ChatFDA: Medical Records Risk Assessment

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Abstract

In the realm of healthcare, patient safety and the reduction of medical errors are paramount. Despite well-intentioned efforts, healthcare systems, particularly in low-resource regions, often lack the robustness to prevent these errors effectively. This research introduces a novel mobile application designed to mitigate this issue by aiding caregivers in assessing potential risk from medical notes. Utilizing multiple input modalities and data from openFDA to provide real-time, actionable insights on prescriptions. Preliminary results on MIMIC-III dataset indicate a proof of concept to reduce in medical errors and an enhancement in patient safety. This application has the potential to significantly improve healthcare outcomes in resource-poor settings. For reproducibility and further research, the complete code for our method is made available on Github. DISCLAIMER: We used ChatGPT as an initial step explore research ideas for this project.

1 Introduction

Every year in the United States only, there are 250000 death due to medical errors, these could come from diagnostics error, surgery, patient care infection, and largely (44%) from medication. And this is the situation in a country will well-developed healthcare system with advanced medical facilities, well-organized and digitalized records with careful maintenance. In low-resource regions, particularly rural areas in third-world countries, the challenge of ensuring patient safety is exacerbated. There are regions where only one nurse need to take care a whole tribe village, and she/he doesn't have the access to a standardized medical records, sometimes it is just hand-written notes or even from parole of the patient from memory.

2 Related Works

2.1 Medical Records Correction

The correction of medical records has been a topic of interest in healthcare informatics for several years. Various studies have explored the use of Electronic Health Records (EHRs) to improve the accuracy and reliability of medical data. Previously probabilistics models have been use to identify and correct inconsistencies in medical records, particularly in the context of medication prescriptions. Recently, large language models (GPT4, PaLM) have been used for error correction in general, but there is no benchmark exist for medical data. These works lay the foundation for the importance of accurate medical record-keeping, which our research aims to extend into evaluating the risk from the records.

2.2 Language Models for Medical Data

The application of language models in the medical domain is a burgeoning field, especially with the advent of more sophisticated models like Med-PaLM 2 and Med-Bert. These models have been

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employed for various tasks, such as medical text summarization, diagnosis prediction, and drug interaction identification. However, there is no existing research on evaluating the efficiency of using LLMs in increasing patient safety, especially for multi-language settings where the information is limited. Our research builds upon these advancements by integrating language models to interpret and verify medical notes, particularly in settings where expert oversight is limited. This work gives an overview about potential research and application directions of LLMs in medical settings.

Both of these areas—medical records correction and language models for medical data—provide valuable insights and foundational knowledge that inform and support the objectives of our research. By combining elements from these two domains, we aim to create an application that can significantly improve patient safety and reduce medical errors in low-resource settings.

3 Proposed Approach

3.1 Pipeline Design

The architecture of our application is organized into a pipeline consisting of several interconnected modules. The first module collects and process medical data, our input could be text, voice, or image. For this experiment, we focused on medical notes since this is a reliable source of information for the caregivers. With the MIMIC-III dataset, we need a module for data processing to standardizes the collected data for analysis. Subsequently, from the raw data, we use GPT4 block to process the medical records in to prescription and medical history part. This step reduce the human error in writting notes and the extract the type of prescriptions of each patient. The prescription then will be sent to openFDA, providing actionable insights like medication interactions and treatment guidelines. The final block of the pipeline take the insights from openFDA and medical history of the patient and return a risk evaluation, as well as save the medical records to the database for the future use.

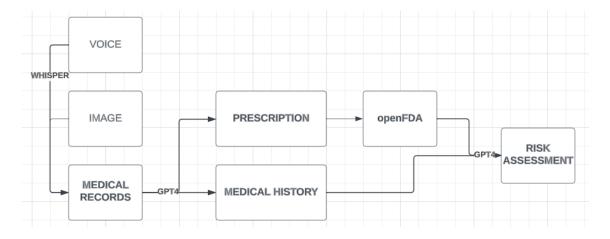


Figure 1: Pipeline Diagram

3.2 Prompt Design

Designing a useful prompt for a language model is critical, especially in high-stakes situations like medical evaluations. In this study, we introduce two separate prompts:

- 1. The first is to extract relevant medical information from a doctor's notes. This information pertains to a patient's pre-existing conditions, symptoms, and prescribed medications.
- 2. The second prompt aims to assess the potential risks related to the extracted medical information. In this section, we elaborate on our approach to designing this risk-assessment prompt.

Prompt Structure: The risk assessment prompt comprises three primary sections:

- Parsed Notes: This section integrates the parsed information from the doctor's notes.
- **Drug Information:** Here, we incorporate drug interactions and warnings retrieved from the FDA database.
- Answer Section: The language model is tasked to analyze the prescribed treatment, identifying potential drug interactions and assessing potential patient reactions based on their pre-existing conditions. The culmination of this analysis is the evaluation of the treatment's dangerousness on a scale: LOW, MEDIUM, or HIGH. An answer template is also provided to ensure consistency in responses.

Actual Prompt:

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"I am a doctor, and I need you to evaluate my prescription: {parsed_notes}

Drug contexts: {drug_info_string}
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Please answer the following in a concise point format, considering the provided drug context:

- Possible interactions between the prescribed drugs?
- Specific adverse effects of the drugs that relate to the patient's pre-existing conditions and

Conclude your response by assessing the treatment's dangerousness based on interactions and adver-

Your answer should adhere to this format:

- * INTERACTIONS:
- <interaction 1>
- <interaction 2>
- ...
- * ADVERSE EFFECTS:
- <adverse effect 1>
- <adverse effect 2>
- ...
- * DANGEROUSNESS: <LOW / MEDIUM / HIGH>

Include only necessary interactions or adverse effects in your response."

3.3 User Interface

The user interface of the application is intentionally designed to be intuitive and user-friendly. It features a series of prompts that guide healthcare workers through the verification process. Initially, users are prompted to select their preferred method of input—image, voice, or text. Based on this selection, the application provides an interface for capturing the image, recording the voice, or typing the text. Once the data is processed and analyzed, a summary report is displayed, and users are prompted to confirm its accuracy. They are also prompted to review the actionable insights generated from openFDA data, allowing for more informed decision-making.

By synergizing an efficient pipeline with user-friendly prompts, our proposed approach aims to offer a robust and accessible application capable of significantly reducing medical errors and improving patient safety, particularly in low-resource settings.

4 Results Analysis

We tested our application on a public sample of the MIMIC-III dataset that contains de-identified health data associated with over 40,000 patients who stayed in critical care units of the Beth Israel Deaconess Medical Center. For this scope of this project, we only test on a small public sample, and focused on medical notes only.



Figure 2: Processed Medical Notes

The results indicate that the our application is effective in verifying medical notes, integrating real-time data for informed decision-making, and improving the user experience for healthcare workers. Most importantly, the application shows promise in its primary objective—reducing medical errors and enhancing patient safety.

5 Limitation and Conclusion

In this project, we introduce an application aimed at reducing medical errors and enhancing patient safety, particularly in low-resource settings. We demonstrate the app's capability to verify medical notes through various input methods and leverage openFDA data for informed decision-making.

However, our work has limitations. The application's effectiveness is currently tested on a limited dataset, questioning its generalizability. Additionally, the reliance on real-time data integration could pose challenges in regions with poor internet connectivity.

Future directions should focus on expanding the dataset for more robust testing and exploring offline capabilities to make the application more versatile. This work serves as a stepping stone for leveraging technology to improve healthcare outcomes in resource-poor settings.

References