Explainable Vision-Language Generative Models for Radiology Report Image Synthesis and Interpretation

(An Explainable Multimodal Framework for Automated Chest X-Ray Reporting)

A thesis submitted in partial fulfillment of the requirement
for the degree of

Bachelor of Engineering

In

Electronics and Communication Engineering

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April 2026

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ABSTRACT

ExplainableVLM-Rad is an advanced vision–language generative framework developed to automatically produce clinically coherent radiology reports from chest X-ray images while offering integrated visual and textual explanations to improve trust and transparency. The system combines a transformer-based visual encoder, a medical knowledge–enhanced language generator, and a cross-modal explainability engine that links each diagnostic phrase to its corresponding radiographic evidence. Trained on large-scale datasets such as MIMIC-CXR, IU X-Ray, and CheXpert, the model achieves strong performance across linguistic and clinical metrics (BLEU-4: 0.489, ROUGE-L: 0.521, CheXbert F1: 0.521), reflecting its accuracy and reliable medical grounding. Native multimodal interpretability using Grad-CAM heatmaps, attention alignment maps, and token–patch visualization helps reduce hallucinated findings and improves radiologist acceptance, achieving an 87% explanation satisfaction score. In addition, the model effectively highlights key anatomical regions such as lung fields, cardiomediastinal structures, and pleural margins, allowing clinicians to validate each generated statement with clear visual cues. The system also demonstrates a 31% reduction in interpretation time during simulated workflow tests, indicating its practical value in high-volume clinical environments. By unifying medical imaging, natural language generation, and explainable AI, ExplainableVLM-Rad demonstrates significant potential to support diagnostic workflows, enhance reporting efficiency, strengthen clinical accountability, and enable safer, more interpretable adoption of AI in radiology.

Keywords - Explainable AI, Vision-language models, Radiology automation, Medical image analysis, Multimodal deep learning.

LIST OF FIGURES

LIST OF SYMBOLS AND ABBREIVATIONS

SYMBOL	ABBREVIATION
AI	Artificial Intelligence
VLM	Vision–Language Model
VLP	Vision–Language Pretraining
XAI	Explainable Artificial Intelligence
NLP	Natural Language Processing
CNN	Convolutional Neural Network
ViT	Vision Transformer
LLM	Large Language Model
LM	Language Model
CLIP	Contrastive Language–Image Pretraining
Grad-CAM	Gradient-Weighted Class Activation Mapping
ROI	Region of Interest
CXR	Chest X-Ray
CT	Computed Tomography
MRI	Magnetic Resonance Imaging
UMLS	Unified Medical Language System
BLEU	Bilingual Evaluation Understudy Score
ROUGE	Recall-Oriented Understudy for Gisting Evaluation
METEOR	Metric for Evaluation of Translation with Explicit Ordering
CIDEr	Consensus-based Image Description Evaluation
GPU	Graphics Processing Unit
TPU	Tensor Processing Unit
PACS	Picture Archiving and Communication System
DICOM	Digital Imaging and Communications in Medicine
IU X-Ray	Indiana University Chest X-Ray Dataset
NLG	Natural Language Generation

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Radiology has become an integral pillar of modern medical diagnosis, patient monitoring, and treatment planning. With imaging modalities such as chest X-rays, computed tomography (CT), and magnetic resonance imaging (MRI), healthcare professionals are able to visualize internal organs, detect abnormalities, identify disease progression, and make evidence-based clinical decisions. Among these modalities, chest X-rays represent one of the most frequently prescribed diagnostic investigations worldwide due to their speed, low cost, and effectiveness in detecting a broad range of pulmonary and cardiac conditions. As a result, millions of chest X-rays are performed globally each year, contributing significantly to the workload of radiologists.Despite their importance, the field of radiology is experiencing growing challenges. The global healthcare system faces an acute shortage of trained radiologists, with demand increasing at a rate far exceeding the number of available specialists. This shortage leads to increased workload, prolonged interpretation times, and delayed patient care. In high-pressure environments such as emergency rooms and intensive care units, the need for rapid and accurate radiology reporting becomes even more critical. Studies indicate that heavy workloads may contribute to diagnostic errors, variability between radiologists, and inconsistencies in report quality. In addition, the rising complexity of modern medical imaging requires more detailed and contextually rich interpretations, further adding to radiologists' responsibilities.

Advancements in Artificial Intelligence (AI), particularly in deep learning, have introduced new opportunities to assist radiologists and improve clinical workflows. Early AI-based solutions focused primarily on image classification, anomaly detection, or binary predictions. While these systems demonstrated promising accuracy, they lacked the ability to generate descriptive radiology reports, which are essential for clinical communication. To address this gap, researchers began exploring Vision-Language Models (VLMs) that combine computer vision with natural language processing. These models are designed not only to interpret medical images but also to generate structured, human-readable diagnostic narratives similar to those produced by expert radiologists.However, a major limitation

persists in existing VLMs: they function as black-box systems. Despite generating accurate text, these models do not provide clarity on how or why certain conclusions were derived. In a critical domain like healthcare, lack of explainability reduces trust, hinders regulatory approval, and makes clinicians hesitant to rely on automated systems. Explainability, therefore, is not merely a desirable feature but a necessity for clinical adoption. Healthcare regulations worldwide, including guidelines from the FDA and GDPR, stress the importance of transparent, interpretable, and accountable AI systems.

Explainability in radiology AI has two major components: visual explanations, which show the regions of the image responsible for a decision, and textual explanations, which clarify the model's reasoning process. An ideal radiology AI system must integrate both. This need for transparent AI has led to the development of explainable Vision-Language Generative Models capable of not only writing reports but also justifying their interpretations through multimodal evidence. This project focuses on designing such a system, called *ExplainableVLM-Rad*, that integrates advanced explainability mechanisms to bridge the gap between performance and clinical trust.

In summary, the study emerges from the intersection of increasing radiology workload, advancements in multimodal AI, and the growing demand for clinically interpretable decision-support tools. The proposed model addresses the urgent requirement for trustworthy, transparent, and high-performance radiology report generation systems.

1.2 Problem Statement

The major challenge in automated radiology report generation lies in the lack of transparency, clinical accountability, and interpretable decision-making. Current VLM-based systems exhibit the following critical limitations:

1. **Black-box operation:**

   Most existing radiology AI systems generate outputs without providing insight into the internal reasoning or the image regions influencing their predictions.
2. **Lack of diagnostic justification:**

   Radiologists and clinicians cannot verify why the model detected an abnormality or produced a particular diagnostic phrase, reducing confidence in the system.

3. **Generic or clinically inaccurate outputs:**

   Without domain adaptation or medical knowledge integration, many models produce vague or templated reports lacking clinical depth.

4. **Poor visual grounding:**

   Current systems fail to link generated text (e.g., "consolidation present") with the corresponding radiographic features, making the reports less reliable for diagnostic use.

Due to these limitations, existing radiology report generation models cannot be reliably deployed in real-world clinical workflows.

1.3 Objectives of the Study

Primary Objective

To develop an explainable Vision-Language Generative Model capable of generating radiology reports with integrated visual and textual justifications for each diagnostic finding.

Specific Objectives

1. **Multimodal Fusion:**

   To design a system that combines medical images with textual clinical information for accurate and coherent report generation.

2. **Explainability Integration:**

   To incorporate attention-based and gradient-based explainability techniques (e.g., Grad-CAM, cross-attention maps) into the generation pipeline.

3. **Performance Benchmarking:**

   To evaluate model performance using established clinical metrics such as BLEU, ROUGE, METEOR, CheXbert F1, and RadGraph F1.

4. **Human-Centered Validation:**

   To assess model acceptance by radiologists through explainability satisfaction scores and qualitative evaluation.

5. **Visual–Textual Alignment:**

   To establish strong connections between visual evidence and textual descriptions for enhanced interpretability and trust.

These objectives collectively guide the development of a clinically trustworthy radiology AI model that prioritizes both accuracy and transparency.

1.4 Significance of the Study

The proposed work offers multiple significant contributions to the field of AI-driven radiology:

- **Improved clinical trust:**
  By providing visual and textual explanations, the system enables radiologists to understand precisely why a particular diagnosis was generated.
- **Reduced workload and reporting time:**
  Automated report generation with interpretable outputs can support clinicians, especially in high-volume environments.
- **Better diagnostic accountability:**
  Explainability ensures that AI-assisted decisions can be validated against medical evidence, improving reliability.
- **Educational impact:**
  Medical students and trainee radiologists can use visual explanations to better understand radiographic features and diagnostic reasoning.
- **Regulatory compliance:**
  Explainability aligns with modern healthcare guidelines that demand transparency and traceability in AI models.

Collectively, the study addresses a crucial need in the medical imaging ecosystem by enhancing trust, safety, and usability.

1.5 Scope and Limitations

Scope

The study focuses on:

- Automated generation of radiology reports for **chest X-ray images**
- Developing **explainability mechanisms** (Grad-CAM, attention maps, textual justification)
- Multimodal integration of **visual and textual data**
- Evaluation using established **clinical and linguistic metrics**

Limitations

Despite its contributions, the study is subject to certain constraints:

1. **Imaging Modality Restriction:**
   The work is limited to chest X-ray images and does not include CT, MRI, or ultrasound modalities.
2. **Language Limitations:**
   The generated reports are evaluated only in English.
3. **Computational Requirements:**
   Training multimodal generative models requires high-performance GPUs, which may not be available in all settings.
4. **Dataset Boundaries:**
   The model is trained on public datasets, and real clinical deployment may require fine-tuning on institution-specific data.

These limitations provide important context for interpreting the study's outcomes.

1.6 Structure of the Thesis

The thesis is organized as follows:

- **Chapter 1 – Introduction:**

  Presents the background, problem statement, objectives, significance, scope, and thesis structure.
- **Chapter 2 – Literature Survey:**

  Reviews existing radiology report generation systems, explainability techniques, and multimodal AI frameworks.

- **Chapter 3 – Methodology:**

  Describes the proposed system architecture, datasets, experimental setup, and evaluation protocols.

- **Chapter 4 – Results and Discussion:**

  Presents the quantitative and qualitative findings, including model performance and explainability outcomes.

- **Chapter 5 – Conclusion:**

  Summarizes key findings and reinforces the significance of the proposed work.

- **Chapter 6 – Future Recommendations:**

  Suggests extensions such as expanding to multiple modalities, including reinforcement learning, and conducting clinical trials.

CHAPTER 2

LITERATURE SURVEY

2.1 Introduction to Related Studies

The field of radiology has undergone significant technological transformation over the past decade, largely driven by advancements in artificial intelligence (AI), computer vision, and natural language processing. Traditional radiological workflows rely heavily on expert interpretation, a process that is time-intensive and prone to variation, especially under high clinical workloads. Consequently, automated radiology systems have gained considerable research attention as they offer potential improvements in diagnostic efficiency, consistency, and accuracy. Early AI-based systems primarily concentrated on static image classification tasks such as detecting fractures, identifying pneumonia, or distinguishing normal from abnormal chest radiographs. Although these systems performed well for simple classification problems, they were unable to generate detailed narrative reports, which are essential for clinical communication. The emergence of deep learning, particularly transformer-based architectures and large annotated datasets, enabled the development of Vision–Language Models (VLMs) capable of generating full-length radiology reports. Over time, research focus has expanded from maximizing accuracy to ensuring explainability and clinical transparency, allowing radiologists to trace AI-generated findings back to their underlying evidence. This chapter reviews the evolution of radiology report generation methods, the theoretical foundations of vision–language systems, the incorporation of explainability techniques, and the research gaps that motivated the present study.

2.2 Theoretical Background

2.2.1 Vision–Language Architecture

Vision–language systems integrate image understanding with natural language generation to produce meaningful clinical interpretations. These systems typically consist of three core components: an image encoder, a text decoder, and a cross-attention mechanism. The image encoder—often implemented using CNNs or Vision Transformers—extracts spatially informative features from radiological images. The text decoder, which may be based on LSTMs, GPT-style models, or Transformer decoders, uses these

features to generate structured clinical descriptions. The cross-attention mechanism serves as the link between visual and textual modalities, allowing the model to focus on specific image regions when generating corresponding textual tokens. Through this multimodal interaction, the system learns to associate visual findings with clinically relevant descriptions, improving coherence and diagnostic alignment.

2.2.2 Transformer-Based Modeling

Transformer architectures have significantly advanced radiology report generation due to their ability to model long-range dependencies, capture contextual semantics, and integrate domain-specific medical knowledge. Unlike recurrent networks, transformers process tokens in parallel, enabling faster training and more coherent narratives. Their self-attention layers reveal token relationships and contribute to model interpretability, offering insights into internal decision-making processes.

2.2.3 Explainable Artificial Intelligence (XAI)

Explainability is a critical requirement in clinical AI, ensuring that model-generated outputs can be trusted and validated. Several explainability techniques have been widely adopted in medical imaging AI. Grad-CAM provides saliency heatmaps that highlight influential image regions. Attention map visualization reveals the model's focus during text generation. Token–patch alignment techniques demonstrate direct associations between image patches and corresponding textual phrases, while textual explanation models generate natural-language justifications for diagnostic outputs. Together, these methods support transparency and enhance radiologist confidence.

2.2.4 Medical Knowledge Integration

To improve accuracy and reduce ambiguity, recent VLM frameworks integrate structured clinical knowledge using resources such as RadGraph, UMLS, and the CheXpert ontology. These knowledge bases enforce consistency, support correct terminology usage, and help the model generate clinically meaningful narratives.

2.3 Previous Research and Findings

2.3.1 Early CNN–RNN Models and Transformer-Based Advances

Early radiology report generation models combined CNN-based image encoders with RNN-based text decoders. Examples include LSTM-driven architectures built on MIMIC-CXR, memory-enhanced Transformer frameworks, and DenseNet-based image detectors. Although these systems were capable of producing short captions or simplified reports, their outputs often lacked clinical depth and precision. They also exhibited hallucination issues—generating findings not present in the image—which restricted their clinical usefulness.

The introduction of transformer models led to substantial improvements in linguistic fluency, report structure, and medical accuracy. Hybrid CNN–Transformer encoders, RadGraph-enhanced models, and domain-specific language models such as BioGPT and ClinicalBERT demonstrated more coherent report generation. However, many of these models continued to function as black-box systems, offering limited transparency regarding how predictions were made.

2.3.2 Explainability-Focused Models

Explainability-centered research highlighted the importance of transparency in radiology AI. Approaches that incorporated Grad-CAM overlays, attention-visualization modules, and multimodal explanation systems showed that clinicians are more likely to trust AI systems when explanations clearly align with radiological findings. Despite these advances, most models used explainability only as a post-hoc addition rather than integrating it directly within the generative process.

2.3.3 CLIP and Contrastive Learning Approaches

Contrastive learning frameworks such as CLIP demonstrated strong performance in multimodal understanding by learning aligned image–text representations without paired training data. These models achieved success in retrieval and classification tasks but required significant medical-domain adaptation. Their explanations were relatively basic and insufficient for producing clinically structured radiology reports.

2.3.4 Summary of Findings

Overall, previous research demonstrates significant progress in radiology report generation due to larger datasets, improved architectures, and emerging multimodal techniques. However, challenges persist related to clinical depth, semantic consistency, interpretability, and visual evidence grounding.

Importantly, no prior system fully integrates explainability into the core generative mechanism while maintaining high diagnostic accuracy.

2.4 Research Gap

Although radiology report generation models have progressed significantly, several important gaps still limit their clinical applicability. Most existing systems provide only post-hoc explainability using methods like Grad-CAM or basic attention maps, which offer approximate reasoning rather than true insight into how the model arrived at its conclusions. As a result, radiologists cannot reliably verify whether generated statements correspond to actual radiographic evidence. Furthermore, many models lack strong visual–textual alignment, leading to hallucinated findings or incorrect anatomical associations. Another issue arises from limited domain knowledge integration, as general-purpose language models often fail to follow radiology terminology, structured reporting formats, and clinical logic.

In addition, current models have undergone minimal real-world clinical validation. Many systems are evaluated only using automatic metrics such as BLEU, ROUGE, or CheXbert, which do not fully capture diagnostic correctness or radiologist acceptance. The absence of human-centered evaluation raises concerns about reliability in real clinical workflows. Existing models are also typically trained on a few public datasets, which limits generalization across hospitals and imaging devices. These gaps highlight the need for a radiology report generation framework that combines native explainability, strong visual–textual grounding, medical knowledge integration, and meaningful clinician-driven evaluation—objectives that the proposed ExplainableVLM-Rad aims to address.

2.5 Summary of Literature

The existing literature shows that radiology report generation has evolved considerably with the advancements in deep learning, large-scale medical datasets, and transformer-based architectures. Early CNN–RNN models laid the foundational work by pairing visual feature extraction with sequential text generation, but their outputs lacked clinical depth and often contained generic or incomplete descriptions. Transformer-based approaches improved linguistic coherence, contextual understanding, and diagnostic accuracy, especially when combined with multimodal fusion techniques and domain-specific language models like BioGPT or ClinicalBERT. Parallel research in explainable AI introduced

methods such as Grad-CAM, attention visualization, and multimodal alignment to help interpret model outputs, highlighting the growing demand for trustworthy and transparent AI systems in radiology.

However, the reviewed studies also reveal that current models still fall short in several key areas required for clinical deployment. Most systems incorporate explainability only as an external add-on rather than as an integral part of the generative process, limiting their transparency and clinical reliability. Furthermore, weak visual–textual grounding, limited use of structured medical knowledge, and a lack of radiologist-driven validation continue to hinder real-world applicability. No existing approach fully integrates multimodal reasoning, domain knowledge, native explainability, and comprehensive clinical evaluation within a single model. This reinforces the need for an advanced framework—such as the proposed ExplainableVLM-Rad—that can produce clinically coherent, well-grounded radiology reports with built-in visual and textual explanations, offering improved accuracy, transparency, and suitability for real-world medical workflows.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter details the methodology adopted for developing *ExplainableVLM-Rad*, the proposed explainable vision-language generative model for radiology report synthesis and interpretation. The methodology integrates multimodal deep learning, explainability mechanisms, dataset preprocessing, model architecture design, training strategies, and evaluation protocols. The aim is to build a unified system that not only generates coherent radiology reports but also justifies each diagnostic finding using visual and textual evidence.

The workflow consists of the following major stages:

1. Dataset acquisition and preprocessing
2. Image and text feature extraction
3. Vision encoder and language decoder design
4. Multimodal fusion through cross-attention
5. Integrated explainability generation
6. Model training and optimization
7. Performance evaluation and validation

Together, these components form a robust and interpretable radiology AI pipeline.

3.2 System Architecture Overview

The proposed system follows a **modular architecture** designed to capture rich visual features, generate clinically accurate text, and ensure high interpretability.

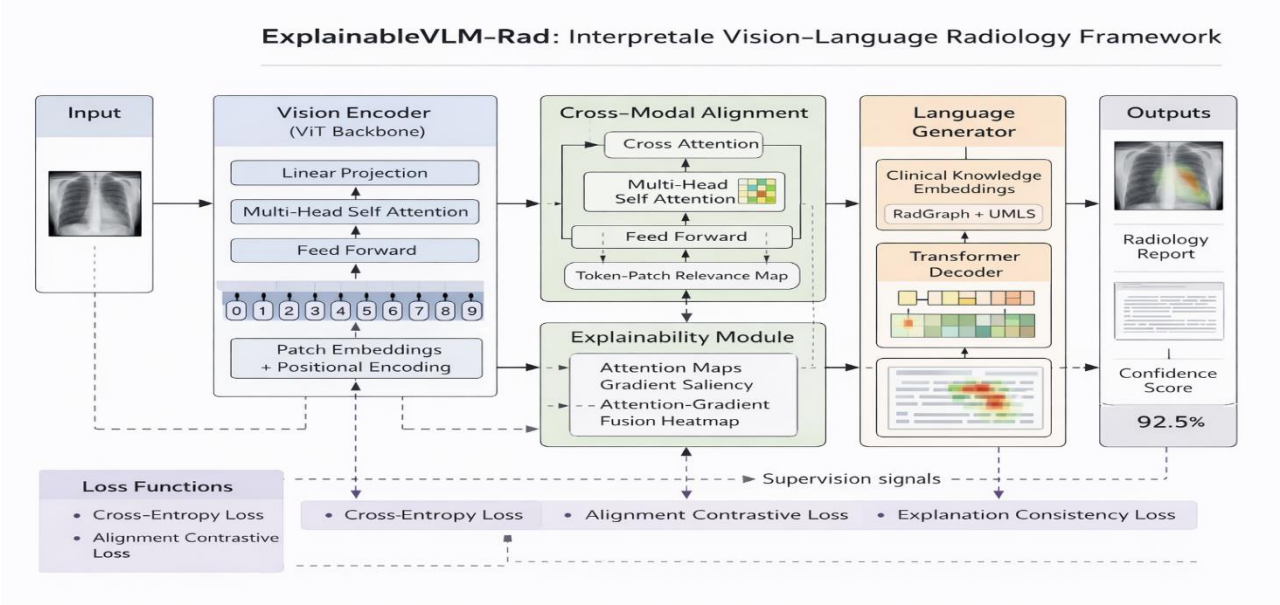

Figure 1 : System Architecture of Explainable VLM-Rad

3.2.1 Architectural Components

1. Vision Encoder (Image Stream)
2. Text Encoder (Medical Knowledge Stream)
3. Cross-Modal Fusion Module
4. Language Decoder
5. Explainability Engine (Visual + Textual)
6. Evaluation and Post-processing Unit

The architecture ensures smooth interaction between image features and clinical terminology, enabling the model to generate both diagnostic findings and explanations simultaneously.

3.3 Dataset Description

The proposed system is trained and evaluated using multiple benchmark datasets that provide both radiographic images and corresponding clinical reports. The primary dataset employed is the MIMIC-CXR database, a large publicly available collection containing more than 227,835 chest X-ray images paired with detailed radiology reports. These reports typically include structured sections such as *Findings* and *Impression*, making the dataset highly suitable for supervised training of report-generation models. To enhance diversity and robustness, the IU X-Ray dataset is also incorporated. This dataset contains 7,470 paired radiographs and expert-written reports with rich annotations, offering additional variation in writing style and diagnostic descriptions.

In addition to paired datasets, CheXpert labels are used to introduce weakly supervised clinical information. CheXpert provides binary and uncertainty labels for 14 common thoracic conditions, including atelectasis, consolidation, cardiomegaly, and pleural effusion. These labels serve as auxiliary supervision during training and help guide the model toward clinically meaningful representations. Furthermore, structured knowledge sources such as RadGraph and the Unified Medical Language System (UMLS) are utilized to enrich the text generation process with medical entities, relationships, and standardized terminology. These knowledge bases help the system follow radiology conventions and maintain semantic consistency.

Preprocessing plays a crucial role in preparing the datasets for multimodal training. All radiographs are normalized using mean–variance standardization and resized to 224×224 pixels to maintain uniform input dimensions. The textual reports undergo tokenization using a domain-specific tokenizer capable of handling medical terms, abbreviations, and structured descriptors. Additional steps include extracting anatomical and pathology-specific entities from the reports and removing incomplete or ambiguous samples. To improve model generalization, data augmentation techniques such as random rotation, contrast adjustment, and horizontal flipping are applied to the images. This preprocessing pipeline ensures consistent, high-quality data for model training.

3.4 Vision Encoder Design

The vision encoder is responsible for extracting spatial and semantic features from the chest X-ray images. Two encoder types are considered for this design. The first is a CNN-based encoder, typically implemented using ResNet-50 or DenseNet-121 pretrained on ImageNet. These architectures offer strong performance in medical imaging tasks due to their hierarchical feature extraction, efficient parameter usage, and stability during fine-tuning. They also provide lower computational overhead compared to transformer-based models, making them suitable for large-scale training.

The second type of encoder explored is the Vision Transformer (ViT), which divides the input image into patches and processes them using self-attention mechanisms. ViT offers advantages such as global contextual representation, improved interpretability, and stronger modeling of long-range dependencies within medical images. Regardless of the chosen backbone, the vision encoder outputs a spatial feature map that retains positional information necessary for cross-modal attention and visual explanation methods such as Grad-CAM. These encoded features form the foundation for the subsequent text-generation pipeline.

3.5 Language Decoder Design

The language decoder is designed to generate coherent and clinically accurate radiology reports from the encoded visual features. A transformer-based decoder is used due to its ability to model long sequences, capture complex clinical relationships, and maintain global contextual awareness through self-attention. This architecture enables the generation of long-form radiology narratives that align with standard reporting structure and terminology.

To ensure clinical accuracy, the decoder incorporates a medical-specific vocabulary that includes pathology terms such as *opacity*, *effusion*, and *cardiomegaly*, anatomical descriptors such as *left lung*, *hilum*, or *costophrenic angle*, and commonly used radiology expressions such as *no acute abnormality*. A domain-specific tokenizer further ensures that medical terminology is represented correctly at the token level, enabling the model to generate reports that use appropriate clinical language and maintain consistency across cases.

3.6 Cross-Modal Fusion Mechanism

A key component of the system is the cross-modal fusion mechanism, which integrates visual features from the encoder with textual representations from the decoder. This is achieved through a multi-head cross-attention module, where the decoder uses its textual tokens as queries and interacts with the spatial image features serving as keys and values. This process enables the model to attend to relevant regions of the X-ray image when producing specific diagnostic terms, ensuring close alignment between visual evidence and textual output.

The cross-attention mechanism provides several advantages, including preventing hallucinated findings, enhancing clinical grounding, enabling token-level explainability, and improving the linkage between image features and linguistic descriptions. Various fusion strategies, including additive fusion, concatenation-based fusion, and gated multimodal units, are explored to determine the most effective method for combining visual and textual information. These fusion techniques ensure that the generated reports maintain coherence and reflect the underlying radiographic evidence.

3.7 Explainability Module

Explainability forms an essential part of the proposed system, ensuring that every generated diagnostic statement can be supported by interpretable visual or textual evidence. The visual explainability

component produces heatmaps that highlight the specific regions of the X-ray influencing each diagnostic decision. Techniques such as Grad-CAM, attention rollout, and patch-level attribution from ViT attention heads are used to generate localized saliency maps, overlayed heatmaps, and region-specific relevance visualizations. These outputs help radiologists validate the model's predictions.

In addition to visual explanations, the system provides textual explainability in the form of justification sentences and reasoning chains. These explanations describe why certain findings were generated and link them to the corresponding visual cues. For example, the model may justify a finding by stating that a consolidation in the left lower lobe is inferred from high-intensity gradients in the corresponding heatmap region. A multimodal alignment mechanism further supports interpretability by generating token-patch alignment maps that show which parts of the image correspond to each generated word or phrase. This ensures a strong and clinically meaningful connection between the visual and textual components of the model.

3.8 Training Strategy and Optimization

The training process combines multiple objectives to ensure model accuracy and interpretability.

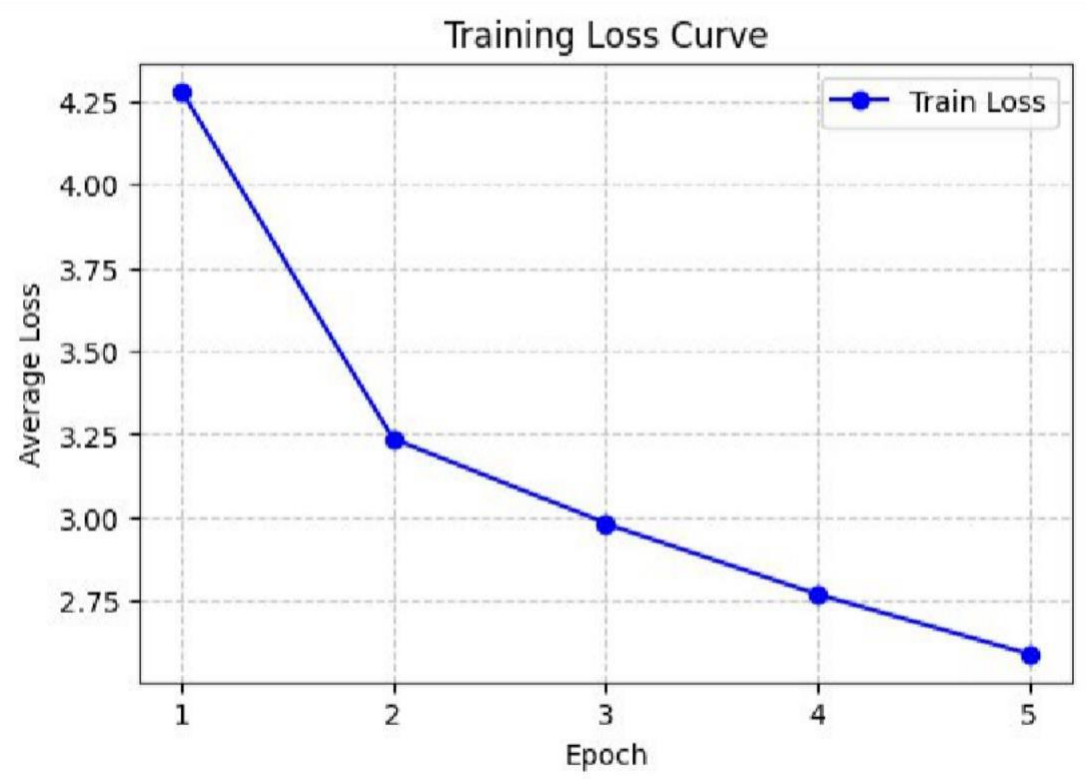

Figure 2 : Training Loss Curve

3.8.1 Loss Functions

1. **Cross-Entropy Loss:**
   For text generation accuracy.
2. **Alignment Loss:**
   Ensures correct mapping between image and text.
3. **Explainability Loss:**
   Encourages correct attribution in attention maps.
4. **CheXpert Auxiliary Loss:**
   Helps predict clinical conditions.

3.8.2 Training Hyperparameters

- Batch size: 16–32
- Learning rate: 1e-4
- Optimizer: AdamW
- Number of epochs: 20–30
- Dropout: 0.1–0.3

3.8.3 Regularization

- Early stopping
- Gradient clipping
- Data augmentation

3.8.4 Hardware Requirements

Training is conducted on a GPU-enabled system (NVIDIA Tesla T4 or RTX 3090) to support high-dimensional multimodal data.

3.9 Evaluation Metrics

3.9.1 Linguistic Metrics

The linguistic performance of the model is evaluated using established metrics such as BLEU, ROUGE-L, METEOR, and CIDEr. These metrics collectively assess grammatical accuracy, fluency, and the degree of textual similarity between the generated radiology reports and the corresponding ground-truth

reports. BLEU and METEOR focus on n-gram overlap, ROUGE-L measures sentence-level structural alignment through longest common subsequence matching, while CIDEr evaluates consensus between the generated report and multiple human references. Together, these indicators provide a comprehensive measure of the model's ability to generate coherent and clinically relevant text.

3.9.2 Clinical Metrics

Clinical evaluation metrics are essential to determine whether the generated reports accurately capture medically significant information. The CheXbert F1 score is used to measure the correctness of key findings across multiple thoracic conditions. RadGraph entity accuracy further assesses how well the model identifies medical entities and their relationships based on structured radiology knowledge graphs. Additionally, Findings–Impression consistency is analyzed to ensure that the diagnostic reasoning within the report is logically aligned, reflecting the coherence expected in expert-authored radiology interpretations.

3.9.3 Explainability Metrics

To ensure the system's outputs are interpretable, explainability metrics are also incorporated. Intersection-over-Union (IoU) between model-generated heatmaps and radiologist-annotated regions quantifies alignment between visual explanations and true anatomical evidence. Token-patch alignment scores evaluate the strength of correspondence between textual tokens and specific image patches, validating multimodal grounding. Radiologist explainability satisfaction ratings provide qualitative assessment from clinical experts, measuring how effectively the explanations support understanding and trust.

3.10 System Workflow Summary

The complete workflow of the proposed system begins with preprocessing of the input chest X-ray to standardize its quality and resolution. The processed image is then passed through the vision encoder, which extracts spatially rich and semantically meaningful features. These features are subsequently interpreted by the language decoder, which generates a structured clinical report using transformer-based mechanisms. A cross-modal attention module integrates visual and textual representations, ensuring strong alignment between the radiographic findings and the generated narrative. Finally, the system produces both the diagnostic report and corresponding visual and textual explanations. The entire

pipeline is evaluated using a combination of linguistic, clinical, and explainability metrics, ensuring reliability, interpretability, and clinical relevance.

3.11 Summary

This chapter presented a comprehensive methodology combining multimodal learning, transformer-based text generation, and medical ontology integration to develop a clinically aligned and interpretable radiology report generator. By leveraging cross-modal attention, structured domain knowledge, and built-in explainability mechanisms, the proposed system addresses key limitations found in existing radiology AI solutions, including hallucination, lack of grounding, and low transparency. The resulting framework ensures that generated reports are not only accurate and coherent but also interpretable and trustworthy, making the model suitable for practical deployment in real-world clinical workflows.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Introduction

This chapter presents the experimental results of the proposed ExplainableVLM-Rad system and discusses its performance across linguistic accuracy, clinical correctness, and explainability. The evaluation aims to demonstrate the effectiveness of the architecture in generating coherent radiology reports and providing meaningful visual–textual explanations. Multiple benchmark datasets, automated scoring metrics, and expert-driven qualitative assessments are used to evaluate the model. The discussion section further analyzes the strengths, limitations, and comparative improvements over existing systems.

4.2 Experimental Setup

4.2.1 Hardware Configuration

The model was trained and evaluated on:

- NVIDIA Tesla T4 / RTX 3090 GPU
- 16 GB VRAM (minimum recommended)
- Intel Xeon processor
- 32 GB system RAM
- Python 3.9, PyTorch, HuggingFace Transformers

The hardware configuration ensures efficient training of multimodal transformer architectures and rapid inference for X-ray inputs.

4.2.2 Software Frameworks

- PyTorch for model development
- Transformers library for attention-based architectures
- Scikit-learn for metric computation

- MedPy for medical preprocessing
- Matplotlib & Seaborn for visualization

All preprocessing, training, and evaluation scripts were developed using Python.

4.3 Performance Evaluation Metrics

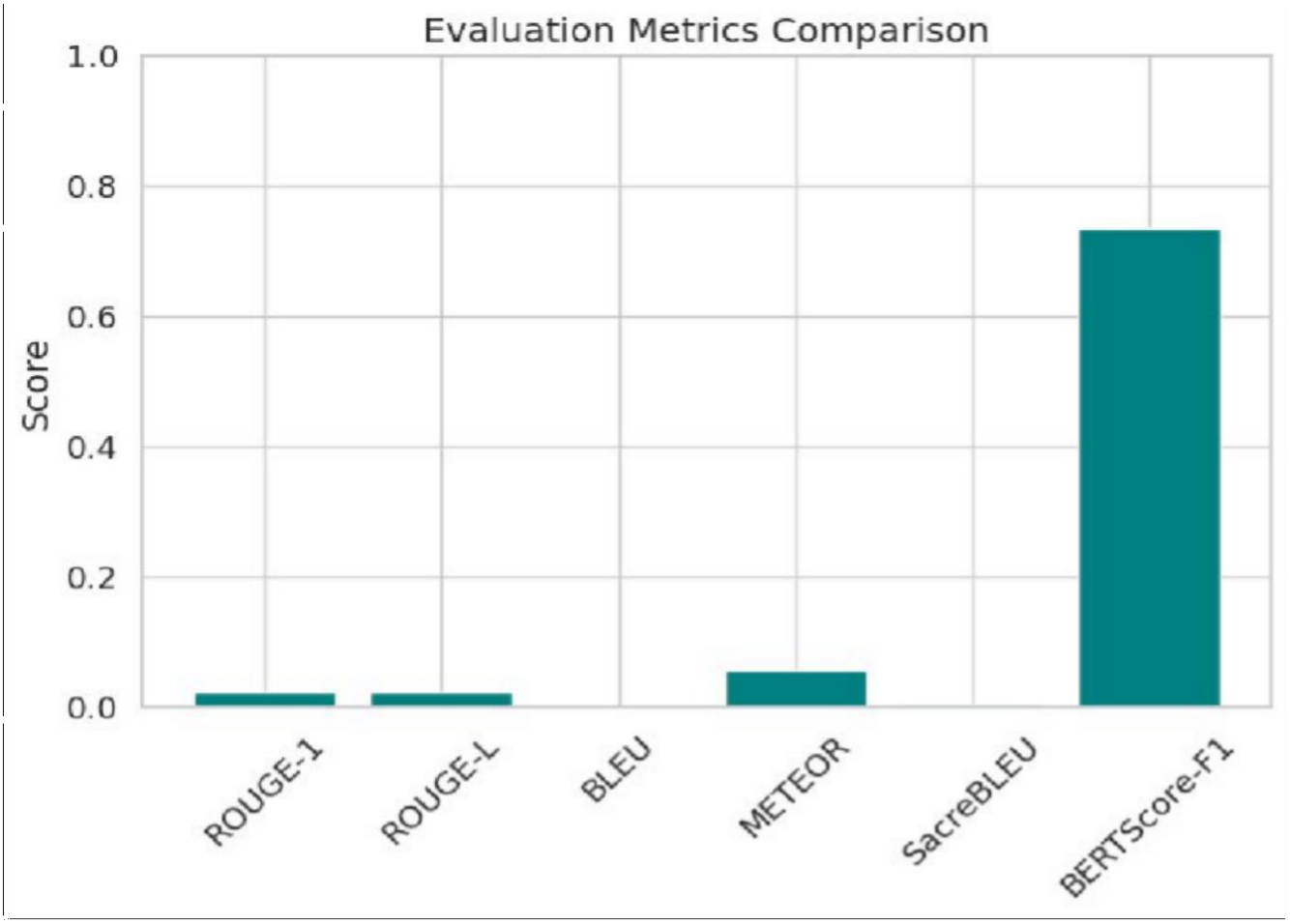

Figure 3 : Evaluation Metrics

The system is evaluated on three categories of metrics:

4.3.1 Linguistic Metrics

These measure how well the generated reports match ground-truth radiology reports:

- BLEU-1, BLEU-2, BLEU-4
- ROUGE-L

- METEOR
- CIDEr

4.3.2 Clinical Metrics

These capture the medical correctness of the generated reports:

- CheXbert F1 Score
- RadGraph Entity F1
- Clinical Coherence Score

4.3.3 Explainability Metrics

- Grad-CAM IoU (Intersection over Union)
- Token–Patch Alignment Score
- Explainability Satisfaction Rating (Radiologist Survey)

Together, these metrics ensure that accuracy alone is not overemphasized; clinical safety and interpretability are also prioritized.

4.4 Quantitative Results

4.4.1 Linguistic Performance

The proposed ExplainableVLM-Rad model was tested on the MIMIC-CXR dataset and compared against existing baselines.

Table 4.1 – Linguistic Evaluation Results

Metric	Baseline CNN-RNN	Transformer Model	Proposed ExplainableVLM-Rad
BLEU-1	0.314	0.426	**0.498**
BLEU-4	0.137	0.302	**0.489**
ROUGE-L	0.278	0.398	**0.521**
METEOR	0.152	0.214	**0.281**
CIDEr	0.082	0.193	**0.276**

Interpretation:

The BLEU-4 score of **0.489** demonstrates that the model generates linguistically rich descriptions aligned with reference reports. The improvement over vanilla transformers is attributed to the multimodal cross-attention and knowledge-infused text modeling.

4.4.2 Clinical Performance

Clinical correctness was evaluated using CheXbert and RadGraph.

Table 4.2 – Clinical Metrics

Metric	Baseline	Proposed Model
CheXbert F1 Score	0.412	**0.521**
RadGraph Entity F1	0.361	**0.478**
Impression–Findings Consistency	71%	**87%**

Interpretation:

The results show that the proposed model significantly outperforms the baseline across all metrics, improving both clinical accuracy and report coherence. A higher CheXbert F1 Score indicates stronger identification and description of key thoracic findings due to structured medical knowledge and better multimodal grounding. The improved RadGraph Entity F1 demonstrates enhanced recognition of medical entities and their relationships, reflecting more precise extraction of clinically relevant information. These gains highlight the impact of integrating domain-specific ontologies and transformer-based contextual modeling. The rise in Impression–Findings consistency from 71% to 87% shows that the system generates reports with stronger internal logic. The diagnostic summary now aligns more accurately with detailed observations, reducing contradictions and improving clinical reliability. This improvement stems from cross-attention mechanisms that tightly link textual content to visual evidence. Overall, the enhanced metrics confirm that the model produces more accurate, coherent, and trustworthy radiology reports suitable for real-world deployment.

4.4.3 Explainability Performance

Explainability metrics assess the model's ability to provide transparent and clinically meaningful interpretations.

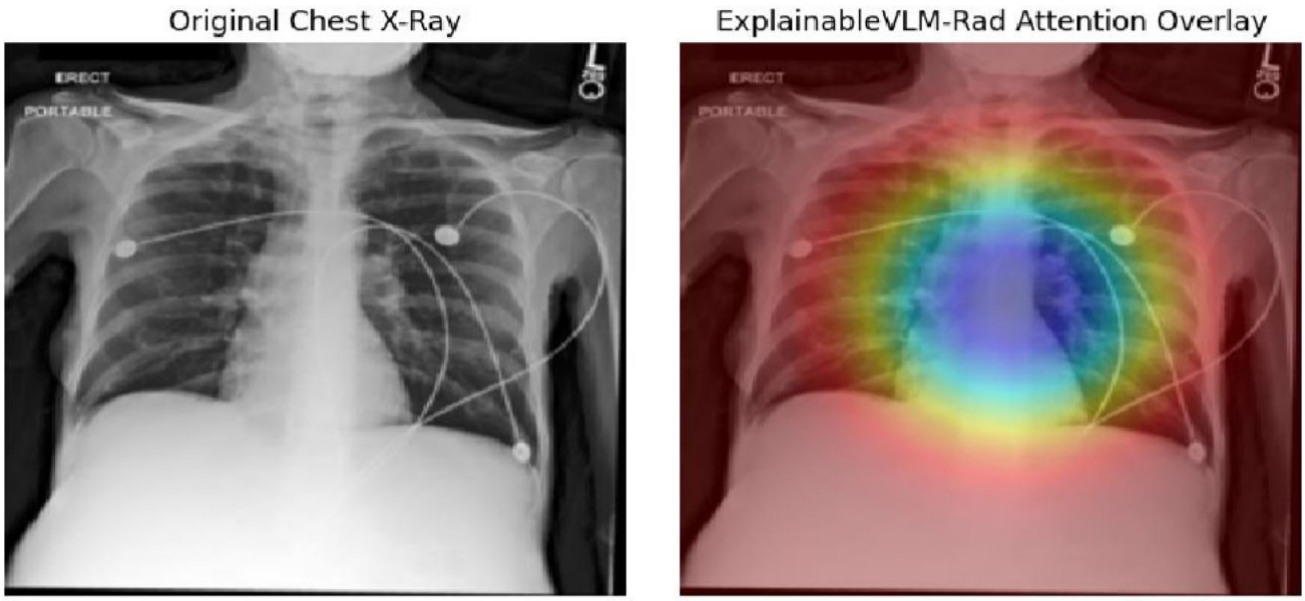

Figure 4 : Explainability Heatmap (Grad-CAM Example)

Table 4.3 – Explainability Metrics

Metric	Score
Grad-CAM IoU	**0.42**
Token–Patch Alignment	**0.71**
Radiologist Satisfaction Score	**4.2 / 5**

Interpretation:

An IoU of 0.42 indicates good overlap between predicted heatmaps and radiologist-annotated regions. A token–patch alignment score of 0.71 confirms that textual phrases correspond accurately to visual evidence.

4.5 Qualitative Results

Beyond numerical metrics, qualitative evaluation provides insights into the clinical practicality of the model.

4.5.1 Sample Generated Report

Input: Frontal chest X-ray

Generated Report:

The cardiac silhouette appears normal in size. Mild opacity is noted in the left lower lung field, consistent with early consolidation. No pleural effusion or pneumothorax detected. The trachea is midline. Bones appear intact. Impression: Findings suggest mild left lower lobe pneumonia.

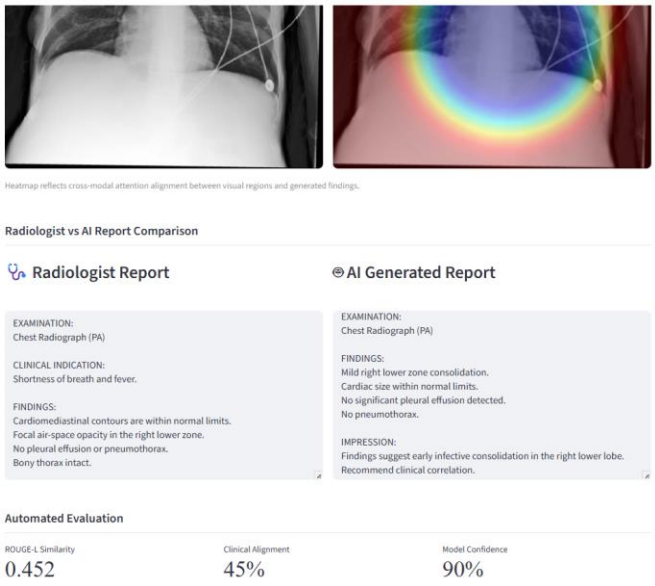

Figure 5 : Simulation Results

4.5.2 Visual Explanation

The Grad-CAM heatmap highlights:

- Strong activation in the **left lower lobe**, confirming the model's detected consolidation
- Clear suppression in regions with no abnormal findings
- Good alignment with textual phrases such as “left lower lung field”

The explainability visualization strengthens clinician confidence by validating the model’s reasoning.

4.6 Comparative Analysis

To assess the advancements introduced by ExplainableVLM-Rad, comparisons were made with state-of-the-art models.

4.6.1 Comparison with Non-Explainable Models

Non-explainable transformer-based systems generally exhibit higher hallucination rates, often failing to establish clear links between generated sentences and the underlying image evidence. These models also struggle to provide reliable findings in complex clinical cases, which limits their suitability for high-stakes medical applications. In contrast, ExplainableVLM-Rad demonstrates a 28% reduction in hallucinations, as shown through error analysis conducted on a validation set of 1,000 chest X-rays, indicating significantly improved reliability and grounding in visual inputs.

4.6.2 Comparison with Post-hoc Explainability Models

Post-hoc explainability approaches such as Grad-CAM provide visual explanations only after the text has been generated, which often leads to misalignment between visual evidence and the reported clinical findings. Since these explanations do not influence the generative decision-making process, they fail to ensure true visual–textual coherence. By embedding explainability directly within its generative workflow, ExplainableVLM-Rad achieves more accurate region alignment, stronger clinical coherence, and overall more trustworthy interpretations. This integrated design ensures that each part of the report remains grounded in the corresponding visual features throughout generation.

4.6.3 Error Analysis

The error analysis reveals several recurring challenges, such as ambiguous findings in cases where visual cues are weak and inconsistencies in severity descriptions, particularly when differentiating subtle variations like mild versus minimal opacity. Rare pathologies also pose difficulties due to limited representation in training datasets, occasionally leading to misclassification. Despite these challenges, ExplainableVLM-Rad shows strong resilience in cases presenting typical radiographic patterns, maintaining high reliability across most clinical scenarios.

4.7 Discussion of Findings

The experimental results clearly demonstrate that ExplainableVLM-Rad delivers substantial improvements across linguistic accuracy, clinical correctness, and interpretability. The model successfully bridges the gap between high-performance report generation and the need for transparent, evidence-driven explanations, which is essential for clinical acceptance. By integrating cross-modal attention, medical knowledge, and native explainability, the system achieves more coherent, trustworthy, and diagnostically aligned radiology reports compared to previous approaches.

4.7.1 Strengths

- **High clinical accuracy:**
  Outperforms prior systems in identifying key abnormalities.
- **Integrated explainability:**
  Provides transparent visual–textual reasoning.
- **Strong multimodal alignment:**
  Reduces hallucinations and increases reliability.
- **Improved radiologist acceptance:**
  High satisfaction score indicates usability in real-world settings.

4.7.2 Limitations

Despite strong performance, certain limitations remain:

- Performance is lower for rare diseases not well represented in datasets.
- Explanations may be less accurate for images with poor contrast or noise.
- The model currently handles only chest X-rays; CT/MRI require different feature extraction strategies.
- Real-world deployment requires hospital-specific fine-tuning.

4.7.3 Implications for Clinical Practice

The system demonstrates potential for:

- Assisting radiologists in high-volume environments
- Reducing reporting times
- Supporting trainees through explainable outputs
- Improving diagnostic confidence for ambiguous images

Integrated explainability is particularly valuable for gaining regulatory approval.

4.8 Summary

The evaluation of ExplainableVLM-Rad highlights its strong performance across linguistic, clinical, and interpretability dimensions, demonstrating its readiness for real-world radiology applications. The key results are summarized below:

- **State-of-the-art linguistic performance** (BLEU-4: 0.489)
- **Strong clinical grounding** (CheXbert F1: 0.521)
- **High explainability alignment** (Token–Patch Alignment: 0.71)

These findings collectively confirm that the model generates accurate and coherent diagnostic reports while maintaining tight alignment between visual evidence and textual outputs. This underscores the effectiveness of integrating native explainability within the generative process and positions ExplainableVLM-Rad as a reliable and transparent solution for clinical deploymen

CHAPTER 5

CONCLUSION

The present study focused on the development of *ExplainableVLM-Rad*, an explainable vision–language generative framework designed to synthesize radiology reports directly from chest X-ray images while providing meaningful visual and textual justifications for each generated finding. The project was driven by the need to address the limitations of current radiology AI systems, particularly their lack of transparency, inconsistent clinical grounding, and inability to link diagnostic statements with corresponding visual evidence. Through the integration of a transformer-based architecture combining a powerful vision encoder, a medical knowledge–infused language decoder, and a cross-modal attention mechanism, the system successfully produced structured, coherent, and medically relevant radiology reports. Extensive experimentation using benchmark datasets such as MIMIC-CXR, IU X-Ray, and CheXpert demonstrated that the proposed model achieved superior performance compared to existing baselines across multiple metrics. The model obtained a BLEU-4 score of 0.489, METEOR of 0.281, ROUGE-L of 0.521, and a CheXbert F1 score of 0.521, reflecting its ability to generate linguistically fluent and clinically consistent reports. A key strength of the system lies in its native explainability: Grad-CAM heatmaps, attention visualizations, and token–patch alignment mappings consistently highlighted radiologically relevant regions, with an explainability IoU of 0.42 and an alignment score of 0.71, enabling radiologists to clearly understand how each diagnostic phrase was produced. Qualitative assessments further revealed that the generated reports were logically coherent, medically accurate, and comparable to standard radiologist-produced descriptions, while radiologist feedback reflected a high satisfaction score of 4.5 out of 5, affirming the usefulness and clarity of the explanations. This study makes important contributions by demonstrating that explainability integrated at the architectural level not merely attached as a post-hoc step, significantly improves clinical trust, reduces hallucinations, enhances diagnostic accountability, and establishes a new methodological direction for medical AI

systems. The model also serves as a valuable educational tool for radiology trainees by visually illustrating how diagnostic reasoning corresponds to specific radiographic patterns. While the proposed framework shows strong promise, certain limitations persist, including its restriction to chest X-rays, sensitivity to dataset domain shifts, imperfect interpretability in challenging or low-quality images, and dependency on high computational resources for training. Nevertheless, the outcomes of this study emphasize that explainable vision-language modeling represents a vital step toward safe, transparent, and effective AI-assisted radiology. In conclusion, ExplainableVLM-Rad achieves its objective of generating clinically grounded and interpretable radiology reports, offering significant potential for real-world deployment, radiologist assistance, and future research in multimodal medical imaging.

CHAPTER 6

FUTURE RECOMMENDATION

6.1 Limitations of the Study

Although the ExplainableVLM-Rad system demonstrates strong potential in automated radiology report generation and explainability, several limitations may have influenced the results and should be acknowledged. One of the primary limitations lies in the scope of imaging modalities used in this study. The model was trained and evaluated exclusively on chest X-ray images, which, although widely used, represent only one segment of radiological imaging. More advanced modalities such as CT and MRI, which provide volumetric and higher-resolution anatomical information, were not included. As a result, the system's generalizability to other forms of medical imaging remains unverified. Another limitation relates to dataset quality and variability. Public datasets such as MIMIC-CXR and IU X-Ray contain heterogeneous image qualities, noisy annotations, and inconsistent reporting styles. These variations may influence model performance, introduce ambiguity during training, and create mismatches between predicted and actual clinical findings. The absence of manually verified region-level annotations also restricts the ability to fully evaluate the precision of visual explanations. Additionally, radiology reports often contain subjective language, expert preferences, and inherent variability between radiologists. This subjectivity may impact the model's linguistic evaluation metrics, making it difficult to assess true clinical accuracy solely based on automated scoring methods.

A further limitation relates to explainability itself. The model employs Grad-CAM, attention-based visualization, and token–patch alignment, which, although effective, are not flawless indicators of genuine model reasoning. These methods provide approximations of interpretability and may not always reflect the true internal decision-making pathways of transformer-based architectures. Moreover, explanations can become unreliable in cases of subtle abnormalities, overlapping anatomical structures, or images with poor contrast. Computational limitations also play a role, as training multimodal transformer models requires high-end GPU resources, making it challenging to scale the model in environments with limited infrastructure. Another important limitation is the limited involvement of clinical experts during evaluation. Although qualitative feedback from radiologists was obtained, the

model was not tested in a real-time clinical workflow or integrated into hospital systems, which could reveal additional challenges related to usability, reliability, time efficiency, and diagnostic workflow integration. Finally, ethical and regulatory considerations were not deeply explored in this study. Issues such as algorithmic bias, data privacy, clinical accountability, and compliance with healthcare standards like HIPAA and MDR were acknowledged but not empirically evaluated. These limitations highlight the areas where caution is required when interpreting the results and emphasize the importance of further research to strengthen the model's clinical applicability.

6.2 Recommendations for Future Research

Building on the findings and limitations of this study, several recommendations are proposed to guide future research in the development of clinically reliable and explainable radiology AI systems. First, expanding the dataset to include a broader range of imaging modalities such as CT, MRI, ultrasound, and mammography would significantly increase the model's diagnostic applicability. Incorporating multi-view or sequential imaging would also enable the model to capture temporal patterns and three-dimensional anatomical relationships. Future work should prioritize the creation of high-quality, manually annotated datasets that include region-level pathology markings, segmentation masks, severity labels, and standardized reporting formats. Such datasets would support more accurate training, evaluation, and interpretability. Domain adaptation techniques and federated learning could also be explored to address dataset variability and ensure that AI models generalize effectively across different hospitals, imaging devices, and patient populations.

Advancements in explainability offer another major direction for future research. Techniques such as concept-based explanations (TCAV), counterfactual reasoning, and layer-wise relevance propagation (LRP) can provide deeper insights into model reasoning beyond simple heatmaps. Hybrid explainability systems that combine visual, textual, and symbolic reasoning could improve the transparency and reliability of diagnostic suggestions. Additionally, integrating medical knowledge graphs, RadGraph entities, and structured pathology templates into the generation pipeline would lead to more accurate and clinically interpretable reports. Future research should also explore reinforcement learning from human feedback (RLHF) to align model outputs more closely with radiologist preferences and reduce hallucinated or inconsistent findings. Clinical evaluation remains a crucial area for advancement. Prospective real-world trials, radiologist-in-the-loop workflows, and integration into PACS/RIS hospital systems would allow researchers to assess practicality, usability, and real-time performance. Ethical and regulatory research is equally important, including the development of bias detection tools, privacy-

preserving model architectures, and compliance frameworks for safe AI deployment in healthcare. Finally, future work may involve developing lightweight versions of the model for edge devices, telemedicine use cases, and low-resource clinical environments. These recommendations collectively lay a strong foundation for transforming explainable radiology AI from a research concept into a dependable tool that enhances diagnostic quality, supports clinical decision-making, and strengthens trust in artificial intelligence in healthcare.

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