

MediXpert: A Vision Language System for Clinical Decision Support

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Abstract- In the context of the current healthcare environment, the accurate diagnosis of a patient's health condition is only possible by the convergence of the self-reported symptoms by the patient and the analysis of medical images such as a chest X-ray, CT scans, or MRI scans. However, the current state-of-the-art models only provide the analysis of self-reported symptoms by the patient using a natural language-based system, which responds to the queries made by the patient (for instance, using transformer-based models such as BERT or GPT), or the analysis of medical images using a vision-based system (for instance, using ResNet or EfficientNet models). Therefore, the current fragmented approach not only affects the potential of accurate diagnosis by using AI-based models but also affects the comprehensive analysis carried out by the diagnostic professionals in the context of self-reported symptoms as well as medical images. A comprehensive analysis system using medical images as well as natural languages is not available in the current context; hence, the accessibility of healthcare has become a significant concern.

Keywords— Vision-Language Models, Multimodal Artificial Intelligence, Clinical Decision Support, Medical Image Analysis, Natural Language Processing, Medical Diagnosis, Telemedicine.

I. INTRODUCTION

The rapid pace at which the development of AI is taking place has significantly impacted the healthcare sector. Today, the practice of medicine depends on the use of both symptoms and imaging techniques such as X-rays and MRI scans. Traditionally, most conventional AI systems process the various data sources individually. Therefore, the diagnostic capability of the system is poor. However, the development of multimodal AI systems has shown promise in the joint analysis of various data sources. Vision-language models, which use the combination of Natural Language Processing (NLP) and Computer Vision (CV), are similar to the actual reasoning process carried out by medical professionals in arriving at accurate diagnoses by relating symptoms to evidence obtained from images. Such systems are particularly useful in resource-constrained environments where access to

skilled radiologists and medical professionals is low. [4]

MediXpert is proposed to function as a smart vision-language assistant in medicine that combines text understanding in terms of symptoms and vision understanding in terms of images into a comprehensive diagnostic system. Users of MediXpert can engage with it through natural language input and can also upload medical images of a case for diagnosis. The integration of multiple vision understanding models enables MediXpert to offer rapid and interpretable diagnostic suggestions. The system emphasizes accuracy, transparency, and usability in order to ensure that the results provided by the AI system can be explained. The system in no way aims at replacing human medical professionals. Rather, it can be used as a supportive tool that assists in making decisions in medical diagnostics. The system can work well in a telemedicine format.

MediXpert is an important benchmark in AI-powered health augmentation and presents an overview of various ways in which multimodal vision and language models could be applied to improve diagnosis as well as the delivery of medical services.

II. RELATED WORK

The recent advancements in the field of medical AI have witnessed a rise in the number of medical AI solutions and applications that take in images and text with the ultimate goal of improving the quality of medical diagnoses and decisions. The early medical AI applications used a unimodal approach in that they processed images or medical texts separately. These applications lacked the ability to comprehend and interpret the end-to-end medical decision and reasoning processes used by medical professionals in making medical decisions. Medical professionals primarily relied on medical images and symptoms for making decisions. [11].

There have been a number of studies on the applications of language models in understanding medical knowledge by using the language. BioBERT and biomedical transformers have been doing well in tasks such as medical text mining, analysis of medical notes, and question answering tasks [2]. Although the language models are doing well in the context of understanding the symptoms of patients, there has been a limitation in the medical interpretability of the visual evidence of the diagnosis.

Vision: Deep CNNs like ResNet and DenseNet have achieved performance close to that of a radiologist in various disease detection tasks using chest X-rays and other medical images. CheXNet has successfully detected various diseases in the thoracic region using deep learning and has shown the potential of using AI in assisted radiology [9]. Similarly, a large database like MIMIC-CXR has enabled the training and testing of a disease diagnostic system using images to be conducted successfully.

Recent research has been conducted using multimodal and vision-language-based approaches. In this context, a new approach called CLIP has been

developed by proposing a contrastive learning approach that can be used to align images and text in a common space to enable cross-modal reasoning between these two modalities [8]. Subsequent research using this idea is LLaVA, which has bridged language and vision models to enable the development of interactive vision-language assistants that can reason using these two modalities together; this research showed excellent general-purpose capabilities for joint multidimensional reasoning but lacked domain knowledge for medical applications.

In order to overcome the problems associated with domains, vision and language models in the health sector, such as BiomedGPT and MedGemma, have been proposed. BiomedGPT has been utilized in the development of the multidisciplinary generative paradigm with the ability to process vision and language in the biomedical sector [3]. MedGemma has further improved the above paradigm with the application of medical dataset fine-tuning in the shared models for the better comprehension of radiology terms and healthcare inferencing in the field of medicine and multi-modal diagnosis [4]. Qwen2.5-VL is an extension of the multi-modal reasoning capability of the model in the sense that it is able to perform contextual reasoning and is multi-lingual in the application of advanced vision and language understanding [1]. Although the model is effective in the application of visual and language reasoning, the application of the model in the field of medicine is very limited.

Despite these improvements, there remain several issues in the deployment of multimodal medical AI systems. The issues include unavailability of paired image-text data, efficiency, lack of interpretability, and validation in medical applications [11]. The MediXpert system uses these recent works in the background by combining vision models that are efficient with domain-specific language models in developing a healthcare decision-support system that is unified, interpretable, and interactive for telehealth settings.

The System Architecture

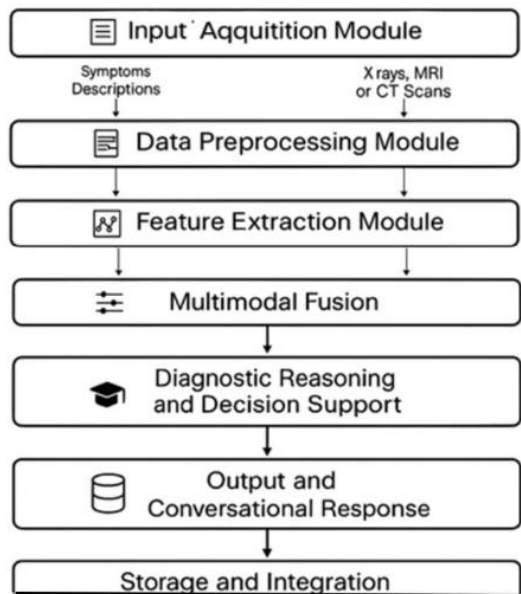


Figure 1: System Architecture of MediXpert.

The MediXpert system uses a vision-language framework based on a vision-language paradigm that is multimodal. The vision-language paradigm used in the system is based on a combination of medical image analysis and natural language processing. The framework used in the system is designed in a modular way that enables efficient processing of patient symptoms and images.

Input Acquisition Module

This input acquisition module may be regarded as a point of entry for the MediXpert system. This allows a user to enter questions in a natural language format regarding their medical conditions, or they may also be allowed to enter images such as those of an X-ray, a CT scan, or even an MRI. This is realities-based since medical experts may be required to look at both medical questions and images.

Data Preprocessing Module

The Data preprocessing module is used for preparing the raw data before it is effectively analyzed. For text data, it may be preprocessed by removing stop words and lemmatization. For images, it may be resized, normalized, and even denoised. These processes may be used to make the model smarter and ensure that it is able to carry out its functions effectively.

Feature Extraction Module

The responsibility of this feature extraction module is to identify the significant features within the text, as well as within the images. The transformer-based architecture of the Gemma Model, MedGemma Model, and Qwen2.5 Model has the potential to identify context representations within the symptom text. On the other hand, unlike this, the ResNet and EfficientNet architectures are capable of identifying features within the images.

Multimodal Fusion Module

The multimodal fusion module is the core of the MediXpert model architecture. This is where it is possible to fuse text embedding and image embedding into a common representation by applying attention-based fusion techniques or transformer-based fusion techniques. As a result, it is possible to establish a connection between patient symptoms and images in order to solve a problem similar to that of human professionals.

Diagnostic Reasoning and Decision Support Module

This is where the diagnostic reasoning module uses the multimodal fusion features learned from their representations and makes a decision on the possible medical diagnoses. It is also the module that is in charge of making recommendations on further questions or diagnoses needed.

Output and User Interaction Module

The output/user interaction module is the module in charge of communicating the results of their findings to the users through an interactive web interface. It is capable of generating natural language explanations of the results, communicating the probability of the diseases to the users, and also indicating the areas of interest in the images using heat maps and segmentation masks. It is also the module that is interpretable by the users and the clinicians.

Implementation

The application of the tool is feasible in different medical situations requiring immediate and accurate diagnosis assistance on a broader scale, including but not limited to the following:

Telemedicine and Remote Consultation

MediXpert is a system that facilitates appropriate telemedicine services through its ability to allow patients to explain their symptoms through natural language processing and to upload images for analysis. The innovations ensure appropriate diagnostic results for patients in physically remote locations.

Rural and Resource-Limited Healthcare

For MediXpert system can be viewed as an auxiliary diagnostic system for rural health facilities where specialized personnel and advanced health equipment may not be readily available. This is through symptom analysis and image analysis, which can assist in diagnosing critical conditions early enough and making appropriate decisions regarding instant referral and treatment. Emergency and Triage Support.

Clinical Decision Support

It acts as a decision support system in a clinical context based on the correlations of symptoms and images. MediXpert facilitates the analysis of images, which in turn assists the doctors in the diagnosis and treatment of the patients, thereby avoiding the uncertainties that exist in the diagnosis process while at the same time ensuring that the supervision and responsibility remain in the hands of the doctors.

Medical Education and Screening Programs

MediXpert has the potential to be used in the educational sector to enlighten the students about the relations of symptoms and images, as well as the logic in the diagnosis process. It has the potential to be used on a large scale in health checks for the identification of healthcare problems in the general public.

Challenges in Design and Implementation

The design and implementation of a multimodal medical AI system like MediXpert involve a lot of issues. These issues arise because of the complexity

of processing medical data that comes in various forms. The system must ensure that it makes reliable predictions while also being easy to use in real-world medical settings

Multimodal Data Integration

One of the major issues in MediXpert is the incorporation of textual and visual medical information. A medical image and medical text have dissimilar structures and formats. For this reason, incorporating their features is not a straightforward or simple process. Effective fusion without distorting the specific information of either a visual or a textual modality is quite a tough task.

Precise Text and Visual Extraction

The performance achieved by deep learning models is largely reliant upon the availability of quality labeled data. However, when it comes to the field of medicine, it becomes quite a challenge to generate a considerable amount of data that is labeled.

Computational Complexity and Resource Constraints

The multimodal models requiring large language models as well as deep vision networks consume large computational resources. Large computational resources are required for the training as well as execution of the multimodal models. It is a challenge to implement the models while ensuring that latency as well as cost-effectiveness are achieved.

Model Interpretability and Explainability

In When AI is used in health care settings, there is a need for transparency and explainability of the outcomes to gain trust on the side of health care professionals. When using deep learning models in AI, it is most likely to work as a black box without being able to explain the outcomes of AI prediction.

III. EVALUATION STRATEGIES

The performance and reliability of the MediXpert system are evaluated using systematic strategies that assess both individual modalities and the overall multimodal framework. These evaluation strategies ensure diagnostic accuracy, robustness,

interpretability, and usability in real-world healthcare scenarios.

Evaluation of Text-Based Analysis

The text processing and language understanding components are evaluated using standard natural language processing metrics. Accuracy, precision, recall, and F1-score are used to measure the correctness of symptom interpretation and medical response generation. These metrics help assess how effectively the language model understands clinical descriptions and generates meaningful diagnostic insights.

Evaluation of Medical Image Analysis

The medical image analysis module is evaluated using computer vision performance metrics. Classification accuracy, sensitivity, specificity, and Area Under the ROC Curve (AUC) are used to measure disease detection performance. For segmentation tasks, metrics such as Dice coefficient and Intersection over Union (IoU) are employed to evaluate the quality of region localization in medical images.

Multimodal Fusion Evaluation

The effectiveness of multimodal fusion is evaluated by comparing system performance with unimodal baselines. Improvements in diagnostic accuracy and confidence scores indicate successful integration of textual and visual features. This evaluation confirms that combining both modalities enhances clinical reasoning compared to using text or images alone.

End-to-End System Performance Evaluation

The overall MediXpert system is evaluated through end-to-end testing using real-world clinical scenarios. Response accuracy, inference time, and system stability are measured to ensure reliable performance. This evaluation validates the system's ability to process user inputs, perform multimodal reasoning, and generate consistent outputs.

IV. DISCUSSION AND CONCLUSION

The implementation of MediXpert is a good example of how a multimodal vision-language system can be effective in medical diagnostics by using a

combination of text understanding based on symptoms and medical image analysis for making correct and timely clinical decisions. By using a combination of patient symptoms and visual evidence from medical images, MediXpert is able to reflect a more realistic process of clinical decision-making and increase confidence in making a preliminary diagnosis. Although MediXpert is not intended to replace a medical practitioner but rather act as a support system, it is able to greatly improve the efficiency of medical diagnostics. In addition, MediXpert is a good example of how multimodal intelligent systems can be used to improve healthcare and increase patient outcomes in the future.

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