

Study of X-Ray interpretation Techniques

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Abstract—This paper presents a study of different deep learning approaches for automatically generating succinct report summaries from X-ray images. This is a comparative study of the models trained on the Indiana University - Chest X-Rays dataset. In this project, we have conducted in-depth literature reviews and suggested improvements to existing deep learning models, all geared towards optimizing the interpretation of Chest X-ray images.

I. INTRODUCTION

Radiology is a branch of medicine that uses imaging technology to diagnose and treat diseases. Doctors specializing in this field, known as radiologists, are equipped with years of training and expertise to interpret X-rays, CT scans, MRIs, nuclear medicine scans, PET scans, ultrasounds, etc. As the number of medical images continues to grow, so too does the workload of radiologists responsible for interpreting them. The sheer volume can overwhelm even the most skilled radiologists, potentially impacting their ability to analyze and interpret them effectively. One possible option is to automate this process.

Machine learning stands out as the most effective way to automate the analysis and diagnosis of medical images. Its diverse applications include:

- **Image segmentation:** Precisely segmenting anatomical structures like the brain, spine, lungs, liver, kidneys, and colon for accurate measurements and analysis.[6]
- **Computer-aided diagnosis and detection:** Detecting and highlighting suspicious lesions in CT or MRI scans, like mammograms and CT colonography, to assist radiologists in making faster and more accurate diagnoses.[10]
- **Brain function analysis:** Analyzing fMRI data to understand brain activity and diagnose neurological diseases, providing valuable insights into brain function and behavior.
- **Content-based image retrieval:** Searching large medical image databases efficiently based on specific features.
- **Text analysis of radiology reports:** Utilizing NLP and NLU to extract key information, identify trends, and even assist in generating reports, streamlining workflow and improving patient care efficiency.

These applications demonstrate machine learning's transformative potential in radiology.

Out of all these applications, we caught our eye on the topic of medical image interpretation and reporting. This process can be error-prone, even for experienced specialists. Many factors can contribute to faulty report generation - lack of knowledge, staff shortage, excessive workload, etc. To reduce the error occurrences, an automated system is needed. [2]

Existing literature on automated medical report generation based on radiological images centers around the recurrent neural network with attention mechanisms[5]. Notably, research concentrating on the Indiana University X-Ray dataset has sequentially addressed the classification of frontal and lateral views [9], the grading of cardiomegaly severity [10], and the computer-aided diagnosis (CAD) of lung diseases [11]. These studies commonly employed CNN and Variational Topic Inference for classification and exploratory analysis. Additionally, recent work in image captioning explores using GRU models [12], knowledge graphs [13], and Multimodal Large Language Models for automated report generation [14].

In this paper, we will present comparative study of the different techniques used for automated report generation.

***** The main contributions of our work toward automated radiology report generation are: (1) we propose a novel recurrent generation model to generate the findings paragraph, sentence by sentence, whereby a succeeding sentence is conditioned upon multimodal inputs that include its preceding sentence and the original images, (2) we adopt an attention mechanism for our proposed multimodal model to improve performance. Extensive experiments on the Indiana University Chest x-rays dataset demonstrate the effectiveness of our proposed methods. *****

II. DATA

In this study, we employ the Indiana University Chest X-Ray collection [15] as our primary dataset for evaluation. This dataset encompasses a total of 7,471 X-ray images, each accompanied by a corresponding medical report. Notably, some reports are associated with more than one image. Each report is uniquely linked to a pair of images representing the frontal and lateral views.

The content of these reports is structured in XML format, necessitating XML parsing to extract and convert the information into a more accessible CSV format. The report sections include essential medical information such as comparison, indication, findings, and impression.

For our model, we consider both image and text inputs. The image data consists of the X-ray images associated with each report. Additionally, we extract textual information from the abstract, comparison, indication, and findings sections of the reports to serve as text input features.

The target variable for our analysis is the "Impression" section of the medical reports, which is treated as a text feature. This approach enables us to develop a comprehensive understanding of the relationship between input features and the diagnostic impressions generated by radiologists. The combination of image and text inputs enriches our model, allowing

it to learn complex patterns and relationships essential for automatic report generation in the field of medical image interpretation.

III. METHODOLOGY

A. Data Pre-processing

B. Page Numbers

Do not type any page numbers. Page numbers will be added in the digest editing/production process.

C. Equations

Equations should be centered in the column and numbered sequentially. Place the equation number to the right of the equation within a parenthesis, with right justification within its column. An example would be

D. Figures

Most of the following applies to Microsoft Word. Figures should utilize as much of the column width as possible in order to maximize legibility. Use a sans serif font, such as Helvetica. Helvetica is larger and much easier to read than Times New Roman. Using 8- to 10-point Helvetica usually results in a legible figure.

IV. RELATED WORK

Use the examples provided [1] - [2] as a guide.

V. CONCLUSION

Write your conclusions here.

VI. FUTURE WORK

As a potential avenue for future research, extending our models to include the PadChest[ZXX] dataset could be valuable. The PadChest dataset stands out as one of the largest publicly available chest X-ray databases, providing substantial data for training supervised models specifically tailored to radiographs. Exploring the integration of this dataset into our model training pipeline could enhance the generalization and performance of our models, fostering a broader and more robust application in the field of medical image interpretation.

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