

You are an expert PyTorch researcher implementing a MICCAI-style anatomy-aware vision–language model for radiology.

Your task is to implement the exact architecture described below, without removing or simplifying any component.

### Project Overview


Implement an Anatomy-Aware Vision–Language Model trained on the ROCov2 dataset for both image–text retrieval and image captioning.

The core novelty is:

Structured radiology text encoding (anatomy / observation / modifier)

Anatomy-guided gating of image tokens

Multi-task learning (retrieval + captioning + optional concept prediction)

 Codebase Structure (MUST FOLLOW)

Copy code

roco\_anatomy\_vlm/

```
|
|— models/
|   |— image_encoder.py
|   |— text_encoder.py
|   |— anatomy_gating.py
|   |— fusion_transformer.py
|   |— retrieval_head.py
|   |— caption_decoder.py
|   |— vlm_model.py
|
|— data/
|   |— roco_dataset.py
|   |— anatomy_parser.py
|
|— training/
|   |— losses.py
|   |— train.py
|
|— configs/
|   |— default.yaml
|
|— utils/
|   |— metrics.py
|   |— visualization.py
```

#### ❶ Image Encoder (image\_encoder.py)

Use ViT-B/16 from timm

Output patch embeddings only (no classification token)

Shape: (B, N, D)

#### ❷ Anatomy Parser (anatomy\_parser.py)

Rule-based

Input: caption string

Output:

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Python

```
{  
  "anatomy": List[str],  
  "observation": List[str],  
  "modifier": List[str]  
}
```

Use a simple dictionary (RadLex-style keywords)

Must be deterministic and dataset-independent

### ③ Structured Text Encoder (text\_encoder.py)

Use shared BERT weights (bert-base-uncased)

Encode anatomy, observation, modifier separately

Mean-pool each group:

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Python

a\_bar, o\_bar, m\_bar

Final text embedding:

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Python

T = concat([a\_bar, o\_bar, m\_bar])

### ④ Anatomy-Guided Gating (anatomy\_gating.py)

Implement:

Copy code

Python

S\_i = cosine\_similarity(a\_bar, p\_i)

g\_i = sigmoid(S\_i / temperature)

p\_i\_prime = g\_i \* p\_i

Must be fully differentiable

Temperature is configurable

### ⑤ Fusion Transformer (fusion\_transformer.py)

Transformer encoder

Input tokens:

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Python

[p\_1', ..., p\_n', a\_bar, o\_bar, m\_bar]

4–6 layers

Output a fused representation

### ⑥ Retrieval Head (retrieval\_head.py)

Projection heads for image and text

CLIP-style contrastive loss

Output Recall@K metrics

### ⑦ Caption Decoder (caption\_decoder.py)

Transformer decoder

Cross-attends to gated image tokens

Teacher forcing during training

### ⑧ Full Model (vlm\_model.py)

Combines all modules

Forward pass supports:

retrieval

captioning

concept prediction (optional)

9 Losses (losses.py)

Implement:

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Python

$L_{\text{total}} = \lambda_1 * L_{\text{retrieval}} + \lambda_2 * L_{\text{caption}} + \lambda_3 * L_{\text{concept}}$

Implementation Constraints (IMPORTANT)

PyTorch only

No Lightning

Modular, readable, research-quality code

Include docstrings and comments

No shortcuts or architectural simplifications

Assume ROCOv2 captions and images are preprocessed

🎯 Output Expectations

The code must run end-to-end

All tensors must have explicit shapes

All modules must be unit-testable

The architecture must exactly match the description

🧠 Reminder

This is not a generic BLIP or CLIP implementation.

The anatomy-guided gating and structured text encoding are mandatory and central.