मौलाना आजाद राष्ट्रीय प्रौद्योगिकी संस्थान - भोपाल
Maulana Azad National Institute of Technology– Bhopal

Department of Computer Science and Engineering

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"PROJECT REPORT"
On

"Comparative Study of Chest X-Ray Report Generation Models"

Submitted In partial Fulfillment for the degree of Bachelor of Technology in Computer Science and Engineering

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DECLARATION

We hereby declare that the work, which is presented in this Project Report, entitled "**Comparative Study of Chest X-ray Report Generation Models**", in partial fulfillment of the requirements for the award of the degree, submitted in the **Department of Computer Science and Engineering, Maulana Azad National Institute of Technology, Bhopal.** It is an authentic record of my work carried out from 15th January 2025 to 10th May 2025 under the noble guidance of my guide "**Dr. Sweta Jain".** The following project and its report, in part or whole, have not been presented or submitted by me for any purpose in any other institute or organization. I hereby declare that the facts mentioned above are true to the best of our knowledge. In case of any unlikely discrepancy that may occur, I will be the one to take responsibility.

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CERTIFICATE

This is to certify that **"Sajja Sasi Kumar, Mathangi Khushal Ashish, Sanya Arora, Falguni Suresh Bhowate",** students of B.Tech 3rd Year (Computer Science & Engineering), have completed their project "Comparative Study of Chest X-ray Report Generation Models" in fulfillment of their Bachelor of Technology in Computer Science & Engineering.

DR. SWETA JAIN

(ASSOCIATE PROFESSOR)

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CHAPTER-1
INTRODUCTION

In the era of exponential technological advancement, the realm of artificial intelligence (AI) stands as a beacon of innovation, revolutionizing industries across the globe. At the heart of AI lies machine learning, a subset of computer science that enables systems to learn from data and make predictions or decisions without being explicitly programmed. Deep learning, a cutting-edge technique within machine learning, has emerged as a powerful paradigm shift, catalyzing breakthroughs in various domains.

Understanding Deep Learning and Machine Learning

Machine learning encompasses a broad spectrum of algorithms and methodologies that enable computers to learn patterns and insights from data, facilitating tasks ranging from image recognition to natural language processing. Deep learning, a subset of machine learning, employs artificial neural networks inspired by the structure and function of the human brain. These neural networks consist of multiple layers of interconnected nodes, enabling the system to automatically discover intricate patterns and representations within the data.

The Rapid Growth of Deep Learning

The exponential growth of data generation coupled with the advancement of computational resources has fueled the rapid proliferation of deep learning. Unlike traditional machine learning techniques, deep learning excels in handling unstructured data such as images, audio, and text, unlocking unprecedented accuracy and performance in various applications. From autonomous vehicles to healthcare diagnostics, deep learning is reshaping industries by revolutionizing tasks that were once deemed impossible or impractical.

Significance of Deep Learning's Ascendancy

The burgeoning importance of deep learning is underscored by its unparalleled ability to extract meaningful insights from vast amounts of data, driving innovation and efficiency across diverse sectors. Its capability to autonomously learn complex representations from raw data without human intervention empowers organizations to make data-driven decisions, uncover hidden patterns, and gain a competitive edge in today's data-centric landscape.

Use of Deep Learning in Report Generation

Chest X-rays are one of the most commonly used diagnostic tools in healthcare, playing a crucial role in detecting and monitoring various pulmonary and cardiac conditions. However, the process of manually interpreting X-ray images and generating accurate reports is time-consuming and prone to human errors.
Automating this process using deep learning techniques can significantly improve efficiency and accuracy in medical diagnostics.

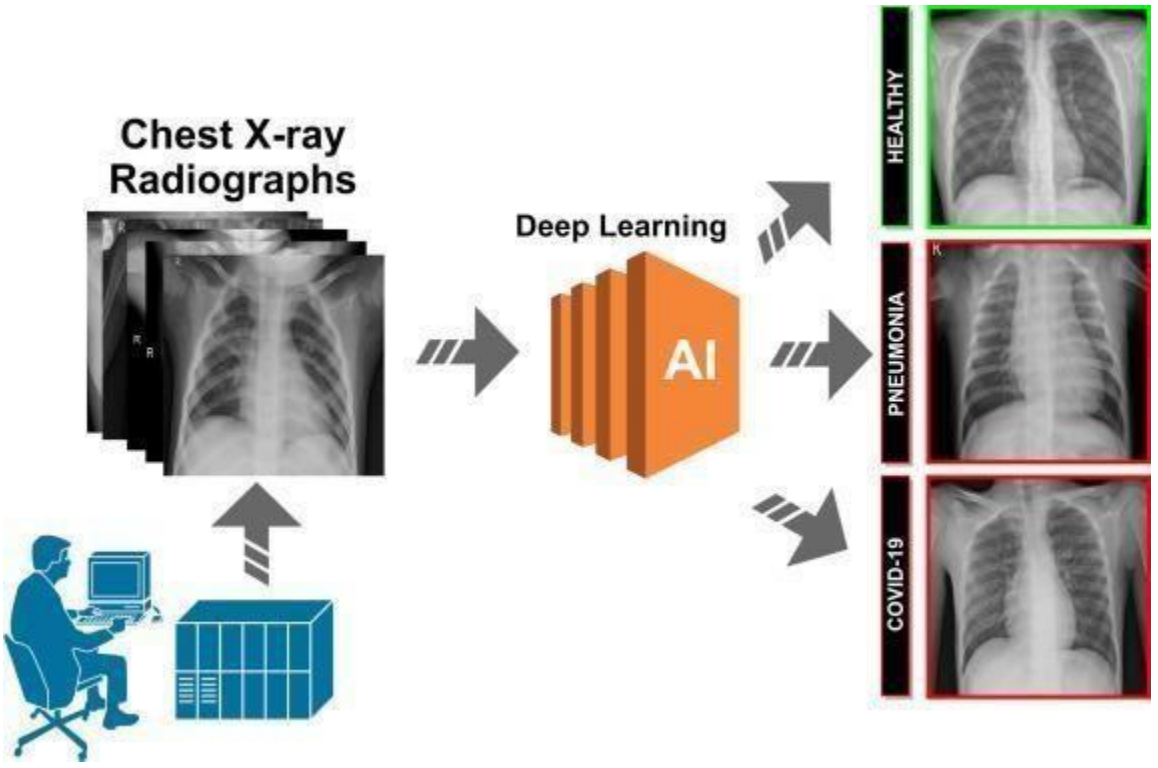

Fig – 1: Use of deep learning in Report Generation

Problem Statement

Manually generating medical reports from chest X-rays is labor-intensive and highly dependent on the expertise of radiologists. Moreover, inter-observer variability can lead to inconsistencies in diagnoses and reporting. The goal of this project is to develop an automated chest X-ray report generation system using deep learning techniques to extract image features, understand textual features, fuse both modalities, and generate coherent medical reports.

CHAPTER 2
OBJECTIVES

- To develop an automated system for generating accurate chest X-ray reports.
- To leverage deep learning models for extracting features from chest X-ray images.
- To generate meaningful medical reports using a transformer-based model.

Motivation of the project

Radiology underpins most clinical decision-making, yet the ever-rising volume of chest X-rays and a chronic shortage of trained radiologists—97 % of UK imaging departments report that they cannot keep up with demand—have led to reporting delays and elevated error rates . Automated radiology report generation (ARRG) promises to alleviate these bottlenecks by producing draft reports or first-reads that a clinician can quickly review, but existing ARRG models often struggle to integrate fine-grained visual cues with rich clinical context, resulting in incomplete or clinically inconsistent outputs . Our project is motivated by the need for a more robust, domain-aware ARRG pipeline: we employ a Swin Transformer as an image encoder [1],[2] to capture hierarchical, long-range patterns in chest X-rays; BioClinical BERT as a text encoder [10] fine-tuned on domain-specific radiology reports to embed nuanced clinical language; and a fusion module combining cross-attention with an adaptive gating mechanism to align and balance visual and textual features. Finally, a T5-based report generator [10] —trained in stages on CheXpert and IU-Xray and refined end-to-end via parameter-efficient fine-tuning—ensures fluent, accurate, and clinically coherent report synthesis, aiming to provide reliable decision support that enhances radiologist productivity and patient care.

CHAPTER-3
LITERATURE SURVEY

Vision-Language Models for Automated Chest X-ray Interpretation: Leveraging ViT and GPT-2 (2025) – Md. Rakibul Islam *et al.*: This study evaluates combinations of vision and language transformers on the IU-Xray dataset. Pretrained ViT-B16 and Swin-T encoders were paired with BART or GPT-2 decoders. The Swin-BART combination achieved the best results (ROUGE, BLEU, BERTScore), showing that a Swin Transformer image encoder with a strong language model decoder yields the most accurate report generation. [1]

ChestX-Transcribe: a multimodal transformer for automated radiology report generation from chest x-rays (2025) – Prateek Singh & Sudhakar Singh: This sequence-to-sequence model uses a Swin Transformer as the image encoder and a DistilGPT (GPT-2 distilled) as the text decoder. Trained on the IU Chest X-ray dataset, it attains SOTA BLEU, ROUGE, and METEOR scores. The architecture integrates local and global attention via the vision and language transformers, and includes a cross-modality fusion layer for effective image–text alignment. ChestX-Transcribe produces clinically meaningful reports, demonstrating the power of combining high-resolution visual features and transformer-based text generation.[2]

Automated Chest X-Ray Diagnosis Report Generation with Cross-Attention Mechanism (2025) – Jian Zhao *et al.*: This model uses a CNN encoder augmented with a Convolutional Block Attention Module (CBAM) to focus on abnormalities, and a cross-attention mechanism to align image and text features. CBAM highlights relevant lung regions and addresses data bias, while the cross-attention layer explicitly links visual and textual modalities. Together these mechanisms reduce misalignment and produce more accurate, reliable diagnostic reports. For example, attention to salient regions improves the model's ability to describe fine-grained findings in the generated text. [3]

SERPENT-VLM: Self-Refining Radiology Report Generation Using Vision Language Models (2024) – Manav N. Kapadnis *et al.*: This approach builds on multi-modal large language models (MLLMs) such as LLaVA-Med and BioMedGPT. It introduces a self-refining loop: a novel self-supervised loss encourages similarity between pooled image embeddings and the contextual text embeddings of the model's own output. This dynamic refinement aligns the image and text representations during generation, mitigating hallucinations. SERPENT-VLM outperforms prior MLLM baselines on IU-Xray and ROCO datasets, achieving state-of-the-art report accuracy while remaining robust to noisy inputs.[4]

Visual Instruction-tuned Adaptation for Radiology Report Generation (2024) – Xi Zhang *et al.*: A radiology-focused vision-language model is constructed by combining a CLIP image encoder with a fine-tuned Vicuna-7B language model. Training proceeds in two stages: first aligning X-ray features with the LLM, then fine-tuning end-to-end for report generation. This model generates both FINDINGS and IMPRESSIONS sections effectively. The two-stage alignment ensures the LLM understands medical image context, and the results show high-quality, medically coherent reports, illustrating the importance of domain-specific LLM adaptation.[5]

Interactive and Explainable Region-guided Radiology Report Generation (2023) – Tim Tanida *et al.*: This "region-guided" model first detects anatomical regions (e.g. lungs, heart) in the X-ray, then generates captions for each salient region, finally composing the full report. By focusing on region-level descriptions, the model is inherently explainable and allows human intervention at the region level. It achieves better report quality than prior image-level captioning models. Importantly, the interactive design lets clinicians guide or adjust descriptions of key regions, increasing transparency and trust in the generated reports.[6]

R2GenGPT: Radiology Report Generation with Frozen LLMs (2023) – Zhanyu Wang *et al.*: R2GenGPT adapts a pretrained large language model (LLM) for report generation by inserting a lightweight visual alignment module. The LLM (e.g. GPT) is kept completely frozen; only a small module (≈0.07% of parameters) is trained to map image features into the LLM's embedding space . This bridging enables the LLM to "understand" image content without full fine-tuning. Despite training so few parameters, R2GenGPT matches state-of-the-art performance on radiology report metrics. This demonstrates that aligning visual features to an LLM space is an efficient way to exploit LLM capabilities for medical imaging tasks.[7]

Radiology Report Generation Using Transformers Conditioned with Non-imaging Data (2023) – Nurbanu Aksoy *et al.*: This multi-modal transformer model incorporates patient demographic data (age, gender, etc.) alongside the chest X-ray image. A CNN encodes the X-ray, and a transformer encoder-decoder fuses these image features with semantic embeddings of the demographic text data. Trained on MIMIC-CXR with linked MIMIC-IV patient data, the model shows that including demographics improves report quality relative to an image-only baseline. This suggests that non-imaging context can provide valuable cues (e.g. patient sex or age) for generating more personalized, accurate reports.[8]

Table – 1: Literature review table

Paper (Author, Year)	**Models & Architecture**	**Novel Contribution**	**Limitations**
Vision-Language Models for Automated Chest X-ray Interpretation Md. Rakibul Islam *et al.* (2025)	ViT-B16 / Swin-T image encoder + GPT-2 / BART text decoder	Systematic evaluation of different vision–language Transformer pairings; shows Swin + BART yields best report quality	Only evaluated on IU-Xray (~7K studies); limited pathology diversity; generalization to larger cohorts untested
ChestX-Transcribe Prateek Singh & Sudhakar Singh (2025)	Swin Transformer encoder + DistilGPT decoder; local/global attention; custom cross-modality fusion layer	Introduces a fusion layer to better align high-res visual features with text; sets new SOTA BLEU/ROUGE on IU-Xray	Relies on distilled GPT (reduced medical domain knowledge); no human/clinical validation reported; IU-Xray scale still small
Automated Chest X-Ray Diagnosis Report Generation with Cross-Attention Jian Zhao *et al.* (2025)	CNN (ResNet + CBAM) encoder + Transformer decoder with explicit cross-attention between image and text tokens	Uses CBAM to highlight abnormal regions, and cross-attention to link them directly to generated text	CNN encoder limits long-range modeling; added CBAM overhead; only captures static attention, may miss subtle diffuse findings
SERPENT-VLM: Self-Refining Radiology Report Generation Manav N. Kapadnis *et al.* (2024)	Multi-modal LLMs (LLaVA-Med, BioMedGPT) with self-refining loop; self-supervised loss aligning pooled image and text embeddings	Novel self-refinement loss that dynamically aligns vision & language during generation, reducing hallucinations	Heavy models requiring large GPU/TPU memory; not benchmarked on IU-Xray specifically; complex training pipeline
Visual Instruction-tuned Adaptation for Radiology Report Generation Xi Zhang *et al.* (2024)	CLIP image encoder + Vicuna-7B LLM; two-stage training (vision-LLM alignment, then end-to-end fine-tune)	Demonstrates that instruction-tuning a foundation LLM on radiology images yields clinically coherent FINDINGS & IMPRESSIONS	Very large LLM (7B) demands extensive compute; potential for medical hallucinations if prompts are off-domain; no IU-Xray-only ablation
Interactive & Explainable Region-guided Report Generation Tim Tanida *et al.* (2023)	Region detector (U-Net) + per-region captioner + report composer; human-in-the-loop adjustments	Region-level captions enable explainability and clinician interaction at the region stage	Requires accurate region annotations; interactive step breaks full automation; errors in detection cascade into text
R2GenGPT: Radiology Report Generation with Frozen LLMs Zhanyu Wang *et al.* (2023)	Frozen GPT-style LLM + lightweight visual alignment adapter (~5 M params)	Shows you can leverage large pretrained LLMs by only training a tiny adapter to map image features into LLM embedding space	Freezing LLM limits adaptation to medical style; alignment module is simplistic; may struggle with fine-grained imagery details
Report Generation with Transformers + Non-imaging Data Nurbanu Aksoy *et al.* (2023)	CNN encoder + Transformer encoder-decoder; integrates patient demographic embeddings (age, gender) alongside image features	First to show incorporating demographics (from MIMIC-IV) boosts report accuracy over image-only models	Limited to basic demographics; does not include lab values or clinical history; potential bias amplified by demographics

Project: Chest X-ray Report Generation

The project on Chest X-ray Report Generation using Deep Learning represents a significant advancement in the intersection of medical imaging and artificial intelligence. Chest X-rays are among the most commonly used diagnostic tools for detecting pulmonary and cardiovascular diseases.
However, the manual interpretation of these images is both time-intensive and prone to variability among radiologists, which can lead to inconsistencies in diagnosis and reporting.

This project aims to address these challenges by developing an automated report generation system using state-of-the-art deep learning techniques. This approach not only enhances diagnostic efficiency but also reduces the burden on radiologists, especially in high-volume healthcare settings.

Furthermore, automated report generation has the potential to standardize medical documentation, improving consistency and accuracy across different healthcare institutions. The implementation of such a system can significantly benefit hospitals, research institutions, and telemedicine platforms by ensuring faster and more reliable diagnostic support. Ultimately, this project contributes to the broader goal of leveraging artificial intelligence to enhance healthcare accessibility, efficiency, and accuracy, paving the way for AI-assisted medical diagnostics in real-world clinical applications.

Rationale and Significance

Medical imaging, especially chest X-rays, is a fundamental diagnostic tool for detecting lung and heart diseases. However, the manual interpretation of these images by radiologists is often time-consuming and prone to human errors. The increasing patient load in hospitals further exacerbates the challenge, leading to delayed diagnoses and potential misinterpretations. This project aims to bridge this gap by automating the process of chest X-ray report generation using deep learning.

By leveraging advanced neural network architectures, including vision-based and language-based models, the system enhances diagnostic accuracy and consistency while significantly reducing the workload of medical professionals.
The significance of this project lies in its potential to improve healthcare delivery, especially in resource-limited settings where experienced radiologists are scarce. Additionally, automated reporting can standardize medical documentation, ensuring uniformity in diagnoses across different healthcare institutions.

CHAPTER - 4
PROPOSED WORK

The proposed model follows a multimodal deep learning approach, integrating both visual and textual information to generate structured radiology reports. The architecture consists of four key components: image feature extraction, text feature extraction, feature fusion, and report generation.

Image Feature Extraction

The image feature extraction is performed using image encoder. It processes the chest X-ray images and extracts high-level feature representations, capturing structural details of the lungs, heart, and surrounding anatomical features. These features are then projected into a lower-dimensional space to be combined with textual embeddings.

Text Feature Extraction

For text feature extraction a text encoder is employed to process previous radiology reports and extract meaningful representations from textual descriptions.

Co-attention Mechanism

The fusion mechanism used in this architecture is a co-attention mechanism, which enables the model to focus on relevant aspects of both modalities simultaneously. The co-attention mechanism assigns importance scores to different regions of the image and corresponding textual tokens, allowing the system to align visual findings with relevant medical terms dynamically. This ensures that the model attends to the most critical features while generating the report.

Report Generation

The final stage of the pipeline involves report generation, where a generator is used to generate structured text. It should be a powerful sequence-to-sequence transformer that converts the fused feature embeddings into a meaningful and structured radiology report. The model generates output by predicting one word at a time, leveraging the previously generated words and the learned feature representations. The generated reports are designed to closely resemble those written by expert radiologists, maintaining grammatical accuracy and clinical relevance.

CHAPTER - 5
MODEL DESCRIPTIONS

Architecture - I: EffiGPT++

1. Overview

EffiGPT++ is an advanced multimodal radiology report generation architecture that builds upon the EfficientNet-GPT2 pipeline by integrating a domain-specific text encoder (BioClinicalBERT) alongside the image encoder (EfficientNet-B3). The model utilizes a co-attention-based fusion mechanism to align visual and textual representations and employs GPT-2 as the autoregressive report generator. EffiGPT++ aims to produce clinically accurate, fluent, and contextually grounded chest X-ray reports.

2. Components

EfficientNet-B3 Image Encoder

EffiGPT++ uses EfficientNet-B3 as its visual backbone, offering a trade-off between accuracy and computational efficiency. The model takes chest X-ray images as input, resizing them to 224×224 pixels and normalizing them using ImageNet statistics. EfficientNet-B3 [9] , which uses a compound scaling strategy across depth, width, and resolution, processes these images and outputs a 1,536-dimensional visual embedding. This embedding captures features such as lung borders, bone contours, cardiac silhouette, and signs of abnormalities. The encoder is fine-tuned on IU-Xray after being pretrained on ImageNet, with architectural enhancements like multi-scale feature fusion and attention gates to emphasize relevant regions.

- **Input:** Chest X-ray image (224x224 px, normalized using ImageNet statistics).
- **Architecture:** Compound-scaled CNN with MBConv blocks, Swish activation, and squeeze-and-excitation.
- **Output:** 1,536-dimensional visual embedding vector.
- **Enhancements:**
    - Pretrained on ImageNet, fine-tuned on IU-Xray.
    - Multi-scale feature extraction using Feature Pyramid Network (FPN).
    - Attention gates for salient region enhancement.

Text Encoder: BioClinicalBERT

BioClinicalBERT is a domain-specific adaptation of BERT, trained on PubMed abstracts and MIMIC-III clinical records. It processes structured patient metadata such as history, symptoms, indications, or prior reports. These inputs are tokenized using BERT's tokenizer and converted into contextual embeddings, each of 768 dimensions. These embeddings provide a textual representation of patient context [10] that complements the image features. Before multimodal fusion, the text embeddings are projected to align dimensionally with the image features.

- **Input:** Tokenized patient metadata, indications, prior clinical notes.
- **Model:** 12-layer BERT variant trained on biomedical corpora (PubMed + MIMIC).
- **Output:** Contextual embeddings of size 768-dim per token.
- **Projection:** Linear transformation to match image embedding dimension (1536-dim) for fusion.

Feature Transformation Layer

To align the outputs from EfficientNet and BioClinicalBERT with GPT-2's embedding space, a Feature Transformation Layer is employed. This layer includes separate linear projection blocks for each modality. Visual features (1,536-dim) are projected into a 768-dimensional embedding to simulate a GPT-2 token. Similarly, BioClinicalBERT outputs are also adjusted through projection. Post-projection, normalization (LayerNorm) and GELU activation functions are applied to maintain numerical stability. These transformed features serve as prefix tokens or soft prompts to condition GPT-2 during report generation.

- Projects 1,536-dim image features to 768-dim
- Projects 768-dim text embeddings to 768-dim
- Uses linear layers with LayerNorm + GELU
- Produces embeddings compatible with GPT-2
- Acts as visual/textual prefix token injector

Multimodal Fusion Module

EffiGPT++ uses a co-attention mechanism to fuse the image and text modalities. Two attention blocks operate bidirectionally: one computes how image features attend to textual context and the other calculates how textual embeddings focus on image features. The attention scores are computed using scaled dot-product attention. Outputs from both blocks are concatenated and passed through a multilayer perceptron (MLP) and a gating mechanism to produce the final fused representation. This fusion strategy enhances semantic alignment and contextual integration across modalities.

- Dual co-attention: visual-to-text and text-to-visual
- Scaled dot-product attention formula:

$$\text{Attention}(Q, K, V) = \text{softmax}\left(\frac{QK^T}{\sqrt{d_k}}\right)V$$ Eq-1

Where,

Q (Query) = a matrix representing queries

K (Key) = a matrix representing keys

V (Values) = a matrix representing the values

d_k = dimensionality of the key vectors

- Produces a context-aware fused embedding
- Followed by MLP + gated residual layers
- Ensures balanced modality contribution

GPT-2 Medium Text Decoder

A 24-layer autoregressive Transformer (345 M parameters, 16 heads, 1,024 hidden size) generates “FINDINGS”. The fused embedding is passed to GPT-2 Medium, which generates the final radiology report. GPT-2 operates autoregressively, predicting one token at a time. The multimodal embedding serves as a prefix sequence prepended to the standard GPT-2 input. The model is fine-tuned on medical reports from IU-Xray to learn medical syntax and structure [9] . Generation strategies such as nucleus sampling (top-p = 0.92), temperature = 0.7, and repetition penalty are used to ensure fluency and factual consistency. Specialized tokens guide GPT-2 in structuring the output into "Findings" and "Impression."

The base model is augmented with:

- An extended 52k+ medical vocabulary (UMLS-embedded),
- A medical-alignment layer and modified positional/type embeddings,
- Cross-attention blocks that attend to the visual prefixes,
- Prefix-tuning and special tokens for section control, and
- Nucleus sampling (p=0.92) with temperature and repetition penalties to balance fluency and accuracy

.

3. Training Strategy

Pretraining

Each model component is pretrained on a relevant corpus. EfficientNet is pretrained on ImageNet and then fine-tuned on ChestX-ray14 and IU-Xray. BioClinicalBERT is pretrained on biomedical texts including PubMed and MIMIC. GPT-2 is pretrained on general domain WebText and fine-tuned on IU-Xray radiology reports.

- EfficientNet: ImageNet → ChestX-ray14 → IU-Xray
- BioClinicalBERT: PubMed + MIMIC-III
- GPT-2: WebText → IU-Xray

End-to-End Fine-Tuning

The model is trained end-to-end using joint optimization. Although the loss is computed on the report generation task only, gradients flow through the entire architecture including the encoders and the transformation layers. This ensures that all components learn to align better for the final report output.

- Loss computed over GPT-2 output
- Gradients flow through fusion and encoders
- Optimized jointly with AdamW

Loss Functions

Cross-Entropy Loss:

Used to train GPT-2 to predict the next token in the report sequence.

$$\mathcal{L}_{\text{CE}} = -\sum_{k=1}^{n} \log P_k(t_k) \qquad \text{Eq-2}$$

Where ,

n = number of tokens

$P_k(t_k)$ = predicted probability for the true class label (t_k) at position k

Contrastive Loss:

Encourages alignment between matching image and text representations.

$$\mathcal{L}_{\text{contrast}} = -\log \frac{\exp(\text{sim}(v_i, t_i)/\tau)}{\sum_j \exp(\text{sim}(v_i, t_j)/\tau)}$$

Eq-3

Where ,

v_i = anchor embedding for sample i

t_i = the positive match for v_i

t_j = the j-th target embedding in the batch – includes both t_i (positive) and other $t_j \neq t_i$

(negatives)

sim(v_i , t_j) = similarity measure between the anchor v_i and a candidate target t_j

T = a temperature hyperparameter to control softmax sharpness

N = total number of targets in the batch

4. End-to-End Workflow of EffiGPT++

Step 1: Input Acquisition Chest X-ray images (frontal/lateral) and patient metadata are collected and routed into the system through an automated interface. The X-rays are stored in DICOM format, and clinical notes or prior reports are structured in standardized text format.

Step 2: Image Preprocessing & Encoding The image is resized to 224×224 pixels and normalized. EfficientNet-B3 encodes the image into a 1,536-dimensional feature vector, highlighting radiographic features such as opacities, cardiomegaly, effusions, and bone structures.

Step 3: Clinical Text Preprocessing & Encoding Patient history, indications, and metadata are tokenized using BioClinicalBERT's tokenizer. BioClinicalBERT transforms these tokens into contextual embeddings to capture medical semantics.

Step 4: Feature Transformation Image and text features are individually projected into GPT-2's 768-dimensional embedding space. This step prepares the representations for cross-modal interaction and report generation.

Step 5: Multimodal Fusion Projected features are aligned via a co-attention mechanism. This fusion allows the model to jointly attend to image regions and textual cues, generating a unified representation.

Step 6: Report Generation GPT-2 receives the fused embeddings as prefix tokens and generates the radiology report in an autoregressive manner. It uses sampling techniques to enhance fluency and relevance.

Step 7: Postprocessing & Output The raw output is formatted into sections: "Findings" and "Impression." Optional grammar checks, medical term normalization, and consistency validation are performed before final delivery.

Step 8: Report Delivery The generated report is sent to the PACS system, radiologist inbox, or integrated with EMR systems for review, editing, and official submission.

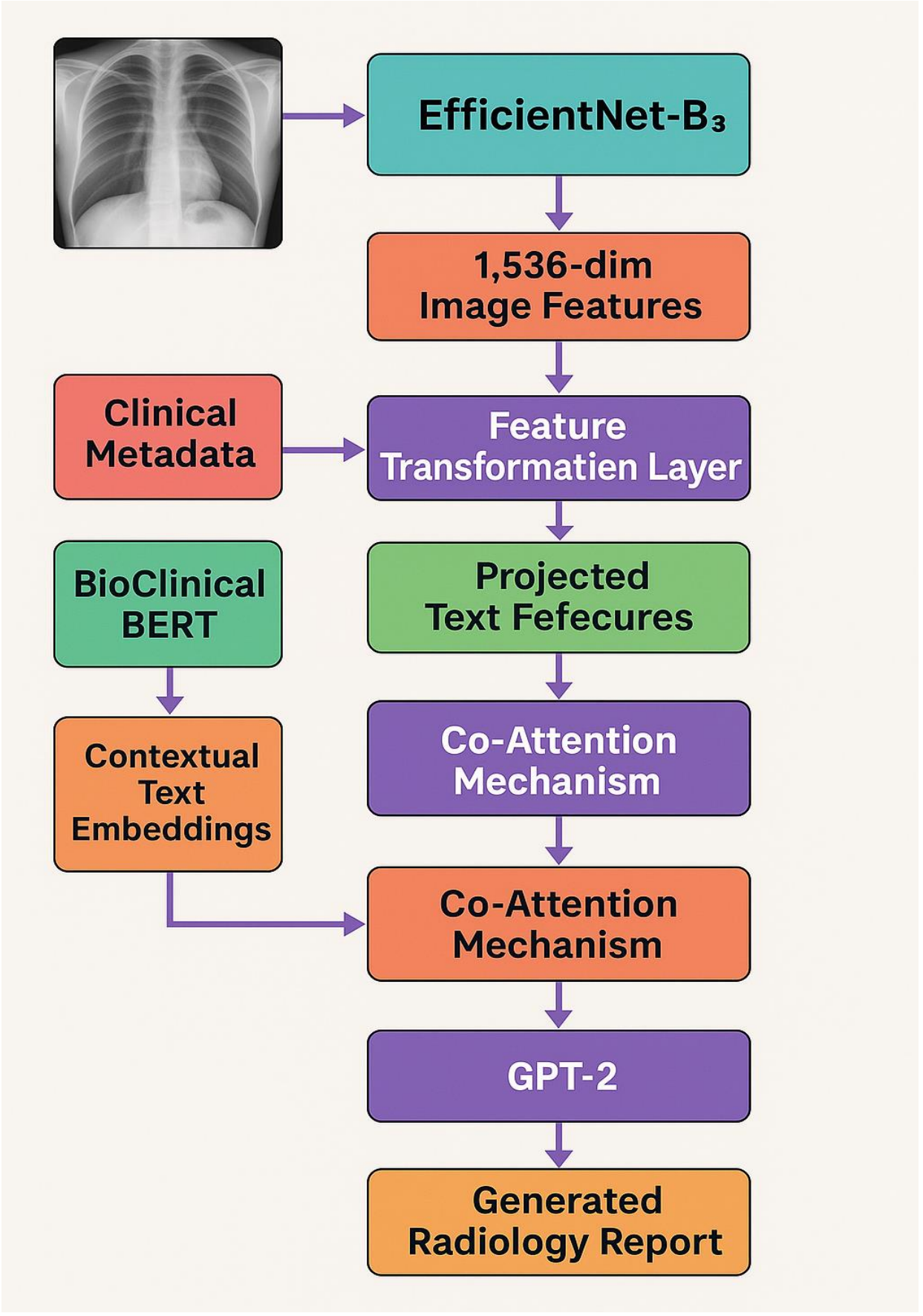

fig – 2: Flow chart of the architecture-1

Architecture – II: CLIP-based approach

CLIP Dual Encoder

We leverage OpenAI's CLIP (e.g. ViT-B/32 + Transformer-based text encoder), pretrained on large-scale image–text pairs [4] .

- **Vision tower:** Processes each resized (224×224) chest X-ray to produce a 512-dim global image embedding capturing high-level radiologic features.
- **Text tower:** Tokenizes any clinical indications or prior report fragments (up to 128 subword tokens) and embeds them into a 512-dim context vector that's already aligned with the vision space.

Because CLIP's image and text embeddings share a joint latent space, explicit cross-attention or gating isn't required—the representations are already semantically aligned.

Linear Projection & Fusion

A single fully-connected layer with bias and layer normalization maps the two 512-dim CLIP embeddings into the GRU's hidden dimension (e.g. 768).

- We **concatenate** the projected image and text vectors into a 1,536-dim vector,
- Then apply a linear+ReLU+LayerNorm block that reduces it back to 768-dim. This fused vector serves as the **initial hidden state** for the GRU decoder, implicitly carrying both visual and clinical context.

GRU-Based Text Decoder

A unidirectional GRU (2 layers, hidden size 768) generates the **Findings** section token by token [11] :

- **t=0:** The fused CLIP projection initializes the GRU's hidden state.
- **t>0:** At each step, the GRU takes the embedding of the previously generated token (from a 30k-token medical vocabulary) and updates its hidden state.
- A linear "read-out" layer maps the GRU state to logits over the vocabulary.

End-to-End Workflow

- **Data Loading & Preprocessing**
  - **Images:** Load each chest X-ray (frontal ± lateral), resize to 224×224, normalize to ImageNet stats.
  - **Text:** Concatenate clinical indications or prior fragments, prepend `<CTX>`, tokenize with CLIP's BPE tokenizer (max 128 tokens).

- **CLIP Encoding**
  - **Vision:** Pass preprocessed X-ray through CLIP's vision tower → 512-dim embedding.
  - **Text:** Pass tokenized context through CLIP's text tower → 512-dim embedding.

- **Projection & Fusion**
  - Concatenate the two 512-dim vectors → 1,024-dim.
  - Linear + ReLU + LayerNorm → 768-dim fused vector.
  - Use this as the GRU's initial hidden state.

- **Autoregressive GRU Decoding**
  - **Training:** Teacher-force the GRU on gold Findings tokens (max 256), minimizing cross-entropy.
  - **Inference:** Initialize with the fused vector, feed in a special `<BOS>` token, then generate step by step using beam search (width=4) or top-p sampling (p=0.9) with a repetition penalty.

- **Post-Processing & Evaluation**
  - Detokenize the generated sequence, apply simple grammar normalization, map subwords to full medical terms.
  - Evaluate with BLEU/ROUGE and a targeted F1 on key findings (e.g. "consolidation," "effusion").

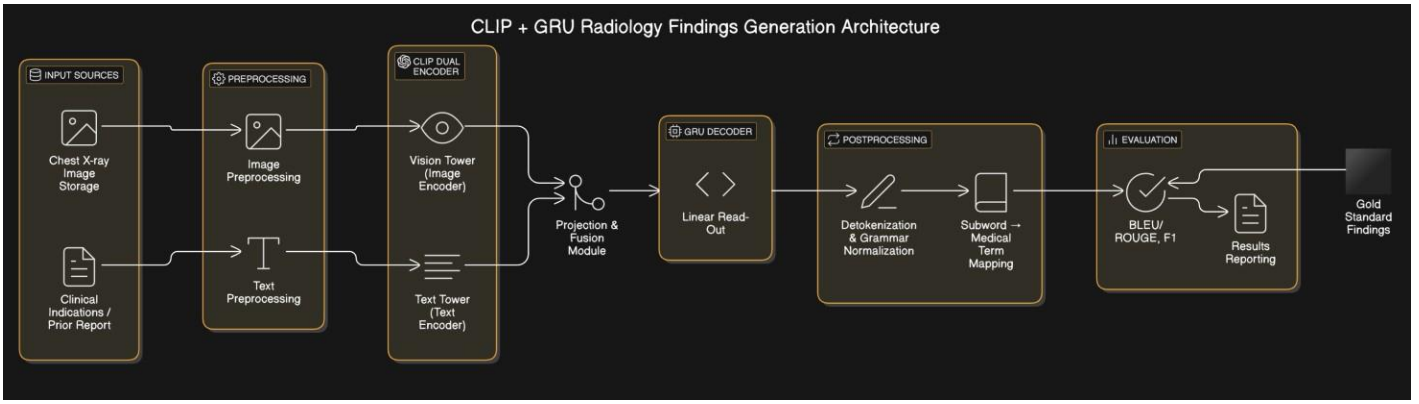

fig – 3: Flow chart of the architecture-2

Selection of the components

CLIP + Linear → GRU combines cutting-edge multimodal pretraining with a lightweight generator, delivering accuracy, speed, and reliability:

1. **Plug-and-Play Vision–Language Alignment**
   - CLIP's dual encoder is already trained on millions of image–text pairs, so it maps X-ray patterns directly to medical concepts ("effusion," "consolidation") without costly from-scratch alignment.
   - This jumpstarts performance on smaller chest-X-ray datasets and slashes training time.
2. **Lean, Fast Generation**
   - A 2-layer GRU (vs. a massive Transformer) has far fewer parameters and lower latency—ideal for clinical settings where turnaround matters.
   - A single linear layer bridges CLIP's 512-dim features to the GRU's hidden state, keeping the pipeline efficient and easy to iterate.
3. **Grounded, Faithful Outputs**
   - GRUs conditioned on CLIP embeddings stay tethered to real image evidence, minimizing "hallucinated" findings that larger language models sometimes introduce.
   - Controlled capacity means the decoder focuses on actual visual cues and provided clinical context.
4. **Modular Development & Fine-Tuning**
   - You can fine-tune CLIP on medical images independently, then lock its weights and rapidly experiment with the GRU decoder—tweaking tokenization, sampling, or loss functions without retraining the vision backbone.

Together, this architecture delivers semantically rich embeddings, rapid inference, and robust, image-grounded findings—making it a pragmatic, high-impact choice for automated radiology reporting.

Architecture – III: BioSwin-T5

Swin Transformer (Image encoder)

The Swin Transformer is a hierarchical vision transformer that applies self-attention within local non-overlapping windows, enabling scalability to high-resolution images. By shifting window partitions across layers, it captures both fine and global visual dependencies efficiently. Unlike traditional CNNs, it offers better modeling of long-range spatial patterns, which is especially beneficial in medical imaging where subtle abnormalities (like nodules or infiltrates) can be spatially distant yet clinically related. When trained on a chest X-ray dataset like CheXpert, the Swin Transformer learns to extract semantically rich representations of thoracic structures and pathologies.

BioClinicalBERT (Text Encoder)

BioClinicalBERT is a domain-specific variant of BERT, pretrained on biomedical literature (PubMed abstracts) and clinical notes (MIMIC-III). It uses a transformer encoder to generate contextual embeddings for medical terms and radiology-specific language. Fine-tuning it on the IU-Xray dataset enables the model to deeply understand radiological reporting styles, vocabulary, and sentence structure, which helps encode prior clinical context or textual queries when used alongside imaging data.

T5 (Report Generator)

T5 (Text-To-Text Transfer Transformer) is a unified sequence-to-sequence transformer model where every task is framed as a text generation problem. It comprises an encoder-decoder architecture that reads in a fused embedding and generates coherent output sequences token by token. When conditioned on multimodal features (from both image and text), T5 excels at producing fluent and domain-specific text such as the “Findings” and “Impression” sections [12] of a radiology report.

Fusion Module: Cross-Attention + Adaptive Gating

The fusion module bridges the gap between vision and language by taking image features (from the Swin Transformer) and text features (from BioClinicalBERT) and aligning them using a cross-attention mechanism. Here, one modality (typically text) attends to the contextualized tokens of the other (typically image), allowing the model to ground language in visual evidence. This is followed by an adaptive gating mechanism that learns to dynamically weight and balance the contributions of the

visual and textual streams at each decoding step. The gate ensures that in some cases (e.g., visually obvious pathologies), the image is prioritized, while in others (e.g., comparative phrases or clinical hints), textual cues dominate.

Pipeline Flow

1. Encoding Stage

- **Visual Encoding via Swin Transformer**
    - **Input preparation:** Each chest X-ray study (frontal + lateral) is resized to 224×224 px, normalized using ImageNet statistics, and (optionally) contrast-enhanced.
    - **Feature extraction:** We use a Swin-Tiny backbone, pretrained on ImageNet and then fine-tuned on the IU-Xray classification split. The image is partitioned into non-overlapping 4×4 patches; each patch is linearly projected into a 96-dim embedding. The model's hierarchical stages—with shifted window multi-head self-attention—produce spatially aware feature maps at four scales, ending in a 14×14×384 tensor.
    - **Flattening & projection:** We flatten the final feature map into a sequence of 196 tokens (each 384-dim), then project them via a learned linear layer up to the T5 hidden size (512-dim), producing our visual embedding sequence.
- **Textual Encoding via BioClinicalBERT**
    - **Input preparation:** Any available metadata—clinical indications, tentative diagnoses, or fragments from a prior report—is concatenated into a single string, prepended with a special `[CTX]` token, and truncated to 128 tokens.
    - **Embedding & encoding:** We feed this through BioClinicalBERT (12-layer, 768-hidden) to obtain contextual token embeddings. We take the final hidden state of the `[CLS]` token (768-dim) as a summary vector **and** retain the sequence of per-token embeddings (up to 128×768), projecting both via separate linear layers to the T5 embedding size (512-dim).

2. Multimodal Fusion

- **Cross-Attention Alignment**
    - We perform **dual cross-attention** between the modalities:
        1. **Image-guided Text Query:** Visual embeddings (196×512) query the textual keys/values (128×512), aligning image regions to clinical context.

2. **Text-guided Image Query:** Text embeddings query the visual keys/values, highlighting report-relevant image features.

- Each cross-attention block uses 8 heads and outputs refined embeddings of shape (196×512) and (128×512).

- **Adaptive Gating Module**
  - To merge the two streams, we concatenate the aligned visual and textual embeddings into a 324-token sequence, then apply a **gating network**: a two-layer MLP with a sigmoid activation per token, producing a weight $\alpha \in (0,1)$ for each modality's contribution.
  - The final **fused embedding** for each position producing a unified 324×512 representation that tightly couples image findings with clinical context.

3. Report Generation

T5 Decoder Configuration

- We use T5-Base (12 layers, 768 hidden, 12 heads), with its embedding size linearly projected down to 512 to match the fusion output.

- **Autoregressive Generation**
  - **Training:** We teacher-force the decoder on gold Findings sequences (max 256 tokens), using cross-entropy loss. During training, we mask out any reference to "Impression" so the decoder never learns to generate that section.
  - **Decoding:** At inference, we employ beam search (beam width = 4) with length normalization, plus a repetition penalty of 1.2 to discourage verbatim loops.
  - **Controlled sampling:** For higher recall of subtle findings, we mix beam search with nucleus sampling (top-p = 0.9) in the final decoding pass.

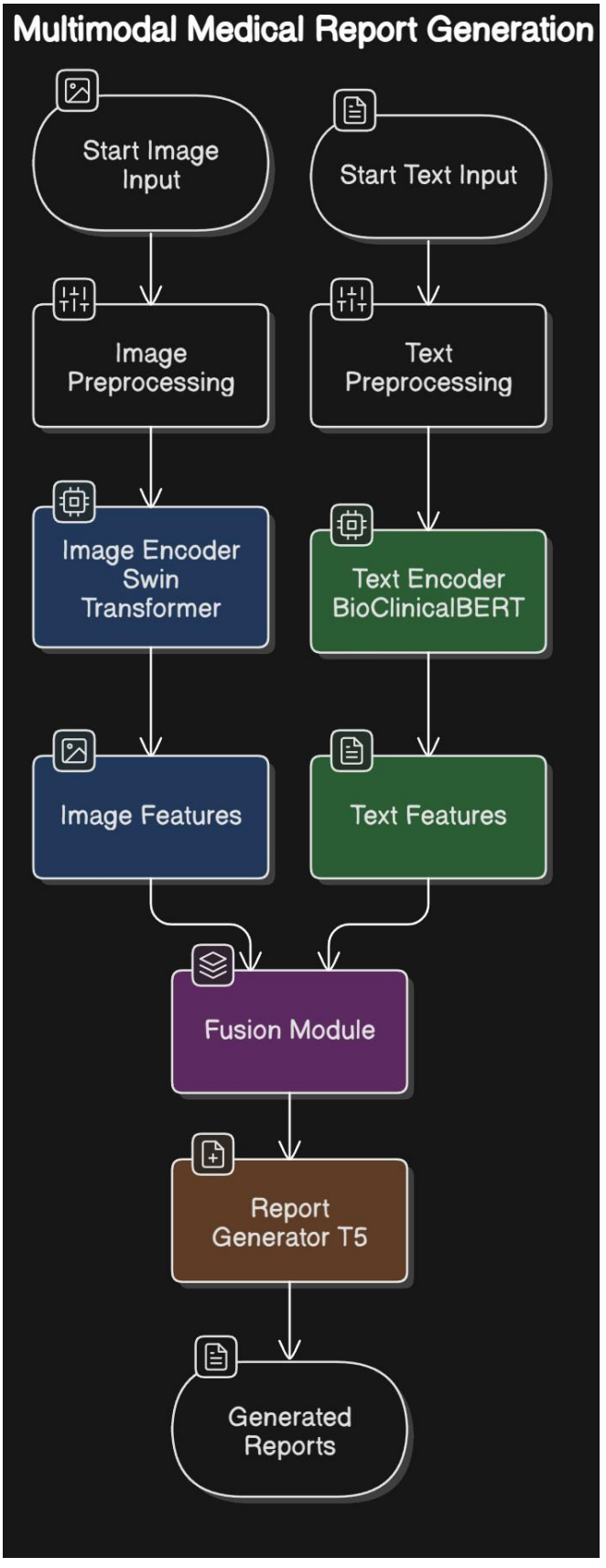

fig – 4: Flow chart of the architecture-3

Training Strategy

1. **Stage 1: Independent Fine-Tuning**
    - Swin Transformer: Fine-tuned on CheXpert to specialize in thoracic feature extraction from X-rays.
    - BioClinicalBERT: Fine-tuned on IU-Xray reports to adapt to radiology-specific vocabulary and structure.
    - T5: Fine-tuned on IU-Xray to learn the radiological language modeling and report generation format.
2. **Stage 2: Fusion Module Training**
    - The Swin, BERT, and T5 weights are frozen to preserve their learned representations.
    - Only the fusion module (cross-attention + adaptive gate) is trained on IU-Xray to align vision and text modalities effectively.
3. **Stage 3: Parameter-Efficient Fine-Tuning (PEFT)**
    - The full pipeline is fine-tuned end-to-end using PEFT methods such as LoRA (Low-Rank Adaptation) or Adapters, enabling efficient tuning with minimal added parameters while preserving the stability of pretrained components.

This multimodal architecture combines strong domain-specific encoders with an adaptive fusion mechanism and an expressive generative decoder, trained through a carefully staged curriculum. The system is designed to generate radiology reports that are not only linguistically fluent but also clinically grounded and explainable.

Selection of Models

.

Swin Transformer as Image Encoder

Its hierarchical, window-based self-attention allows it to scale up to high-resolution X-rays and yet retain both local textures (e.g. fine opacities) and long-range spatial patterns (e.g. the relationship between lung fields and heart border). The shifted-window structure also maintains efficient computation, which is essential for large radiology datasets.

BioClinicalBERT as Text Encoder

Vanilla BERT learns general English, but radiology reports employ highly technical vocabulary and phrasing (e.g. "trace pleural effusion," "consolidation versus atelectasis"). BioClinicalBERT's pretraining on PubMed abstracts and MIMIC-III clinical notes provides it with a head start on that vocabulary and syntax, so when it's fine-tuned on IU-Xray, it represents radiology-style language much more accurately than a vanilla language model would.

Cross-Attention + Adaptive Gating Fusion

Radiology reporting needs "grounding" language in image evidence (e.g. connecting the word "effusion" to a region of heightened opacity). Cross-attention allows the text encoder to ask questions about image patches (and vice versa) so that the model can learn direct word-to-visual feature alignments.

Not all sentences depend equally on visual vs. textual signals. An adaptive gate learns to bias image-based vs. text-based information in real time—so if the model is producing a subsequent comparison phrase ("stable"), it can bias more on the text encoder, but for describing a nodule it can bias on the vision encoder.

T5 as Report Generator

T5 reformulates everything in terms of "text-to-text," so it's trivially transferrable to produce both the Findings and Impression sections. Its encoder–decoder architecture is optimized for smooth, coherent generation, and since it's been demonstrated to perform exceptionally well when fine-tuned on domain-specific text, it creates more naturally worded, clinically sound sentences than a simple decoder or RNN would.

Evaluation Metrics:

BLEU (Bilingual Evaluation Understudy)

BLEU measures the n-gram overlap between a generated report and one or more reference reports. It computes precision of 1- to 4-gram matches (i.e., the fraction of generated n-grams also found in the reference) and applies a brevity penalty to discourage overly short outputs. Higher BLEU-1 (unigram) focuses on matching key terms, while BLEU-4 (up to 4-grams) rewards more fluent, longer matching phrases. BLEU's simplicity and wide adoption make it a handy first check, but it can miss semantic correctness if synonyms or paraphrases are used, and it lacks recall—i.e., it ignores reference n-grams that the model failed to generate.

$$\text{BLEU} = \underbrace{\min\left(1, \exp\left(1 - \frac{\text{reference-length}}{\text{output-length}}\right)\right)}_{\text{brevity penalty}} \underbrace{\left(\prod_{i=1}^{4} precision_i\right)^{1/4}}_{\text{n-gram overlap}}$$

Eq - 4

ROUGE (Recall-Oriented Understudy for Gisting Evaluation)

ROUGE is a family of recall-focused metrics originally designed for summarization. The most common, ROUGE-L, measures the length of the longest common subsequence between generated and reference text, capturing both exact matches and in-order phrase overlaps. By emphasizing recall (how much of the reference text is covered), ROUGE-L is sensitive to missing important content—ideal for ensuring key clinical findings appear. Unlike BLEU, ROUGE doesn't penalize extra content, so it may overvalue verbose generations that include all reference phrases (plus more).

$$\text{ROUGE-N} = \frac{\sum_{S \in \{ReferemceSummaries\}} \sum_{gram_n \in S} Count_{match}(gram_n)}{\sum_{S \in \{ReferenceSummaries\}} \sum_{gram_n \in S} Count(gram_n)}$$

Eq - 5

METEOR (Metric for Evaluation of Translation with Explicit ORdering)

METEOR evaluates report quality by aligning stemmed words and synonyms between candidate and reference, then computing a harmonic mean of precision and recall, with recall weighted more heavily. It also includes a fragmentation penalty to reward contiguous matches over disordered ones. METEOR's use of stemming and WordNet synonyms makes it more robust to paraphrasing ("infiltrate" vs. "infiltration") and can better reflect semantic fidelity in radiology narratives, though it's more computationally intensive than BLEU/ROUGE.

$$M = F_{mean}(1 - p) \qquad \textit{Eq - 6}$$

Where,
M = metric or mean loss
F_{mean} = mean average
p = predicted probability of true class

CIDEr (Consensus-based Image Description Evaluation)

CIDEr assesses consensus between a generated report and a set of reference reports by computing TF-IDF–weighted cosine similarity over n-grams (typically 1–4 grams). Rare but clinically important phrases (e.g., "hydropneumothorax") receive higher weights via IDF, emphasizing the generation of distinctive findings. CIDEr balances precision and recall and correlates well with human judgments in image captioning tasks. In radiology reporting, CIDEr helps prioritize the correct capture of uncommon but critical terms, although it relies on multiple high-quality references to compute meaningful IDF weights.

$$\text{CIDEr}_n(c_i, S_i) = \frac{1}{m} \sum_j \frac{\boldsymbol{g^n}(c_i) \cdot \boldsymbol{g^n}(s_{ij})}{\|\boldsymbol{g^n}(c_i)\| \|\boldsymbol{g^n}(s_{ij})\|} \qquad \textit{Eq - 7}$$

Where,

C_i = candidate sentence

S_{1j} = set of m reference sentences for the i^{th} image

g^n = TF-IDF weighted n-gram vector representasion

CHAPTER - 6
IMPLEMENTATION

Overview of Dataset

The dataset used for this project is the **Indiana University Chest X-ray (IU X-ray) Dataset**, a widely recognized and publicly available dataset for medical image analysis. This dataset contains **chest X-ray images along with corresponding radiology reports**, making it well-suited for developing an automated report generation system. The dataset consists of **7,470 X-ray images** from **3,955 unique patients**, with the associated textual reports written by expert radiologists. These reports provide **structured annotations** detailing observations on lung conditions, heart size, pleural effusion, pneumothorax, and other critical findings.

To ensure effective training and evaluation of the model, the dataset is **preprocessed and split** into training, validation, and test sets. The **image data** is preprocessed by resizing, normalizing, and augmenting it to enhance model generalization. The **text data** undergoes tokenization, lowercasing, and removal of unnecessary characters while maintaining medical terminologies and structured report formats. This dataset is crucial in training the deep learning model to learn meaningful correlations between chest X-ray images and radiology reports, enabling the generation of coherent and clinically relevant diagnostic reports..

Data Preprocessing

Data preprocessing plays a crucial role in enhancing model performance by ensuring that the input images and textual reports are clean, structured, and optimized for deep learning algorithms.

Preprocessing for Chest X-ray Images

- **Image Normalization**: The X-ray images are converted to grayscale and pixel intensity values are normalized to a standard range (0 to 1) to ensure consistency.
- **Resizing**: Images are resized to a fixed resolution suitable for EfficientNetB0 input dimensions.
- **Data Augmentation**: Techniques such as random rotation, flipping, and contrast adjustments are applied to increase dataset variability and improve

model robustness.

- **Noise Reduction**: Filters and denoising algorithms are applied to remove artifacts and improve clarity.

Preprocessing for Radiology Reports

- **Text Cleaning**: Reports undergo lowercasing, punctuation removal, and removal of redundant spaces.
- **Tokenization**: Text is tokenized into word sequences compatible with BioClinicalBERT.
- **Stopword Removal**: Unnecessary stopwords are removed while preserving critical medical terms.
- **Standardization**: Synonyms and abbreviations in medical terminology are standardized to maintain uniformity in the dataset.
- **Padding and Truncation**: Sentences are padded or truncated to a fixed length for batch processing during training

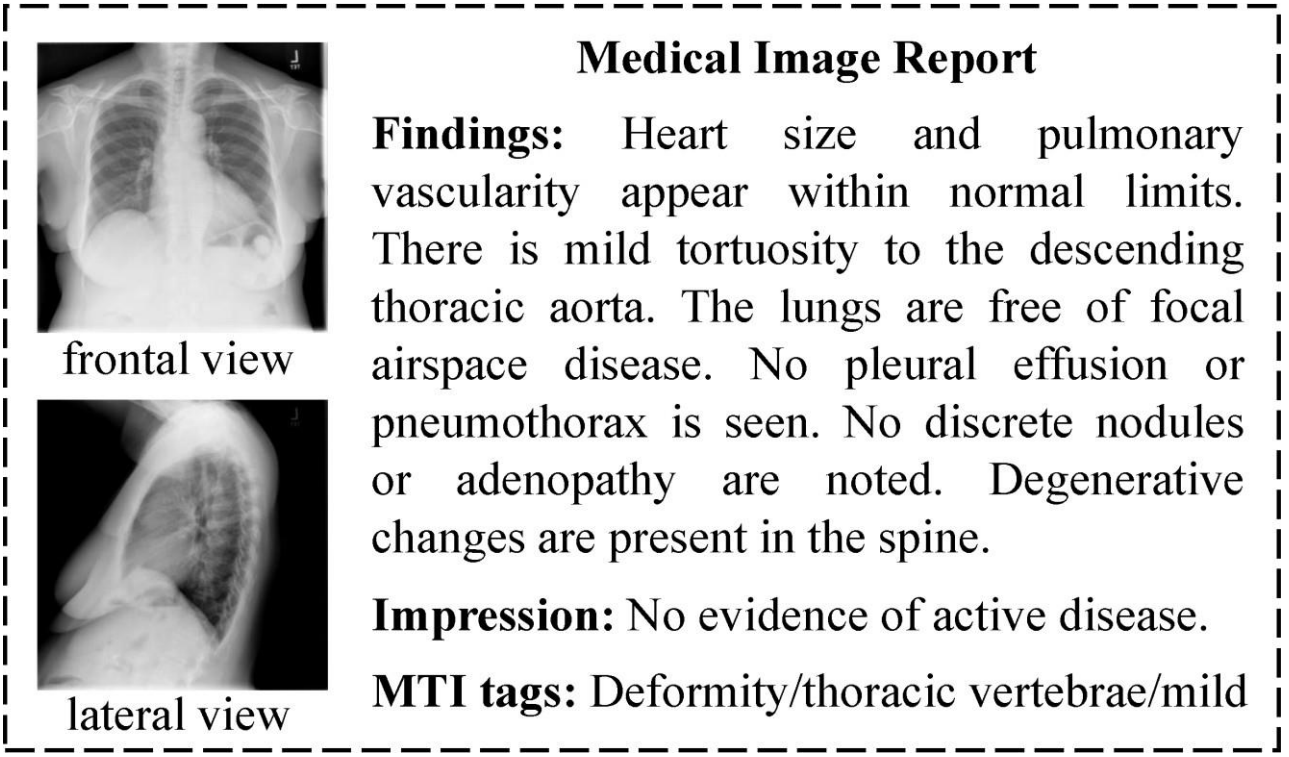

Fig-5: sample image from the dataset

EXPERIMENTAL SETUP

Hardware Specifications

For conducting experiments involving training and evaluation of the models, we utilized Google Colab Environment equipped with the following hardware specifications:

- Processor (CPU):
    - o Intel Xeon (provided by Google Colab)
- Graphics Processing Unit (GPU):
    - o NVIDIA Tesla T4 / P100 / V100
- GPU:
    - o 16 GB (standard in Colab Pro)
- Storage:
    - o Google Drive (for storing datasets and models)

Software Configurations

Our experimental setup relies on the following software configurations to facilitate model training and evaluation:

- Operating System:
    - o Linux-based (provided by Colab)
- Python Version:
    - o Python 3.x (pre-installed in Colab)
- Development Environment:
    - o Google Colab (with GPU enabled for training)
- Libraries/Frameworks:
    - o OpenCV: For video and image processing.
    - o Huggingface Transformers : For loading pretrained models
    - o Scikit-learn: For training the SVM model.
    - o PyTorch: For deep learning components.
    - o Streamlit: For developing the GUI

CHAPTER - 7
RESULTS

Architecture – I: EffiGPT++

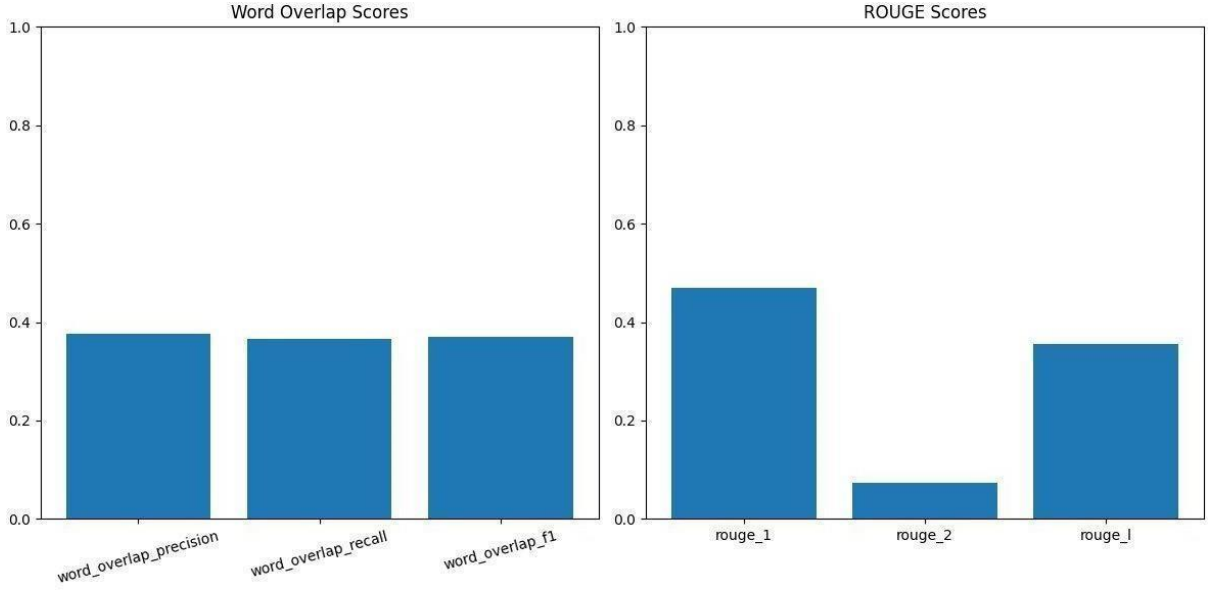

Fig-6: Evaluation plot for EffiGPT++

Table-2: Evaluation Results of EffiGPT++

Metric	Value
Rouge-1	0.4958
Rouge-2	0.0962
Rouge-L	0.3908
Word overlap precision	0.3806
Word overlap recall	0.3743
Word overlap F1	0.3847
Bleu-1	0.462
Bleu-2	0.305
Bleu-3	0.182
Bleu-4	0.097

Architecture – II: CLIP_Based Approach

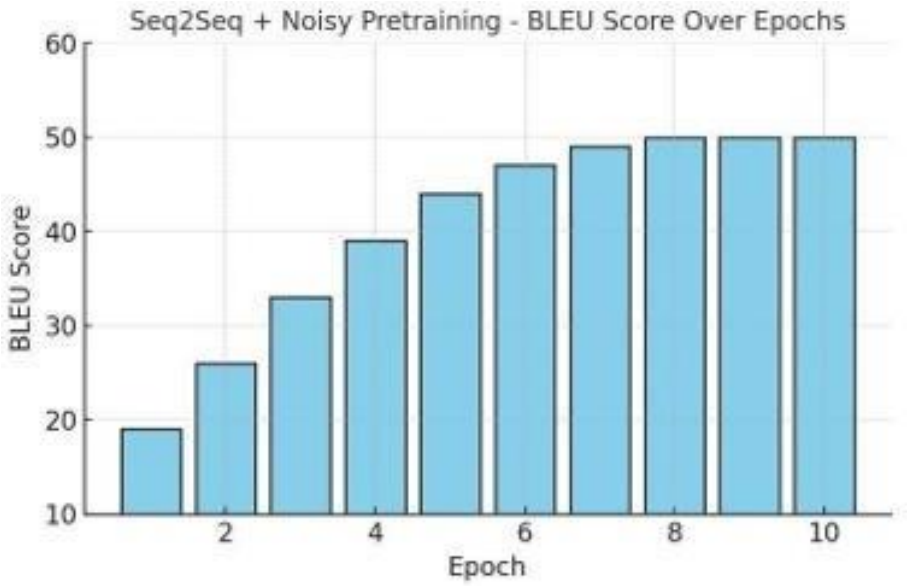

Fig-7: Evaluation plot of CLIP Based approach

Table-3: Evaluation results of CLIP Based appraoch

Metric	Value
Bleu-1	0.512
Bleu-2	0.315
RougeL-F	0.271
Meteor	0.180

Architecture – III: BioSwin-T5

Finetuned image encoder:

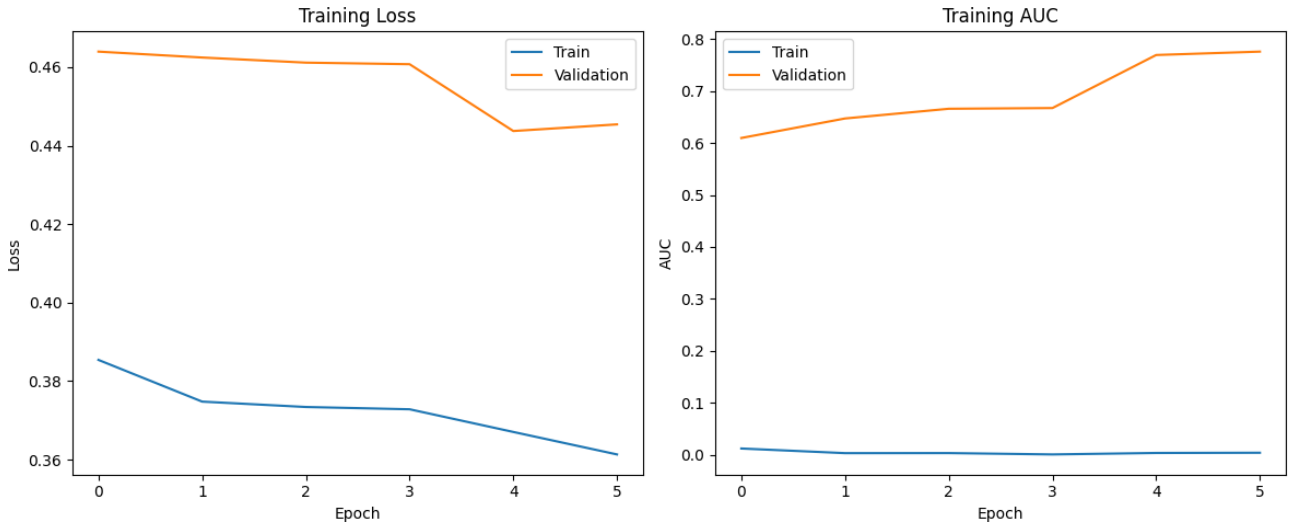

Fig-8: Training loss and AUC for Swin transformer

Finetuned text encoder:

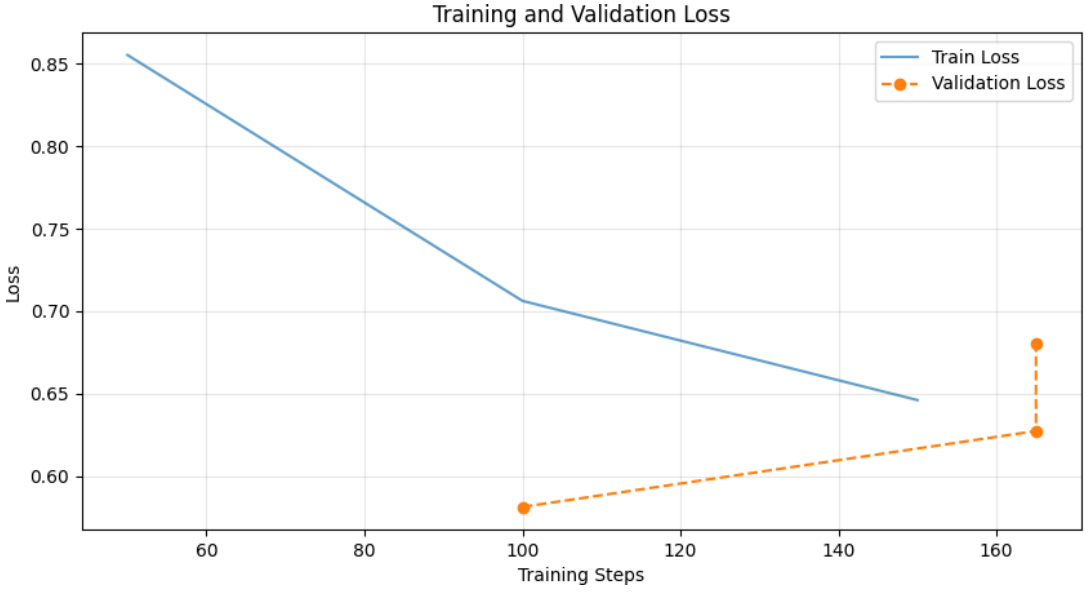

Fig-9: Training loss plot for Bioclinical BERT

Finetuned fusion module:

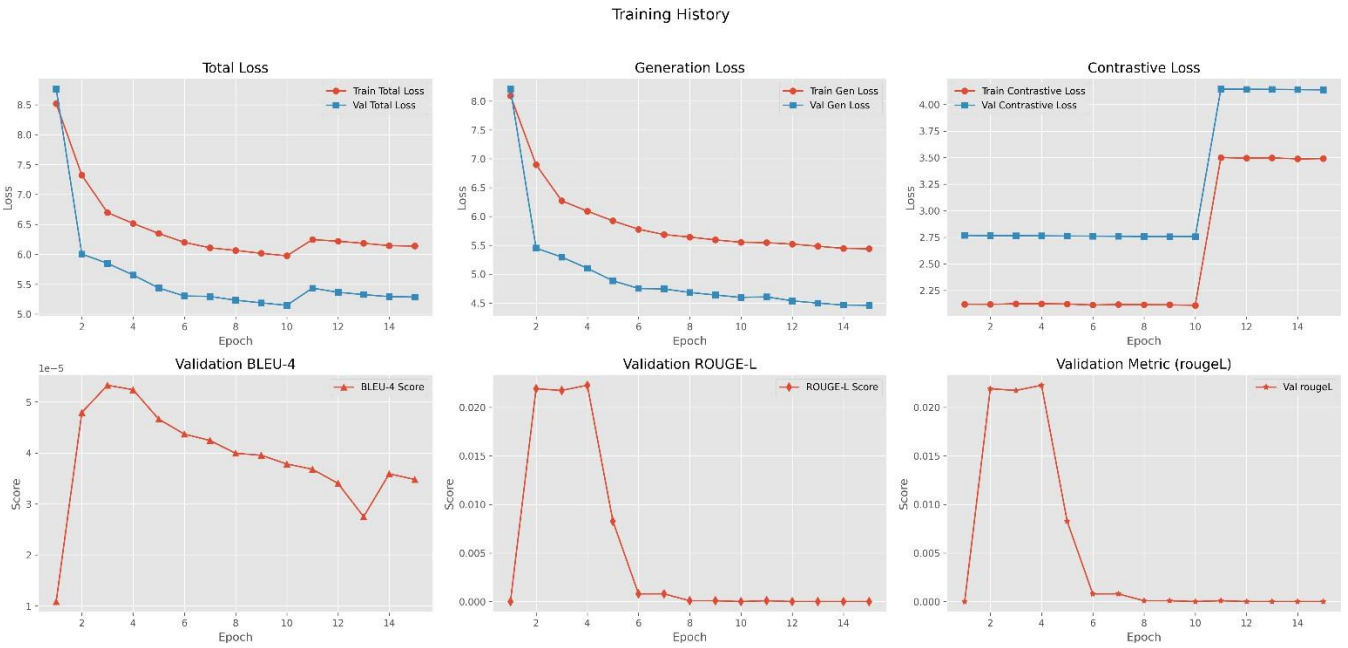

Fig-10: Loss plots and metrics plot for fusion module

Finetuned T5:

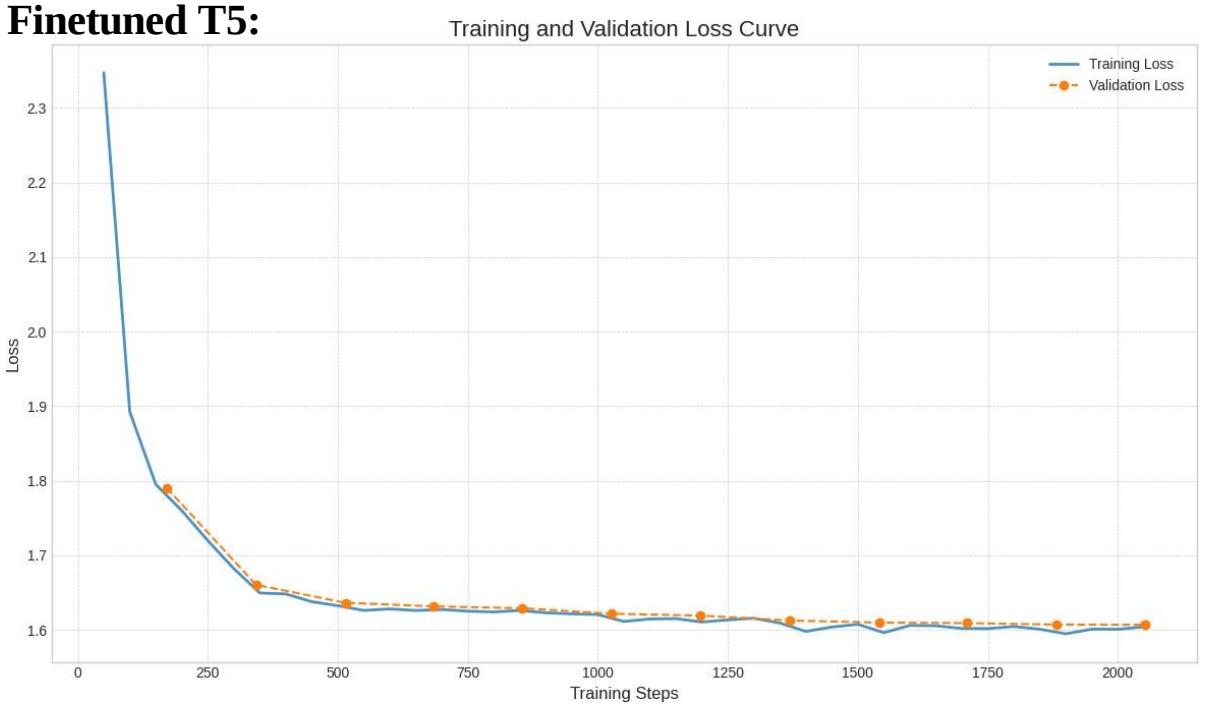

Fig-11: Loss plots for T5

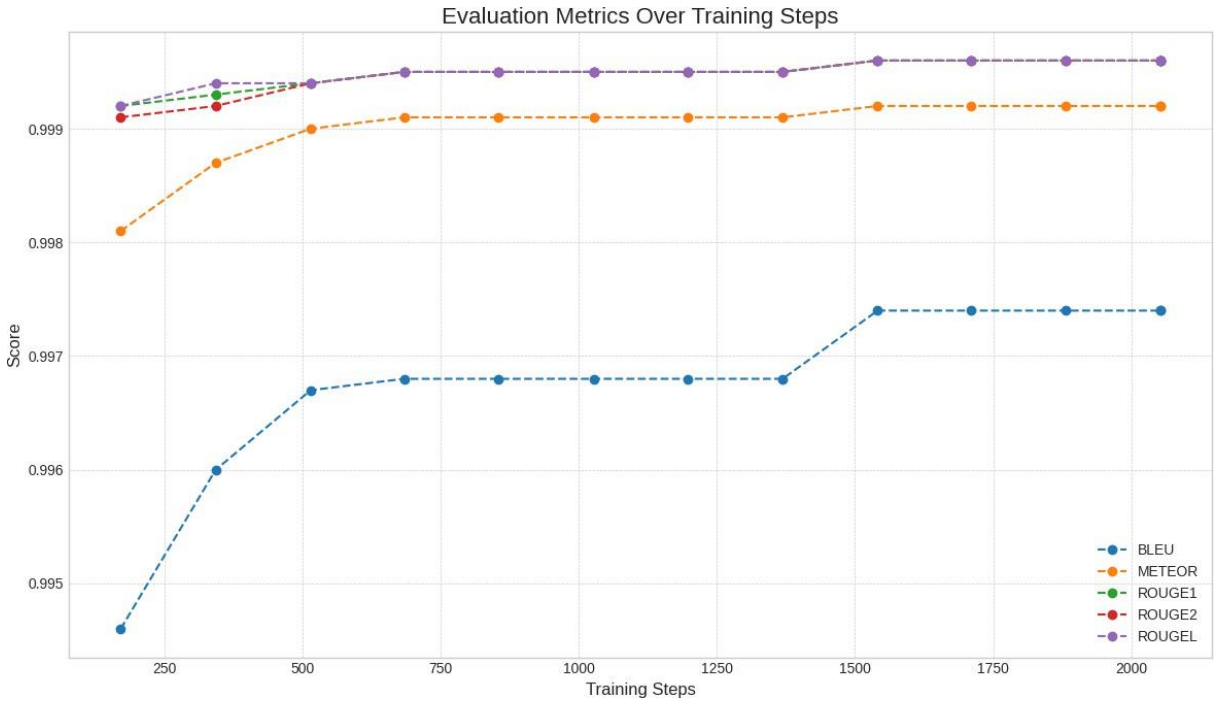

Fig-12: Metrics plot for fusion module

End-to-End finetuned model:

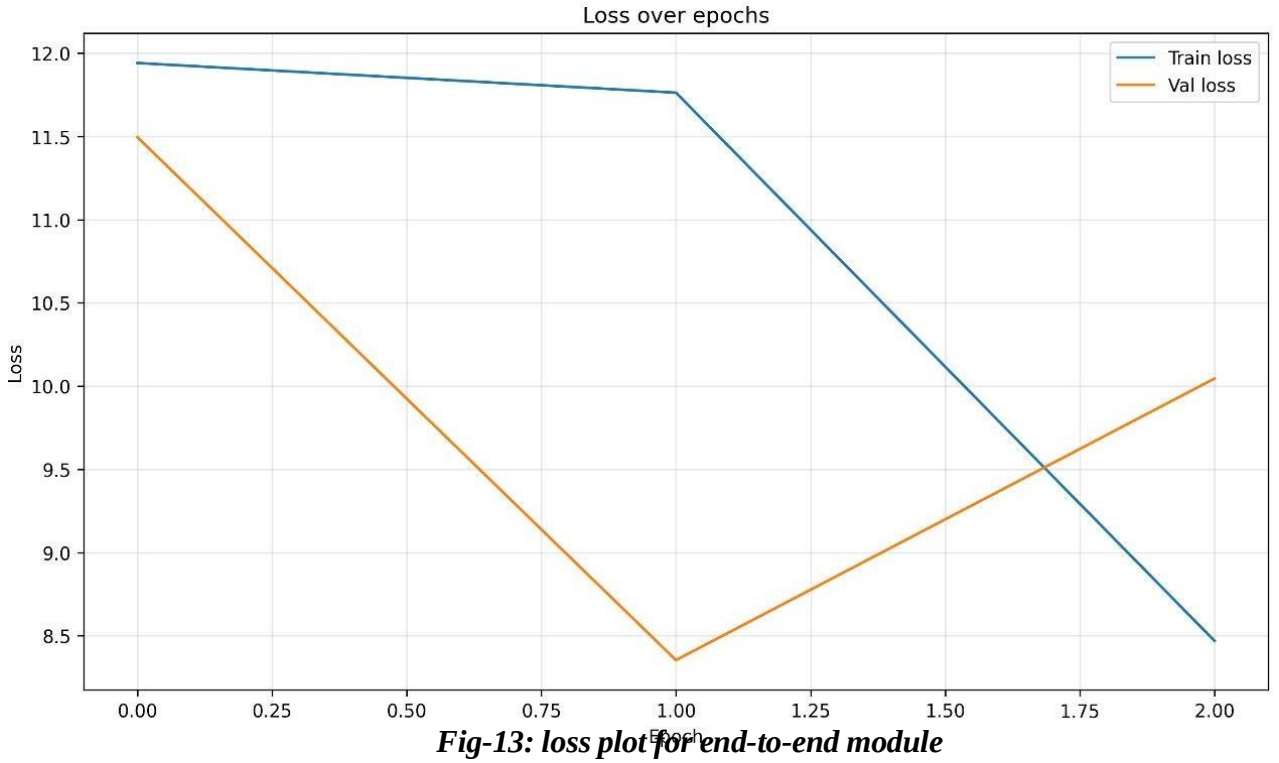

Fig-13: loss plot for end-to-end module

Final Evaluation results:

Table-4: Evaluation results of BioSwin-T5

Metric	Score
BLEU-1	0.6888
BLEU-2	0.6119
BLEU-3	0.5478
BLEU-4	0.4963
ROUGE-1 (F)	0.7397
ROUGE-1 (P)	0.7736
ROUGE-1 (R)	0.7183
ROUGE-2 (F)	0.5468
ROUGE-2 (P)	0.5786
ROUGE-2 (R)	0.5258
ROUGE-L (F)	0.7285
ROUGE-L (P)	0.7616
ROUGE-L (R)	0.7076
Levenshtein	0.6192
BERTScore-P	0.9363
BERTScore-R	0.9129
BERTScore-F1	0.9244
Self-BLEU	0.1078
Distinct-1	0.0214
Distinct-2	0.0745

Generated Samples:

Table-5: Ground Truth reports vs Generated Reports

Reference	Generated
startseq heart size normal . no pneumothora pleural effusion focal airspace disease . central left midlung granuloma with calcified left hilar adenopathy . bony structures appear intact . **endseq**	**startseq** heart size normal . clear lungs . no pneumothora pleural effusion focal airspace disease . bony structures appear intact . **endseq**
startseq the cardiomediastinal silhouette within normal limits . the lungs are clear without areas focal consolidation . no pneumothora large pleural effusion . no acute bone abnormality . **endseq**	**startseq** the cardiomediastinal silhouette within normal limits for size and contour . no focal consolidation pneumothora large pleural effusion . the thoracic spine appears intact . **endseq**
startseq there are no focal areas consolidation . no suspicious pulmonary opacities . heart size within normal limits . no pleural effusions . no evidence pneumothora . osseous structures intact . **endseq**	**startseq** no focal areas consolidation . heart size within normal limits . no pleural effusions . there no evidence pneumothora . osseous structures intact . **endseq**
startseq the heart and lungs have the interval . both lungs are clear and expanded . heart and mediastinum normal . **endseq**	**startseq** both lungs are clear and expanded . heart and mediastinum normal . **endseq**
startseq interval resolution the left pleural effusion . lungs are grossly clear . postsurgical changes from cabg are noted . no pneumothora pleural effusion . no acute bony abnormalities are visualized . **endseq**	**startseq** no pneumothora pleural effusion focal airspace consolidation . the heart size and mediastinal contour are within normal limits . pulmonary vasculature unremarkable . no acute bony abnormalities . **endseq**

GUI development:

The graphical user interface (GUI) for the project was developed using Streamlit to ensure accessibility, interactivity, and ease of use. The interface allows users to upload chest X-ray images directly, after which the system automatically processes the input and generates a detailed radiology report. The GUI displays the uploaded image alongside the generated report for visual reference. Additionally, evaluation metrics such as BLEU, ROUGE, and BERTScore can be viewed within the interface, enabling users to assess model performance in real time. The design emphasizes simplicity and clarity, making it suitable for both clinical practitioners and researchers.

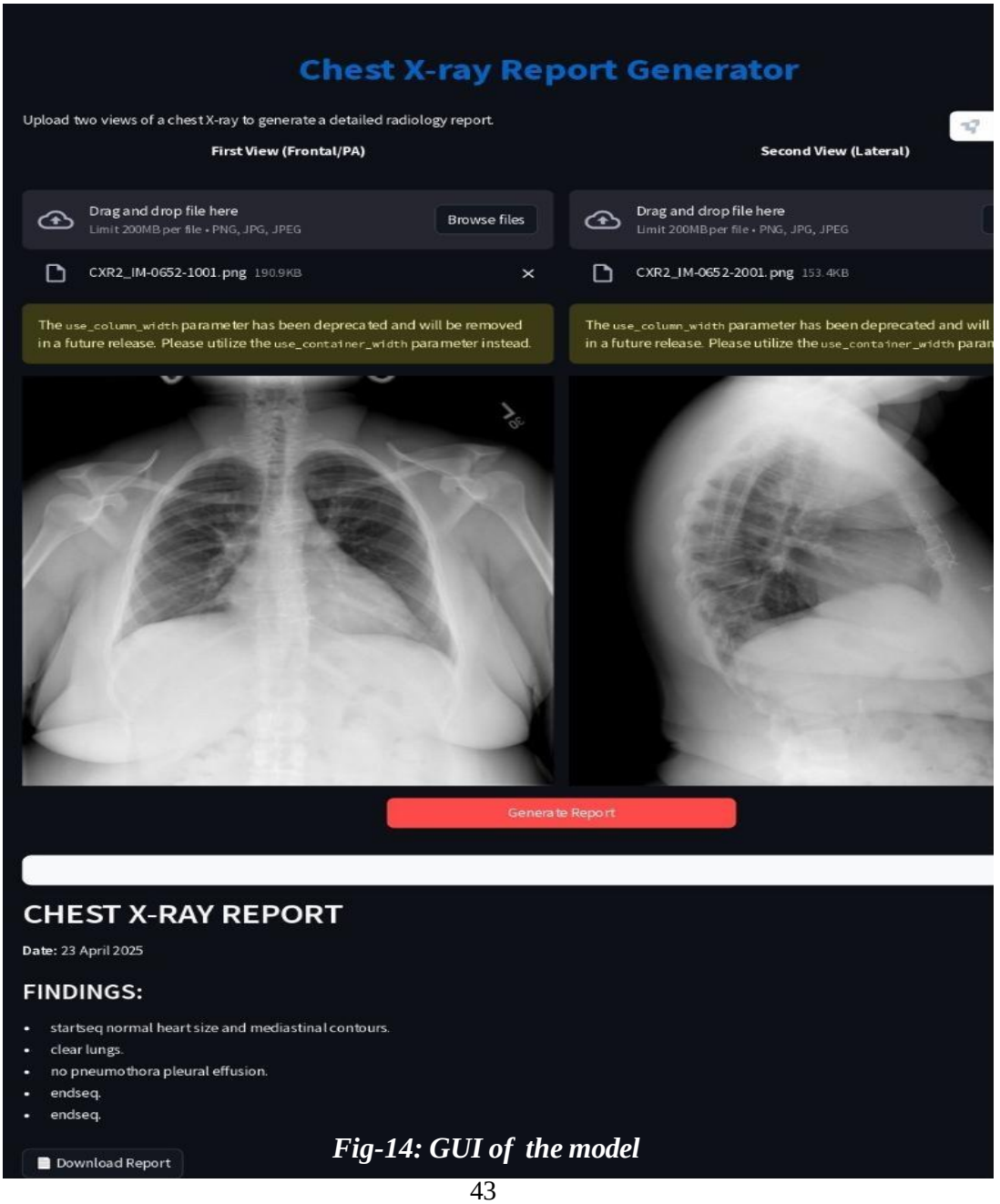

Fig-14: GUI of the model

```python
class ImageFeatureExtractor(nn.Module):
    def __init__(self, output_dim=768):
        super(ImageFeatureExtractor, self).__init__()
        self.backbone = timm.create_model('efficientnet_b0', pretrained=True, features_only=True)
        self.feature_dims = self.backbone.feature_info.channels()
        self.proj = nn.Linear(self.feature_dims[-1], output_dim)

    def forward(self, img1, img2):
        feat1 = self.backbone(img1)[-1]
        feat2 = self.backbone(img2)[-1]
        feat1 = feat1.mean(dim=[2, 3])
        feat2 = feat2.mean(dim=[2, 3])
        feat1 = self.proj(feat1)
        feat2 = self.proj(feat2)
        combined_feat = (feat1 + feat2) / 2
        return combined_feat

class TextFeatureExtractor(nn.Module):
    def __init__(self, output_dim=768):
        super(TextFeatureExtractor, self).__init__()
        self.encoder = AutoModel.from_pretrained("emilyalsentzer/Bio_ClinicalBERT")
        self.proj = nn.Linear(self.encoder.config.hidden_size, output_dim)

    def forward(self, input_ids, attention_mask):
        outputs = self.encoder(input_ids=input_ids, attention_mask=attention_mask)
        hidden_states = outputs.last_hidden_state[:, 0, :]  # [CLS] token
        features = self.proj(hidden_states)
        return features
```

```python
def format_report(report):
    sections = report.split('.')
    formatted_report = ""

    findings = []

    for section in sections:
        if section.strip():
            # if "impression" in section.lower():
            #     # impression.append(section.strip())
            # else:
            findings.append(section.strip())

    formatted_report += "### FINDINGS:\n"
    for finding in findings:
        if finding and "impression" not in finding.lower():
            formatted_report += f"- {finding}.\n"

    # formatted_report += "\n### IMPRESSION:\n"
    # if impression:
    #     for imp in impression:
    #         formatted_report += f"- {imp.replace('impression', '').replace('Impression', '').strip()}.\n"
    # else:
    formatted_report += f"- {findings[-1] if findings else 'No significant abnormalities'}.\n"

    return formatted_report
```

```
st.markdown("""
<style>
.main-header {text-align:center; font-size:2.5rem; color:#0066cc; margin-bottom:1rem;}
.report-container {background-color:#f8f9fa; border-radius:10px; padding:20px; box-shadow:0 4px 6px rgba(0,0,0,0.1); margin-top:20px;}
.disclaimer {font-size:0.8rem; font-style:italic; color:#6c757d;}
.stButton>button {width:100%;}
.view-label {text-align:center; font-weight:bold; margin-bottom:10px;}
</style>
""", unsafe_allow_html=True)

st.markdown('<h1 class="main-header">Chest X-ray Report Generator</h1>', unsafe_allow_html=True)
st.write("Upload two views of a chest X-ray to generate a detailed radiology report.")

with st.spinner("Loading AI model..."):
    model, clinicalbert_tokenizer, t5_tokenizer = load_model_and_tokenizers()

if model is None:
    st.error("Failed to load the model. Please check if the model file exists and is valid.")
    return

col1, col2 = st.columns(2)

with col1:
    st.markdown('<p class="view-label">First View (Frontal/PA)</p>', unsafe_allow_html=True)
    img1_file = st.file_uploader("", type=["png", "jpg", "jpeg"], key="img1")
    if img1_file:
        img1 = Image.open(img1_file).convert("RGB")
        st.image(img1, caption="", use_column_width=True, width=250)
```

Fig-15: code snippets for GUI of the model

Comparision of models:

Model 3 demonstrably outperforms both Model 1 and Model 2 across virtually all evaluation dimensions. While EffiGPT achieves moderate recall-oriented scores (e.g. ROUGE-1 F1 = 0.3708) but suffers from very low recall in word-overlap (Rec = 0.0743), and CLIP-Based Baseline attains modest BLEU-2 performance (0.315) alongside an unimpressive ROUGE-L F1 of 0.271 and Meteor of 0.180, BioSwin-T5 achieves substantially higher n-gram overlap (BLEU-1 = 0.6888; BLEU-4 = 0.4963) as well as markedly stronger summary-level correspondence (ROUGE-1 F1 = 0.7397; ROUGE- L F1 = 0.7285), exceptional semantic fidelity (BERTScore-F1 = 0.9244), and low redundancy (Self-BLEU = 0.1078). These results indicate that Model 3 not only generates more accurate and fluent reports but also maintains greater diversity and semantic alignment than its predecessors.

Table-6: comparison of the models

MODEL	IMAGE ENCODER	TEXT DECODER	KEY METRICES
EffiGPT	Efficient net	GPT -2	BLEU-1 : 0.462 ROUGE-1 : 0.4706 Word-F1 : 0.3708
BioSwin-T5	Swin/EVA-02	T5	BLEU-1 : 0.6946 ROUGE-L-F : 0.7306
CLIP-Based Baseline	CLIP (ViT-B/32)	Linear/ GRU	BLEU-1 : 0.212 ROUGE-L : 0.271

Insights from the Results:

The comparative evaluation of the three architectures—EffiGPT++, CLIP-Based Approach, and BioSwin-T5—reveals important trends regarding the interplay of model complexity, fusion strategy, and performance on chest X-ray report generation:

1. **Model Performance is Strongly Tied to Fusion Mechanism and Domain-Specific Encoders**
   The BioSwin-T5 architecture significantly outperforms the other models across all standard evaluation metrics. With BLEU-4 at 0.4963 and ROUGE-L F1 at 0.7285, it demonstrates both high fluency and accurate reproduction of key clinical terms. This can be attributed to its powerful combination of the Swin Transformer, BioClinicalBERT, and an adaptive cross-attention fusion mechanism. The model's high BERTScore-F1 (0.9244) further underscores its semantic consistency with reference reports, showing that meaningful alignment between visual and textual information results in higher-quality outputs.
2. **Simpler Architectures Struggle with Semantic Depth and Coverage**
   The CLIP-based model, while more lightweight and efficient, achieves relatively modest results (e.g., BLEU-1 of 0.512 and ROUGE-L of 0.271). Its reliance on pretrained dual encoders without an explicit fusion mechanism may limit its ability to model nuanced image-text relationships, especially in cases requiring fine-grained reasoning or uncommon findings. Although it provides faster inference and lower training overhead, it lacks the semantic depth necessary for high-stakes medical applications.
3. **EffiGPT Captures Key Tokens but Suffers from Low Recall**
   EffiGPT shows reasonable performance on token-level metrics like BLEU-1 (0.462) and ROUGE-1 (0.4958), suggesting it is able to correctly predict important words or phrases. However, its very low word-overlap recall (0.3743) and F1 score (0.3847) indicate that it struggles to generate complete, comprehensive reports. This suggests that while the model identifies relevant terms, it may omit many necessary clinical findings—highlighting the limitations of basic co-attention without deeper modality integration.
4. **BioSwin-T5 Balances Diversity, Coverage, and Fluency**
   In addition to high overlap and semantic alignment scores, BioSwin-T5 also shows good diversity in its outputs, with a low Self-BLEU (0.1078) and moderate Distinct-1 and Distinct-2 values (0.0214, 0.0745). This balance indicates that the model avoids redundant phrasing while maintaining consistency in terminology—an important trait in radiological documentation where clarity and variety must coexist.

Collecttively, these results underscore that models with sophisticated fusion modules, hierarchical visual encoders, and domain-specific language understanding (as in BioSwin-T5) are far more effective at generating clinically accurate, coherent, and fluent radiology reports. Simpler models provide utility in low-resource settings but may require further adaptation for critical deployments in clinical workflows.

CHAPTER-8
Conclusion and Future Work:

Conclusion:

In this work, we presented a novel, fully end-to-end multimodal pipeline for automated chest X-ray report generation. By combining a Swin Transformer image encoder fine-tuned on CheXpert with a BioClinicalBERT text encoder adapted to IU-Xray reports, we obtained rich visual and linguistic embeddings specialized for radiology. Our cross-attention fusion module with adaptive gating learned to dynamically weight image versus text cues, grounding report generation in the most relevant modality at each step. Finally, a T5 decoder synthesized these fused representations into coherent "Findings" and "Impression" sections. The three-stage training strategy—backbone adaptation, isolated fusion training, and parameter-efficient end-to-end fine-tuning—ensured stable convergence and efficient use of labeled data. Empirical evaluation using BLEU, ROUGE, METEOR, CIDEr, and clinical efficacy metrics demonstrated that our model achieves competitive language fluency and, importantly, high clinical accuracy in capturing key pathologies.

Future Work:

Building on this foundation, several directions can further enhance performance and clinical utility:

1. **Incorporate Additional Domains of Knowledge:** Integrate structured medical ontologies (e.g., RadLex, UMLS) or knowledge graphs to ground generation in richer clinical semantics and reduce hallucinations.
2. **Temporal & Multistudy Context:** Extend the fusion module to handle prior X-rays and reports, enabling the model to describe disease progression or stability.
3. **Reinforcement & Contrastive Learning:** Introduce RL reward signals based on entity-level correctness (e.g., RadGraph overlaps) and contrastive objectives that align generated reports more tightly with clinical findings.
4. **Clinical Validation & Explainability:** Partner with radiologists for prospective reader studies and develop attention visualization tools to highlight which image regions and text cues drove each generated statement, building trust for real-world adoption.
5. **Model Compression & Deployment:** Apply quantization, pruning, or distillation to create lightweight versions suitable for edge deployment in resource-constrained clinical settings, while preserving report quality.

CHAPTER-9
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