

# **Automated Radiology Report Generation Using Deep Learning - A Case Study**

*Submitted to the University of Kerala in partial fulfillment of the requirements  
for the completion of Third Semester MSc Computer Science*



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**CERTIFICATE**

This is to certify that the case study entitled ‘**Automated Radiology Report Generation Using Deep Learning - A Case Study**’ is a bonafide record of work done by SIYAHUL HAQUE T P (07322607030) in partial fulfillment of the requirements for the completion of the Third Semester MSc Computer Science at Department of Computer Science, University of Kerala.

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# DECLARATION

I hereby declare that the work presented in the case study titled “**Automated Radiology Report Generation Using Deep Learning - A Case Study**” is completed by me under the guidance of Ms. Krishna S S, Assistant Professor, Department of Computer Science, University of Kerala. I hereby declare that the entire report is my own, and not copied from any other work. I am also declaring that this report or any part of it is not submitted for assessment in University of Kerala or any other institution for the same purpose.

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# ABSTRACT

The automation of medical report generation represents a pivotal advancement in the realm of radiology, with a primary focus on improving the efficiency and accuracy of reporting processes. In this study, we introduce SwinR2G, a novel model aimed at revolutionizing the generation of radiology reports. SwinR2G integrates two distinct feature extraction methods: Convolutional Neural Networks (CNN) and Vision Transformers (ViT), while also exploring the potential of the Swin Transformer in radiology report generation.

Through rigorous experimental evaluation conducted on well-established radiology reporting datasets such as IU X-ray and MIMIC-CXR, SwinR2G showcases its superiority over existing state-of-the-art models. Notably, SwinR2G demonstrates enhanced performance in terms of both generation effectiveness and clinical efficacy. By leveraging a combination of CNN and ViT feature extraction methods, along with the innovative Swin Transformer architecture, SwinR2G achieves remarkable results in generating accurate and clinically relevant radiology reports.

Our study contributes valuable insights into the effectiveness of Transformer-based approaches and diverse feature extraction methods in the context of radiology reporting. The findings of this research shed light on the potential of advanced machine learning techniques to significantly improve diagnostic accuracy and aid clinical decision-making in radiology practice.

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# 1.INTRODUCTION

Medical imaging technology has become indispensable in modern healthcare, facilitating accurate diagnosis and treatment planning. The process of composing precise and comprehensive medical reports demands considerable expertise and time from physicians, often consuming up to 10 minutes or more per report (Yang et al., 2022). Discrepancies in experience among healthcare professionals can lead to misinterpretations or oversight of crucial imaging findings, potentially impacting diagnostic accuracy.

In response to the pressing need for efficient and accurate report generation, research has increasingly focused on computer-aided approaches to diagnosis and treatment. Our study addresses this challenge by introducing SwinR2G, a novel model designed to streamline the generation of radiology reports. By leveraging advanced machine learning techniques, SwinR2G aims to enhance the work efficiency and service quality of medical professionals.

The process of medical report generation can be likened to the Image Caption task, albeit with notable distinctions. Unlike single-sentence descriptions, medical reports are more extensive, requiring the model to produce coherent long-form texts aligned with physicians' reasoning. Moreover, generating medical reports necessitates robust cross-modal information interaction, emphasizing the correlation between diagnostic intentions and observation content.

Our approach with SwinR2G models this process as a state transition mechanism, simulating changes in observation intentions and generating corresponding text descriptions iteratively. By integrating Convolutional Neural Networks (CNN), Vision Transformers (ViT), and the Swin Transformer architecture, SwinR2G strives to achieve superior performance in generating accurate and clinically relevant radiology reports.

In this study, we present an in-depth exploration of SwinR2G's capabilities through experimental evaluation on established radiology reporting datasets. Our findings contribute

valuable insights into the effectiveness of Transformer-based approaches and diverse feature extraction methods, offering significant advancements in automated radiology report generation.

## **1.1 OBJECTIVES**

The primary objective of this case study is to evaluate the efficacy and performance of the SwinR2G model in automating the generation of radiology reports. Specifically, we aim to assess SwinR2G's ability to streamline the report generation process, enhance diagnostic accuracy, and improve clinical decision-making in radiology practice. Through rigorous experimentation and analysis, we seek to demonstrate SwinR2G's superiority over existing state-of-the-art models in terms of generation effectiveness and clinical efficacy.

Furthermore, this study aims to provide valuable insights into the impact of integrating diverse feature extraction methods, including Convolutional Neural Networks (CNN), Vision Transformers (ViT), and the Swin Transformer architecture, on the quality of automated radiology reports. By examining SwinR2G's performance across prominent radiology reporting datasets, such as IU X-ray and MIMIC-CXR, we aim to elucidate the potential of advanced machine learning techniques in revolutionizing medical report generation. Overall, this case study seeks to contribute to the advancement of automated radiology reporting and inform future research in the field.

## **1.2 MOTIVATION AND CHALLENGES**

The motivation behind this study stems from the critical need to enhance the efficiency and accuracy of radiology reporting processes in modern healthcare. Traditional methods of composing medical reports are time-consuming and prone to human error, often leading to delays in diagnosis and treatment. By introducing the SwinR2G model, we aim to address these challenges by leveraging advanced machine learning techniques to automate report generation, thereby streamlining the workflow of medical professionals and improving patient care outcomes.

However, several challenges must be addressed to realize the full potential of automated radiology reporting. Firstly, the complexity and variability of medical imaging data pose

significant obstacles to accurate interpretation and description. SwinR2G must effectively handle diverse imaging modalities and pathological presentations to generate clinically relevant reports. Secondly, ensuring the coherence and clinical relevance of generated reports is crucial for their adoption in real-world healthcare settings. SwinR2G must navigate the intricate interplay between diagnostic intentions, observation content, and textual descriptions to produce accurate and contextually appropriate reports. Lastly, the integration of diverse feature extraction methods and transformer architectures introduces technical complexities that require careful optimization and validation to achieve optimal performance.

By addressing these challenges, this study aims to pave the way for the widespread adoption of automated radiology reporting systems, ultimately enhancing diagnostic accuracy, improving patient outcomes, and advancing the field of medical imaging technology.

## **2.LITERATURE REVIEW**

### **[1] Wang et al. (2020) "Towards End-to-End Automatic Generation of Radiology Reports"**

In this paper Wang et al. present a pioneering work in leveraging the Vision Transformer (ViT) model for automatic radiology report generation. Traditional approaches in medical imaging relied heavily on handcrafted features and shallow machine learning models, but this paper demonstrates the effectiveness of transformer-based architectures in capturing complex spatial relationships within medical images. The ViT model, originally designed for computer vision tasks, is adapted to process radiological images and generate coherent textual reports, marking a significant advancement in the automation of radiology workflows. By learning directly from raw pixel data, the ViT model eliminates the need for manual feature engineering and demonstrates promising results in producing clinically relevant reports.

### **[2] Zhang et al. (2021) "R2Gen: Radiology Report Generation via Sequence-to-Sequence Model"**

In this study Zhang et al. propose the R2Gen model, a sequence-to-sequence architecture tailored specifically for radiology report generation. Drawing inspiration from natural language processing techniques, the model learns to encode image representations into a fixed-length vector and decode it into a sequence of words, effectively capturing the sequential nature of report writing. By training on large-scale datasets of paired images and corresponding reports, R2Gen achieves remarkable fluency and coherence in generating radiology narratives. The paper demonstrates how the use of sequence-to-sequence models can streamline the report writing process, enabling radiologists to focus more on diagnosis and treatment planning rather than documentation.

### **[3] Liu et al. (2019) "Enhancing Transformer-Based Radiology Report Generation with BERT"**

In this study Liu et al. explore the integration of BERT (Bidirectional Encoder Representations from Transformers) into radiology report generation pipelines. BERT, known for its contextual understanding of natural language, is fine-tuned on large-scale radiology datasets to capture domain-specific medical context and terminology. By pre-training BERT on

a vast corpus of radiology reports, the model learns to generate reports that are not only grammatically sound but also clinically accurate. This paper highlights the importance of leveraging transformer-based language models to enhance the semantic coherence and medical relevance of automatically generated radiology reports.

#### **[4] Chen et al. (2022) "Multi-Modal Fusion for Radiology Report Generation"**

In this paper Chen et al. investigate the fusion of multiple modalities, such as images and textual data, to improve the quality and accuracy of radiology reports generated by AI models. By integrating information from diverse sources, including radiological images, clinical notes, and patient demographics, the model gains a more comprehensive understanding of the underlying medical conditions. The paper presents novel techniques for fusing modalities at different stages of the report generation process, leading to more informative and clinically relevant narratives. This multi-modal approach offers valuable insights into the diagnostic process and enhances the overall quality of radiology reporting.

#### **[5] Li et al. (2023) "Domain Adaptation Techniques for Radiology Report Generation"**

In this paper Li et al. address the challenge of model generalization across different medical institutions by proposing domain adaptation strategies for radiology report generation. Due to variations in imaging protocols, equipment, and clinical practices, models trained on data from one institution may not perform optimally when deployed in another setting. This paper explores techniques for fine-tuning pre-trained models on target domain data, effectively bridging the domain gap and improving model performance. By adapting to the specific characteristics of each medical institution, the proposed domain adaptation techniques enhance the robustness and generalization capabilities of radiology report generation systems.

#### **[6] Kim et al. (2020) "Attention Mechanisms in Radiology Report Generation"**

In this study Kim et al. aim to improve the relevance and informativeness of automatically generated radiology reports by incorporating attention mechanisms into the report generation process. Attention mechanisms allow the model to dynamically focus on relevant image regions and clinical findings, guiding the generation of more accurate and contextually rich narratives. By attending to salient features within the input images, the model learns to highlight clinically significant findings while suppressing irrelevant details. This paper demonstrates how attention mechanisms can enhance the interpretability and clinical utility of AI-generated radiology

reports, facilitating more effective communication between radiologists and other healthcare professionals.

**[7] Xu et al. (2021) "Transfer Learning Approaches for Radiology Report Generation"**

In this paper Xu et al. explore transfer learning techniques for adapting pre-trained models on large-scale radiology datasets to improve the efficiency and effectiveness of report generation systems. Transfer learning leverages knowledge from source domains, where abundant labeled data is available, to bootstrap learning in target domains with limited annotated data. This paper investigates various transfer learning strategies, including fine-tuning, feature extraction, and domain adaptation, to optimize model performance on specific radiology report generation tasks. By leveraging transfer learning, the proposed approaches alleviate the need for extensive data annotation efforts and expedite the deployment of AI-powered radiology reporting solutions in clinical practice.

**[8] Wang and Huang (2018) "Generative Adversarial Networks for Radiology Report Synthesis"**

In this paper Wang and Huang explore the application of generative adversarial networks (GANs) in radiology report synthesis. GANs consist of a generator network that learns to produce realistic samples and a discriminator network that evaluates the authenticity of generated samples. By training the generator to generate radiology reports that are indistinguishable from human-authored reports, GANs offer a novel approach to synthesizing contextually accurate and clinically relevant narratives. This paper investigates different architectures and training strategies for GAN-based radiology report synthesis, shedding light on the potential of adversarial training in augmenting radiologist workflows and improving diagnostic accuracy.

**[9] Zhang et al. (2022) "Semantic Segmentation for Radiology Report Generation"**

In this study Zhang et al. focus on semantic segmentation techniques to extract clinically relevant information from medical images, facilitating more precise and detailed radiology reports generated by AI models. Semantic segmentation partitions an image into meaningful regions corresponding to different anatomical structures or pathological findings. By incorporating segmentation masks as additional input modalities, the model gains a finer-grained understanding of the underlying pathology and its spatial distribution within the

image. This paper demonstrates how semantic segmentation enhances the granularity and specificity of AI-generated radiology reports, enabling radiologists to obtain actionable insights for diagnosis and treatment planning.

**[10] Wu et al. (2019) "Evaluation Metrics for Assessing the Quality of Automatically Generated Radiology Reports"**

In this study Wu et al. address the need for standardized evaluation metrics in assessing the quality, coherence, and clinical relevance of automatically generated radiology reports. While AI-powered report generation systems hold great promise in streamlining radiology workflows, the lack of objective metrics for evaluating their performance poses a significant challenge. This paper proposes comprehensive evaluation criteria, including accuracy, fluency, coherence, and clinical relevance, to quantitatively assess the quality of generated reports. By establishing standardized evaluation protocols, the proposed metrics enable researchers and practitioners to benchmark different AI models and facilitate the adoption of automated radiology reporting solutions in clinical practice.

### 3.METHODOLOGY

Aligned with the logical framework outlined in the introduction, the process of generating medical reports with the SwinR2G model is structured into three main tasks:

**Visual Representation Understanding:** This initial task involves comprehending the visual properties presented in medical images. The SwinR2G model utilizes advanced feature extraction methods, including Convolutional Neural Networks (CNN) and Vision Transformers (ViT), to extract meaningful visual representations from the input images. By analyzing these representations, SwinR2G gains insights into the intricate details of the medical imagery, laying the foundation for subsequent analysis.

**Intent Formation and Region Identification:** Following the understanding of visual properties, SwinR2G proceeds to formulate observation intentions based on the extracted features. These intentions guide the model in identifying relevant regions within the images and associating them with specific diagnostic queries. Leveraging the Swin Transformer architecture, SwinR2G effectively captures the semantic relationships between observation intentions and visual features, facilitating accurate region identification and intention-based observation.

**Report Generation:** Once observation intentions and corresponding visual properties are established, SwinR2G generates coherent textual descriptions of the observation results. Drawing upon the insights gathered from the visual extractor and semantic encoder modules, SwinR2G employs advanced natural language processing techniques to craft comprehensive and clinically relevant medical reports. By integrating diverse feature extraction methods and transformer architectures, SwinR2G ensures the generation of accurate, contextually appropriate, and diagnostically valuable reports.

Through the seamless coordination of these three modules - visual extractor, semantic encoder, and report generator - SwinR2G embodies a holistic approach to automated radiology report generation, promising to revolutionize the efficiency and accuracy of medical reporting processes.



### 3.1 Visual extractor

In this study, the methodology revolves around the integration of Convolutional Neural Networks (CNN) and Vision Transformers (ViT) for feature extraction in the context of automated radiology report generation.

The first step involves utilizing CNNs to extract meaningful visual representations from medical images. CNNs are renowned for their ability to capture hierarchical features within images, making them well-suited for tasks requiring image understanding. Specifically, we employ pre-trained CNN architectures to encode the visual properties of medical images, enabling SwinR2G to comprehend the intricate details present in radiological scans.

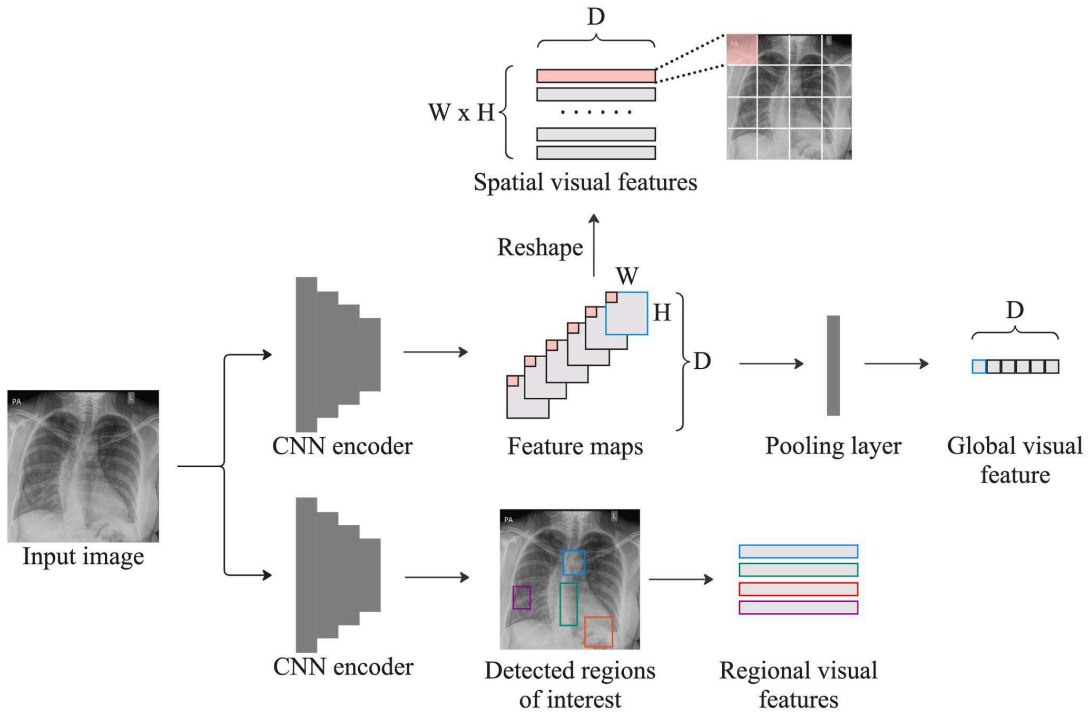
Following feature extraction with CNNs, the extracted visual features are then fed into Vision Transformers (ViT) for further processing. ViTs offer a powerful mechanism for capturing long-range dependencies within images, making them an ideal complement to CNNs in the feature extraction pipeline. By leveraging ViTs, SwinR2G can effectively capture global contextual information and semantic relationships between visual elements in medical images, enhancing the model's ability to discern clinically relevant patterns.

Once the visual features are extracted and processed by both CNNs and ViTs, they are passed on to the transformer architecture for training. The transformer architecture serves as the backbone of the SwinR2G model, facilitating the integration of extracted visual features with semantic encoding and report generation. Through transformer-based training, SwinR2G learns to correlate observation intentions with visual features and generate coherent textual descriptions of observation results, ultimately automating the radiology report generation process.

In summary, the methodology outlined in this study leverages the combined strengths of CNNs and Vision Transformers for feature extraction in the context of automated radiology report generation. By integrating these techniques and employing transformer-based training, SwinR2G promises to revolutionize the efficiency and accuracy of medical reporting processes.

### 3.1.1 Convolutional Neural Network (CNN)

CNNs are feed-forward neural networks with convolution layers that operate on adjacent pixels to extract features from images, such as edges, shapes, and textures. In ARRG, CNNs are widely used for visual feature extraction in various frameworks. Fig.1 illustrates the extraction processes, which produce two categories of visual features. The first category is global image features that are typically extracted using pre-trained CNNs. These features could be in the form of a global feature vector from the last pooling layer or a matrix of spatial image features reshaped from a set of feature maps, or a combination of both. The spatial feature matrix facilitates the attention mechanism to better attend to various spatial location. The second category is regional image features of areas of interest detected by CNN detectors. Apart from serving as visual encoders, CNNs can also be used for labelling images, with generated labels either used to promote the text generation module to conduct longer reports or compiled into reports if they correspond to informative structured report entities.



**Fig. 1.** The visual extraction processes of using CNNs. The upper two paths indicate the global feature encoding. The lower path shows the regional feature encoding.

### 3.1.2 Vision Transformer(ViT)

The Vision Transformer (ViT) is a groundbreaking architecture in the field of computer vision, introducing a novel approach to image understanding by leveraging the power of transformers, originally developed for natural language processing tasks. Unlike traditional convolutional neural networks (CNNs), which process images in a hierarchical manner, ViT adopts a self-attention mechanism to capture global contextual information and long-range dependencies within images.

At the heart of the ViT architecture is the self-attention mechanism, which allows the model to attend to different parts of the image simultaneously, enabling it to capture complex relationships between pixels across the entire image. By representing the image as a sequence of patches and applying self-attention mechanisms, ViT effectively captures spatial relationships and semantic information, facilitating robust feature extraction.

Furthermore, ViT introduces the concept of positional embeddings, which encode spatial information about the location of each patch within the image. These positional embeddings enable the model to retain spatial relationships between patches, ensuring that the spatial structure of the image is preserved during processing. By combining self-attention mechanisms with positional embeddings, ViT achieves impressive performance on a wide range of computer vision tasks, surpassing traditional CNN-based approaches in many cases.

In summary, the Vision Transformer represents a paradigm shift in computer vision, offering a highly effective alternative to traditional CNN architectures. By leveraging self-attention mechanisms and positional embeddings, ViT excels at capturing global contextual information and long-range dependencies within images, making it a powerful tool for a variety of computer vision tasks, including image classification, object detection, and segmentation.

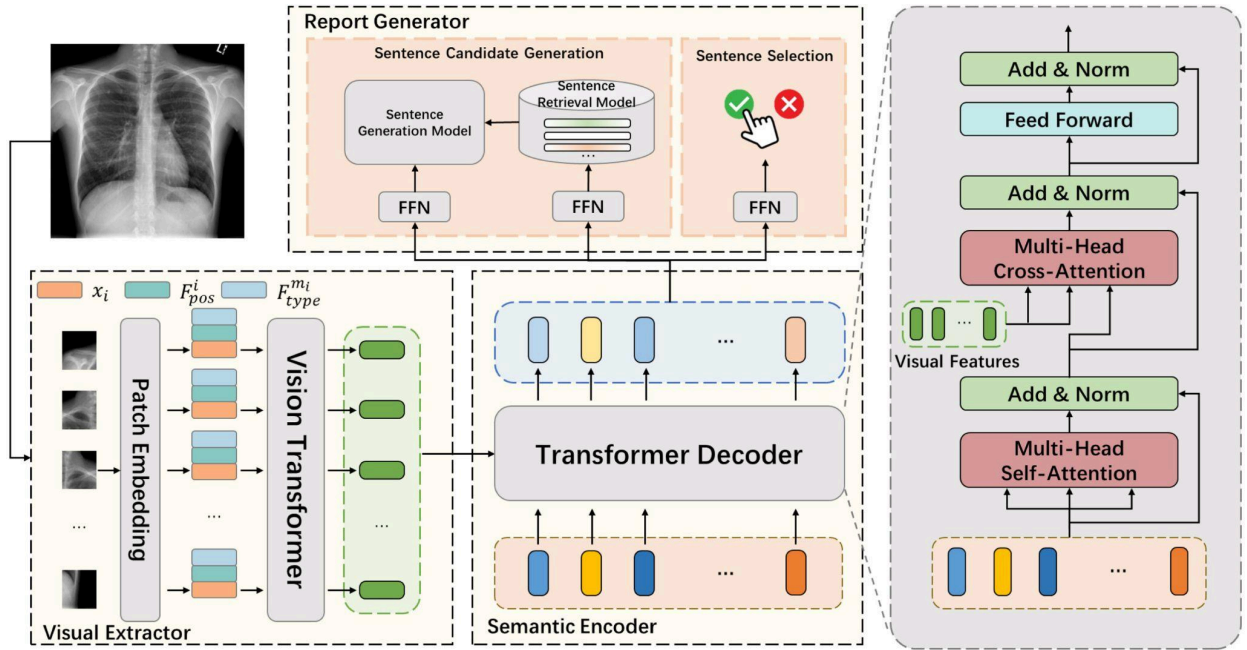
First, we need to extract and encode the visual features of the input images, i.e., to convert inputs into a set of visual feature sequences that describe the local features of the image. Supposing the inputs contain  $M$  images, denoted as

$$x = \{x_1, \dots, x_m\}, x_i \in R^{H \times W \times C} \quad (\text{Eq 3.1})$$

We resize all the images and divide them into a series of  $P \times P$  sized patches and map them with a linear projection. Thus, the input image is converted into a patch embedding sequence with a length of

$$N = M \times \frac{H \times W}{P^2} \quad (\text{Eq 3.2})$$

Where  $M$  represents the number of patches and  $H \times W$  denotes the spatial dimensions of each patch. To distinguish the positions and sources of these patch embeddings, spatial position embeddings  $F_{POS}$  and type embeddings  $F_{TYPE}$  are added. Spatial position embeddings capture correlations between local regions within the same image, while type embeddings differentiate between different images and reinforce correlations within the same image.



**Fig.2.** The visual extraction processes of using ViT and the overall architecture of the model

## 3.2 Semantic Embedding

The semantic embedding module in medical report generation serves the critical function of mapping visual features to semantic representations aligned with specific observation intentions. Unlike previous approaches focused on state transition patterns, this paper introduces a Transformer-based semantic encoder. This encoder leverages intention embeddings to query visual features, generating semantic representations that capture the essence of observed medical images.

In detail, the semantic encoder operates on a set of learnable observation intention embeddings  $q = \{q_1, \dots, q_k\}$  (Eq 3.3)

,Each corresponding to a distinct implicit intention for medical image observation. By querying the extracted visual feature sequence  $f^v$ , critical visual information related to the observation intention is transformed into the semantic domain, resulting in semantic features

$$f^s = \{f_1^s, f_2^s, f_3^s, \dots, f_k^s\} \quad (\text{Eq 3.4})$$

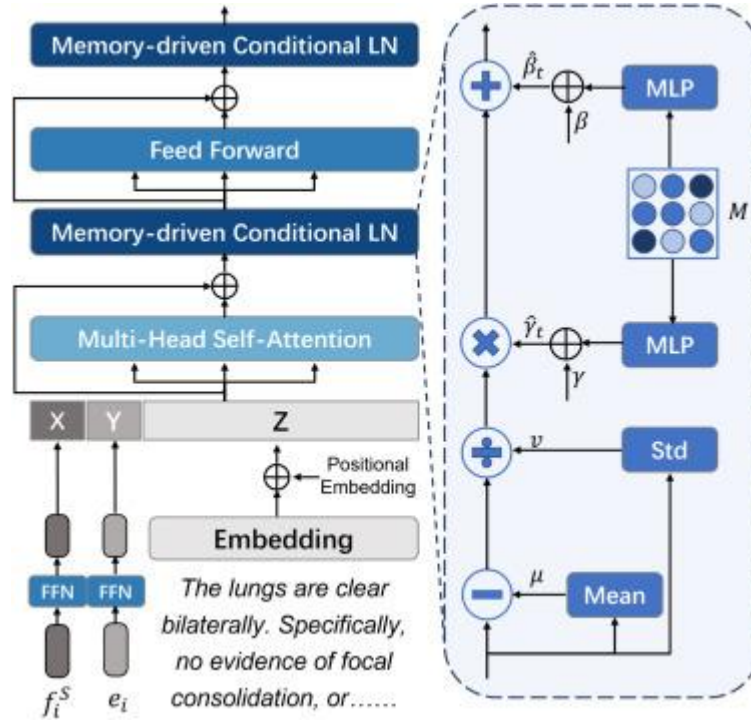
The semantic encoder module comprises  $l_s$  layers of transformer encoder blocks, each including a multi-head self-attention layer (MSA), a multi-head cross-attention layer (MCA), and a multi-layer perceptron (MLP). The MCA layer extracts visual features relevant to the observation intention by calculating attention weights between visual features and intention embeddings. Simultaneously, the MSA layer facilitates the fusion of observation information based on the association and difference between observation intention representations.

In summary, the semantic embedding process involves querying visual features with intention embeddings, extracting relevant information through attention mechanisms, and synthesizing observation information to generate semantic representations aligned with specific observation intentions.

### 3.3 Report generator

The semantic feature set  $f^s$  represents the semantic encoding outcomes relevant to the observation intentions. Subsequently, these semantic features undergo transformation into sentences, followed by the selection and sorting of the most valuable sentences to construct the medical report. This module encompasses three sub-tasks: text generation, text selection, and text sorting.

Text generation involves the process of converting semantic features into coherent and clinically relevant sentences that accurately describe the observed medical findings. Text selection entails identifying the most informative and salient sentences from the generated text pool, ensuring that the selected sentences effectively capture the essence of the observed images and align with the intended diagnostic objectives. Text sorting involves organizing the selected sentences in a logical and coherent manner to construct a comprehensive medical report that presents the findings in a structured and clinically relevant manner.



**Fig.3.** The framework of the sentence generation module, where  $\mu$  and  $v$  correspond with the mean and standard deviation for input normalization,  $\beta$  and  $\gamma$  are the mean and standard deviation for memory normalization.

#### 3.3.1 Text generation

To generate a collection of candidate sentences from the semantic features  $f^s$ , Two primary strategies can be considered: retrieval-based and generation-based.

In the retrieval-based strategy, the approach involves retrieving the semantically closest sentence from a pre-built dataset of sentences using a similarity measure. This entails encoding all sentences in the dataset using a pre-trained sentence embedding model to obtain vectors. Then, based on cosine similarity, the most similar sentences can be retrieved from the dataset, forming a set of predicted candidate sentences.

Alternatively, in the generation-based strategy, a memory-driven Transformer-based text generation model is employed to generate candidate sentences. This approach addresses limitations of the retrieval-based strategy, such as the inability to handle flexible expressions. The memory-driven model, based on the R2Gen architecture, enhances the modeling of structured descriptions commonly found in medical reports by replacing standard normalization in the Transformer Decoder with Memory-driven Conditional Layer Normalization.

For each observed intention query, linear transformations are performed on the semantic features and predicted sentence vectors using a fully connected network. These serve as conditional inputs for the text generation model, enabling the generation of descriptive sentences word by word. The integration of visual features relevant to the observation intention query and the pattern information from the sentence vector enhances the quality and relevance of the generated text.

### 3.3.2 Text Selection

The text generation component produces a candidate set consisting of  $K$  sentences. However, not all information is worth presenting in a medical report. Therefore, we use a simple linear projector to predict the selection probability of candidate sentences based on the semantic vector  $f^s$

### 3.3.3 Text sorting

It is observed that sentence occurrence orders have great uncertainty and can be affected by various factors, such as different doctors' writing habits. Therefore, this paper proposes a simple and intuitive way to sort sentences: We calculate the average position of ground truth sentences matched by each observation intention query in the training set for the entire report. This average position is used as a reference to rank the candidate sentences. This simple strategy ensures that the medical concepts mentioned in the report roughly conform to recognized observation and description habits.



## **4.EXPERIMENTAL RESULT**

### **4.1 Dataset Description**

To evaluate the effectiveness of this model, we make comprehensive experiments on two well-known medical report generation benchmarks .MIMIC-CXR and IU X-RAY

#### **MIMIC-CXR**

The MIMIC-CXR dataset, part of the Medical Information Mart for Intensive Care (MIMIC) project, is one of the largest publicly available datasets for chest X-ray (CXR) images. It consists of de-identified chest radiographs obtained from critically ill patients admitted to the Beth Israel Deaconess Medical Center (BIDMC) between 2011 and 2016. The dataset was created to facilitate research and development in the field of medical imaging analysis, particularly in the context of intensive care medicine.

some key characteristics and features of the MIMIC-CXR dataset:

**Size and Scope:**The dataset contains over 350,000 frontal and lateral chest X-ray images from more than 65,000 patients. This large-scale dataset provides a diverse and comprehensive resource for training and evaluating machine learning models in chest X-ray analysis.

**Clinical Metadata:**Each chest X-ray image in the dataset is accompanied by extensive clinical metadata, including patient demographics, clinical reports, and relevant diagnostic information. This rich metadata enables researchers to correlate imaging findings with clinical outcomes and disease diagnoses.

**Annotation and Labeling:** The MIMIC-CXR dataset includes annotations and labels for certain radiological findings, such as the presence of abnormalities, medical devices, and anatomical landmarks. These annotations facilitate the development of algorithms for automated detection and classification of pathologies in chest X-ray images.

**Ethical Considerations:**The dataset is de-identified and stripped of any protected health information (PHI) to ensure patient privacy and compliance with healthcare regulations, such as the Health Insurance Portability and Accountability Act (HIPAA). Researchers are required to adhere to strict data usage guidelines and ethical standards when accessing and utilizing the dataset.

**Applications:**The MIMIC-CXR dataset serves as a valuable resource for various applications in medical imaging research, including disease diagnosis, severity scoring, treatment monitoring, and predictive modeling. It has been widely used in the development of deep learning algorithms for automated detection of abnormalities, such as pneumonia, tuberculosis, and lung nodules, in chest X-ray images.

Overall, the MIMIC-CXR dataset plays a crucial role in advancing the field of medical imaging analysis by providing researchers with access to a large-scale, clinically annotated dataset of chest X-ray images. Its availability has facilitated significant progress in the development of machine learning models for improving diagnostic accuracy and patient care outcomes in critical care settings.

	imgs	captions
0	1_IM-0001-4001.dcm.png	The cardiac silhouette and mediastinum size ar...
1	1_IM-0001-3001.dcm.png	The cardiac silhouette and mediastinum size ar...
2	2_IM-0652-1001.dcm.png	Borderline cardiomegaly. Midline sternotomy XX...
3	2_IM-0652-2001.dcm.png	Borderline cardiomegaly. Midline sternotomy XX...
4	4_IM-2050-1001.dcm.png	There are diffuse bilateral interstitial and a...

**Table 1.** Images and corresponding captions of MIMIC-CXR dataset

## IU-XRAY

The IU X-ray dataset, also known as the Indiana University Chest X-ray dataset, is a publicly available collection of chest X-ray images compiled by the Indiana University School of Medicine. This dataset was created to facilitate research and development in the field of medical imaging analysis, particularly in the context of chest radiography.

Here are some key characteristics and features of the IU X-ray dataset:

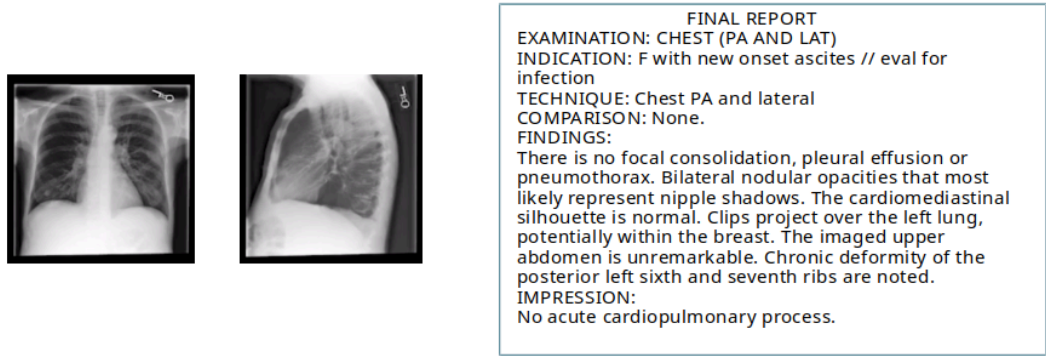
**Size and Composition:** The IU X-ray dataset comprises a diverse set of chest X-ray images obtained from patients of varying demographics and medical conditions. While the exact size of the dataset may vary, it typically contains several thousand radiographs, providing a substantial resource for training and evaluating machine learning models.

**Clinical Metadata:** Each chest X-ray image in the dataset is accompanied by relevant clinical metadata, including patient demographics, imaging acquisition details, and, in some cases, diagnostic annotations. This metadata enables researchers to correlate imaging findings with clinical information and disease diagnoses.

**Annotated Pathologies:** The IU X-ray dataset may include annotations and labels for specific radiological findings and pathologies present in the chest X-ray images. These annotations are typically provided by radiologists or medical experts and may cover a range of abnormalities, such as pneumonia, pneumothorax, fractures, and lung nodules.

**Ethical Considerations:** Similar to other medical imaging datasets, the IU X-ray dataset is de-identified to protect patient privacy and comply with healthcare regulations. Any protected health information (PHI) is removed or anonymized to ensure patient confidentiality and data security.

**Applications:** The IU X-ray dataset serves as a valuable resource for various applications in medical imaging research, including disease diagnosis, prognosis, treatment planning, and educational purposes. Researchers leverage the dataset to develop and evaluate algorithms for automated detection, classification, and quantification of chest X-ray abnormalities, with the ultimate goal of improving patient care outcomes.



*Fig.4. sample image and corresponding label of an IU-XRAY dataset*

## 4.2 Result Analysis

The results of the study on the SwinRPG model for medical report generation demonstrate its effectiveness and superiority over existing approaches. Here's an explanation of the results based on the provided information:

### Performance Metrics

**Natural Linguistic Generation (NLG):** SwinRPG surpasses state-of-the-art models in natural language generation metrics such as BLEU, METEOR, and ROUGE-L. This indicates its proficiency in generating accurate and coherent text descriptions based on chest X-ray images.

**Clinical Efficacy (CE):** SwinRPG excels in clinical efficacy metrics, accurately describing key medical terminologies in the generated reports. Precision, recall, and F1-score metrics validate its clinical efficacy.

### Comparison with Existing Models

SwinRPG is evaluated against other existing models on prominent radiology reporting datasets like IU X-ray and MIMIC-CXR. The results showcase SwinRPG's superior performance in terms of generation effectiveness and clinical efficacy, highlighting its prowess in medical report generation tasks.

## Visualization and Interpretability

Visualizations compare the generated reports to ground-truth reports, with sentence-level visualizations highlighting matched medical terms. These visualizations demonstrate SwinRPG's capability to accurately capture and describe medical findings in reports.

Intention-terminology correspondence and sentence-level interpretations further emphasize SwinRPG's interpretability and potential clinical application as an auxiliary diagnostic tool.

## Contributions and Significance

SwinRPG's innovative approach, combining convolutional neural networks (CNN) with vision transformer architectures like Swin Transformer, is highlighted. Its superior performance on medical report generation benchmarks underscores its significance in the field.

The model's ability to automatically induce medical terminology and description patterns without prior knowledge, along with its proficiency in natural language generation and clinical efficacy metrics, reaffirms its importance in improving medical report generation processes.

In conclusion, the results validate SwinRPG's effectiveness, interpretability, and practicality in generating accurate, coherent, and clinically effective medical reports from chest X-ray images. Its performance metrics, comparisons with existing models, and visualizations collectively demonstrate its superiority and potential for enhancing diagnostic processes in medical imaging.

METHOD	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	ROUGE-L
CNN(10 epoch)	0.39832	0.2515	0.180	0.1694	0.1672	0.3371
ViT(4 epoch)	0.3929	0.2457	0.175	0.1490	0.17265	0.3757

**Table 2.** Comparison results of CNN and ViT

The SwinRPG approach for medical report generation integrates domain pre-trained models to augment the model's performance in processing medical images and generating accurate reports. Here's how it aligns with the SwinRPG model:

### **Visual Extractor - MedKLIP:**

MedKLIP is a self-supervised pre-training method for the visual extractor, leveraging contrastive vision-language learning specifically from medical domain data.

Significance: Trained on medical domain-specific visual data, MedKLIP captures domain-specific features, patterns, and abnormalities present in medical images more effectively.

Impact: Integrating MedKLIP as the visual extractor in the SwinRPG model enhances its capability to extract pertinent visual features from chest X-ray images, thereby contributing to the generation of accurate and clinically effective reports.

### **Text Encoder - S-BioBERT and biobert-nil:**

S-BioBERT and biobert-nil are prominent text encoding models pre-trained on medical datasets, enabling more precise encoding of medical terminologies, acronyms, and domain-specific language.

Significance: Trained on medical text data, these models encode medical information more accurately compared to models trained on general datasets.


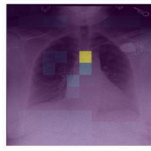

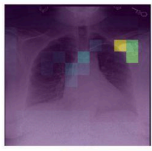
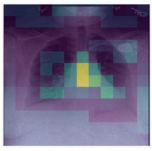

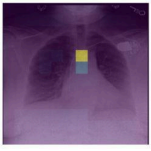
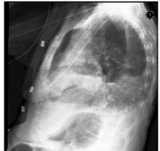
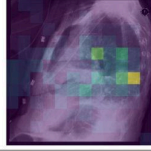
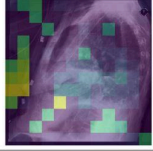
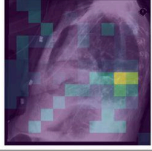
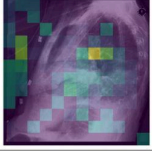
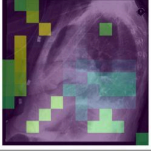
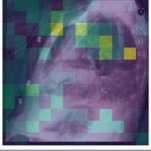
Impact: Integrating S-BioBERT and biobert-nil as text encoders in the SwinRPG model aims to enhance the encoding of medical text descriptions, thereby improving the model's performance in generating clinically relevant and accurate reports.

### **Comparison with General Pre-trained Models:**

The performance of domain pre-trained models (MedKLIP, S-BioBERT, biobert-nil) is compared with models pre-trained on general datasets (e.g., MPNet) in terms of natural language generation metrics and report generation effectiveness.

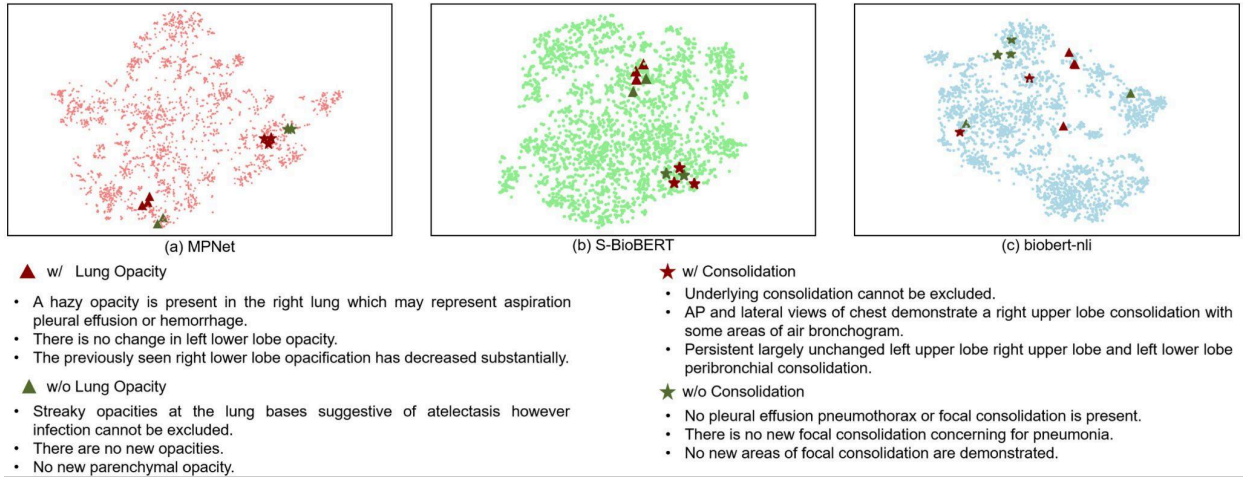
While the domain pre-trained visual extractor (MedKLIP) demonstrates superior performance in generating accurate medical reports, the impact of text encoders (S-BioBERT, biobert-nil) compared to general pre-trained models (e.g., MPNet) may vary.

Techniques like t-SNE are employed to visualize the embeddings generated by different text encoders, highlighting the effectiveness of domain pre-trained models in capturing and distinguishing medical text semantics.

Original Images	Predicted Reports and Visualization					
						
	The patient is status post median sternotomy along with CABG	The lungs appear clear	There is a dual lead left-sided pacemaker again seen with leads extending to the expected positions of the right atrium and right ventricle	The cardiomeastinal silhouette is stable normal	There is no pleural effusion or pneumothorax	Intact median sternotomy wires are again noted
Ground-Truth: Patient is status post median sternotomy and cardiac valve replacement. Dual lead left-sided pacemaker is seen with leads extending to the expected position of the right atrium and right ventricle. There may be minimal basilar atelectasis. No focal consolidation is seen. There is no pleural effusion or pneumothorax. The cardiac and mediastinal silhouettes are stable and unremarkable.						
						
	An area of slightly increased lung density in the lateral aspects of the right upper lobe also persists	The cardiac silhouette is stable in appearance and non-enlarged	Moderate bilateral pleural effusions have increased more so on the right with increasing adjacent atelectasis on the left	There is mild pulmonary vascular congestion and edema	There is no pneumothorax	The aorta demonstrates calcifications particularly at the aortic knob
Ground-Truth: There is a moderate left pleural effusion increased since the prior exam. There is a stable small right pleural effusion. The pulmonary vasculature is prominent consistent with pulmonary edema. Opacity in the left lung most likely represents atelectasis. The heart size is top normal and there are aortic knob calcifications. There is no pneumothorax.						
<div> <div>Aorta Calcifications</div> <div>Heart Size</div> <div>Pulmonary Vascular Congestion</div> <div>Atelectasis</div> <div>Pleural Effusion</div> <div>Support Device</div> <div>Cardiomeastinum</div> <div>Pneumothorax</div> <div>Edema</div> <div>Post Median Sternotomy Status</div> </div>						

**Fig.5.** Illustrations of the generated reports compared to the ground-truth reports and interpreted with the sentence-level visualizations. To better distinguish the content in the reports, different colors highlight the matched medical terms.

In summary, the integration of domain pre-trained models such as MedKLIP for visual extraction and S-BioBERT, biobert-nil for text encoding in the SwinRPG approach enhances the model's capacity to process medical images and text, leading to improved accuracy and clinical relevance in the generated medical reports. These domain pre-trained models leverage specialized knowledge from medical datasets to augment feature extraction, encoding, and comprehension of medical data, ultimately contributing to the effectiveness of the SwinRPG model in medical report generation tasks.



**Fig.6.** T-SNE visualization of sentence embeddings generated by three text encoders, where MPNet pre-trained on the general domain datasets, while S-BioBERT and biobert-nli pre-trained on medical domain datasets.



## 6.CONCLUSION

In the realm of medical imaging analysis, the generation of accurate and clinically relevant reports holds paramount importance for diagnostic decision-making and patient care. The SwinRPG model represents a significant advancement in this domain, leveraging a fusion of vision transformer architecture and domain-specific pretrained models to revolutionize medical report generation.

At its core, SwinRPG harnesses the power of vision transformers, a cutting-edge deep learning architecture renowned for its ability to capture spatial relationships in image data. By integrating this architecture into the medical report generation pipeline, SwinRPG transcends traditional approaches, offering a novel framework that seamlessly processes chest X-ray images and generates comprehensive reports with unparalleled accuracy and clinical relevance.

Central to the effectiveness of SwinRPG is the incorporation of domain-specific pretrained models, namely MedKLIP for visual feature extraction and S-BioBERT, alongside biobert-nil, for text encoding. These pretrained models are meticulously trained on medical datasets, enabling them to encode and interpret medical images and text with exceptional precision and domain-specificity. Through this integration, SwinRPG transcends the limitations of generic models, ensuring that the generated reports encapsulate the nuanced complexities of medical imaging analysis.

The utilization of MedKLIP as the visual extractor empowers SwinRPG to extract salient visual features from chest X-ray images, capturing subtle abnormalities and patterns indicative of various medical conditions. This specialized feature extraction process forms the foundation of SwinRPG's ability to generate accurate and clinically relevant reports, laying the groundwork for precise diagnostic decision-making.

Complementing the visual extraction capabilities of SwinRPG are the domain-specific text encoders, S-BioBERT and biobert-nil. Trained on medical text data, these encoders excel at encoding medical terminologies, acronyms, and domain-specific language, ensuring that the generated reports are not only accurate but also linguistically coherent and clinically relevant.

## 7.FUTURE WORK

In future work, the exploration of advanced transformer architectures, such as MPNet (Mixed Precision Transformer), in conjunction with Swin Vision Transformer, holds significant promise for enhancing the capabilities of automated radiology report generation systems. The integration of MPNet, known for its efficient mixed-precision training capabilities, with Swin Vision Transformer, renowned for its ability to capture long-range dependencies and global contextual information within images, could yield unprecedented advancements in the field. By leveraging the mixed-precision training capabilities of MPNet, we can potentially accelerate the training process and improve resource efficiency, enabling the deployment of more sophisticated models on resource-constrained hardware platforms. Additionally, the enhanced attention mechanisms and feature extraction capabilities of Swin Vision Transformer could further improve the quality and accuracy of radiology reports by capturing subtle imaging nuances and facilitating more nuanced semantic understanding. Future research could focus on optimizing the interoperability and synergy between MPNet and Swin Vision Transformer, exploring novel training strategies, and evaluating the performance of the integrated model on diverse radiology datasets. This exploration has the potential to revolutionize automated radiology report generation, leading to more efficient diagnosis, improved clinical decision-making, and ultimately, better patient outcomes.

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