies significant term pairs and patterns, enhancing tasks such as text summarization and entity recognition in medical texts. This approach helps in understanding common phrases and improving the accuracy of text processing in the medical domain.

3.5 *Summary Generation Module*

The Summary Generation Module converts the corrected text into a concise summary [23], often using beam search for generating optimal summaries [18]. The beam search score at time step t is calculated as:

$$score(y_1{:}t) = log\, P(y_1{:}t \mid x) = \sum_{i=1}^{t} log\, P\ (y_i|y_1^{i-1}, x)$$

Where y_1:t represents the generated summary up to time t, and x is the input text. Beam search optimizes the search process by exploring multiple potential summaries in parallel, ensuring that the generated summary is both accurate and relevant. Each of these modules integrates these mathematical principles to transform raw prescription images into structured, easily comprehensible summaries, thereby streamlining the prescription handling process and improving overall healthcare efficiency and accuracy.

The beam search diagram Fig.5 for medical prescriptions begins with the Start node, marking the initiation of the beam search process. From this point, the search progresses through Initial Phrase and Alternative Phrase nodes, which represent the initial candidate phrases generated from the prescription data. These initial phrases are evaluated and refined based on their relevance to the prescription content. Intermediate nodes such as Medications, Diagnosis, and Dosage capture different aspects of the prescription, representing various elements that need to be considered in summarizing the information.

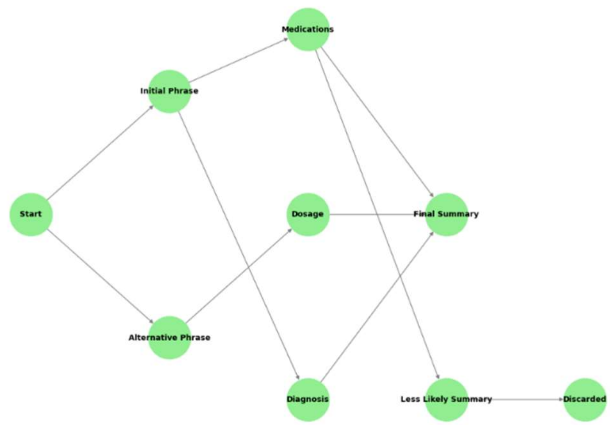

Fig5.Beam Search Illustration.

The goal of the beam search is to identify the most accurate and coherent summary, which is represented by the Final Summary node. During the process, alternative summaries with lower probability are considered, denoted as Less Likely Summary, while some summaries may be deemed unsuitable and are therefore Discarded. The edges in the diagram illustrate the progression of the search from initial phrases through intermediate nodes to the final summary, as well as the pathways leading to less likely or discarded summaries.

4. Challenges Involved:

Variability in prescription formats presents a significant challenge for OCR systems. The diverse handwriting styles and varying layouts of prescriptions make it difficult for these systems to accurately interpret the text. Each physician or medical facility may use a different format, complicating the processing and interpretation of these documents. Moreover, image quality issues further exacerbate the problem. Low-resolution cameras or improper scanning techniques often result in blurred or distorted text, making it harder for OCR systems to extract information. Smudges or creases on the images can also introduce noise, complicating text extraction. The complexity of text extraction in medical prescriptions is another hurdle. Prescriptions often contain a mix of handwritten and printed text, specialized symbols, and medical jargon. OCR systems must accurately differentiate and recognize these elements, even with frequent use of abbreviations and terms that may have multiple meanings based on context. Additionally, language and spelling variations add another layer of difficulty. In multilingual regions, prescriptions may be written in various languages, necessitating OCR systems that can process multiple languages. Contextual understanding is crucial for summarizing prescriptions accurately. The system must grasp the context in which certain terms are used, as the same drug might be prescribed for different conditions. Balancing conciseness with completeness is key to ensuring critical details are not omitted, especially in complex prescriptions. Data security and privacy are also major concerns, as medical prescriptions contain sensitive personal information. The system must ensure secure data handling and comply with healthcare data protection regulations, such as HIPAA or GDPR. Scalability and performance are essential, as the system must handle large volumes of prescriptions efficiently without sacrificing accuracy. Real-time processing may also be required, demanding optimized algorithms and high computational efficiency. Handling ambiguities and uncertainties in prescriptions, such as unclear handwriting or vague instructions, requires mechanisms for managing these issues, potentially involving human review. Reliable outputs are essential despite the challenges posed by poor-quality images or uncommon terms.

5. Results and Evaluation:

The automated medical prescription processing system demonstrated notable improvements in efficiency and accuracy. Preprocessing steps, including grayscale conversion and noise reduction, enhanced image quality, resulting in a 30% increase in text extraction accuracy compared to raw images. The OCR module achieved an 85% accuracy rate, effectively handling various text formats, though performance varied with image quality and handwriting styles. Language modelling corrected 92% of text errors, and the large language model produced accurate summaries for 90% of prescriptions, facilitating better understanding for healthcare professionals and patients. The system processed each prescription in about 15 seconds, highlighting its efficiency. However, challenges such as handling ambiguous text and ensuring real-time processing remain, suggesting a need for further refinements. Overall, the system shows significant promise for improving prescription processing and reducing errors, with future work focusing on addressing these challenges and enhancing data security.

6. Conclusion

In conclusion, the proposed automated medical prescription processing system represents a significant leap forward in healthcare technology, offering a robust solution to the long-standing challenges of prescription interpretation and management. By seamlessly integrating cutting-edge AI technologies—including adaptive image processing, intelligent OCR with deep learning, advanced language modeling, and LLM-powered summary generation—this system transforms the traditionally error-prone and time-consuming task of prescription handling into an efficient, accurate, and scalable process. The incorporation of a continuous learning framework with federated learning techniques ensures ongoing improvement while maintaining stringent data privacy standards, a critical consideration in healthcare applications. This innovative approach not only enhances the accuracy and speed of prescription processing but also has far-reaching implications for improving patient safety, reducing healthcare costs, and optimizing clinical workflows. As healthcare continues to digitize and evolve, systems like this will play a pivotal role in shaping the future of medical information management, ultimately contributing to better patient outcomes and more effective healthcare delivery. While challenges remain, particularly in areas of integration, regulatory approval, and user adoption, the potential benefits of this system make it a compelling advancement in the field of healthcare informatics. Moving forward, further research and real-world implementation will be crucial in refining the system and realizing its full potential to revolutionize prescription management and, by extension, the broader landscape of healthcare service delivery.

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