LARGE-SCALE AND FINE-GRAINED VISION-LANGUAGE PRE-TRAINING FOR ENHANCED CT IMAGE UNDERSTANDING

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ABSTRACT

Artificial intelligence (AI) shows great potential in assisting radiologists to improve the efficiency and accuracy of medical image interpretation and diagnosis. However, a versatile AI model requires large-scale data and comprehensive annotations, which are often impractical in medical settings. Recent studies leverage radiology reports as a naturally high-quality supervision for medical images, using contrastive language-image pre-training (CLIP) to develop language-informed models for radiological image interpretation. Nonetheless, these approaches typically contrast entire images with reports, neglecting the local associations between imaging regions and report sentences, which may undermine model performance and interoperability. In this paper, we propose a fine-grained vision-language model (fVLM) for anatomy-level CT image interpretation. Specifically, we explicitly match anatomical regions of CT images with corresponding descriptions in radiology reports and perform contrastive pre-training for each anatomy individually. Fine-grained alignment, however, faces considerable false-negative challenges, mainly from the abundance of anatomy-level healthy samples and similarly diseased abnormalities, leading to ambiguous patient-level pairings. To tackle this issue, we propose identifying false negatives of both normal and abnormal samples and calibrating contrastive learning from patient-level to disease-aware pairing. We curated the largest CT dataset to date, comprising imaging and report data from 69,086 patients, and conducted a comprehensive evaluation of 54 major and important disease (including several most deadly cancers) diagnosis tasks across 15 main anatomies. Experimental results demonstrate the substantial potential of fVLM in versatile medical image interpretation. In the zero-shot classification task, we achieved an average AUC of 81.3% on 54 diagnosis tasks, surpassing CLIP and supervised methods by 12.9% and 8.0%, respectively. Additionally, on the publicly available CT-RATE and Rad-ChestCT benchmarks, our fVLM outperformed the current state-of-the-art methods with absolute AUC gains of 7.4% and 4.8%, respectively.

1 INTRODUCTION

Medical image interpretation is a critically important yet exceptionally burdensome task in clinical workflows, particularly when dealing with 3D imaging scans Udare et al. (2022). Radiologists are required to examine hundreds of slices across dozens of anatomies meticulously Blankemeier et al. (2024). As a result, there is a growing demand for versatile and reliable AI to assist in the automated interpretation of medical images for a wide range of diagnostic needs. Supervised learning is a prominent strategy for automating this process, demonstrating remarkable success in natural scene images, such as ImageNet Deng et al. (2009). In the medical domain, specific disease category information must be precisely defined in advance, necessitating extensive annotations from specialized annotators Isensee et al. (2021); Wang et al. (2023); Zhang et al. (2023a); Guo et al. (2024). Unlike natural images, medical images encompass a complex variety of conditions, making it challenging to fulfill all clinical diagnostic requirements through a predefined one-hot label space Liu et al. (2023c). Furthermore, the labor-intensive annotation constitutes an additional burden on doctors outside of their regular duties. These challenges make it particularly difficult to apply supervised learning methodologies effectively within the medical field.

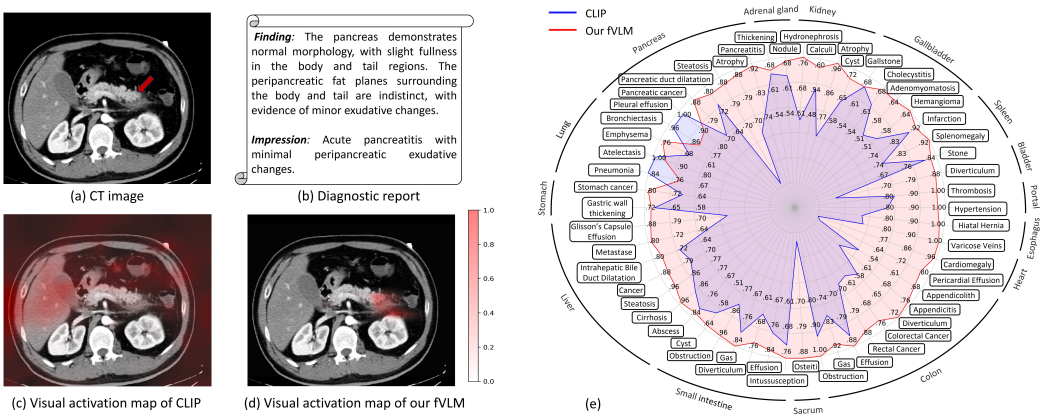

Figure 1: Comparative analysis of vanilla VLM (CLIP) and our fine-grained VLM (fVLM). (a,b) A representative CT slice and its corresponding radiological report. (c,d) Visual activation maps generated by CLIP and fVLM respectively, illustrating regions of interest for pancreatitis diagnosis. (e) Quantitative comparison of AUC scores across 54 disease diagnosis tasks in 15 anatomies.

Recently, Vision Language Models (VLMs) Zhang et al. (2022); Tiu et al. (2022); Lin et al. (2023); Wu et al. (2023); Blankemeier et al. (2024) have gained considerable attention, presenting a promising alternative to supervised learning paradigms. The fundamental concept involves supervising model training directly through diagnostic reports, thus eliminating the need for specific disease category labels Cao et al. (2024). Radiology reports are highly condensed recordings of the diagnostic process, meticulously documenting the evaluations conducted by at least one experienced radiologist. During this evaluation, they can reference patient history and clinical information, resulting in a text-based annotation. Current VLMs predominantly employ global contrastive learning, wherein embeddings of entire images and reports from the same patient are brought closer together, while those from different patients are pushed apart Bai et al. (2024); Hamamci et al. (2024). However, this global contrast is inherently coarse-grained, overlooking local similarities or disparities between anatomical regions and report sentences. Pulling certain anatomical regions closer to unrelated text or vice versa may result in misleading alignment, making it challenging to align complex medical images and reports within a unified representation space. As illustrated in Fig. 1 (c), the attention map of the CLIP Radford et al. (2021), a vanilla coarse-grained VLM, is visualized when executing certain diagnostic tasks. The result demonstrates that such a global alignment mechanism can readily induce the model to focus on the regions that are not relevant to the diagnosis, potentially compromising its performance and interpretability.

In this paper, we propose a fine-grained vision-language model (fVLM) for automated CT image interpretation. This model moves beyond the traditional global image-text contrastive learning pipeline, enabling anatomy-level fine-grained alignment between CT scans and reports. Our motivation arises from the fact that diagnostic reports typically document clinically significant abnormal findings in various organs or body structures in the CT images per anatomy level, thus establishing an intrinsic fine-grained vision-language correspondence between any text-described finding and its image location. Specifically, we perform anatomical-level decomposition and matching for both the images and reports, followed by fine-grained alignment of the matched visual embeddings and the corresponding report embeddings of the same anatomy. This explicit matching alleviates the misalignment issues associated with global contrastive learning and enhances the interpretability of VLMs, as illustrated in Fig. 1 (d). Moreover, fine-grained alignment encounters significant challenges related to false negatives, primarily arising from the prevalence of anatomy-level healthy samples and similar abnormalities across different diseases, which could result in ambiguous pairings at the patient level. We introduce a simple yet effective method to identify and manage the massive false negatives from both normal and abnormal samples, and advocate for a shift in contrastive learning from a broad patient-level pairing to a more nuanced disease-aware pairing approach.

Due to privacy concerns and the scarcity of quality medical data, the limited availability of vision-language data has been one of the most significant bottlenecks for medical VLMs. To overcome this limitation, we have curated the largest CT dataset to date, named MedVL-CT69K, which includes

272,124 CT scans from 69,086 unique patients and their corresponding diagnostic reports. On this extensive dataset, our fVLM has demonstrated outstanding zero-shot diagnostic capabilities, achieving an average AUC of 81.3% across 54 disease diagnosis tasks, surpassing the competing CLIP model by 12.9% (see Fig. 1 (e)) and the supervised baseline by 8.0%. Moreover, on the publicly available CT-RATE and Rad-ChestCT datasets, our fVLM outperforms the state-of-the-art approach by 7.4% and 4.8% absolute AUC value gains, respectively. Beyond diagnostic tasks, the model also exhibits remarkable proficiency in downstream report-generation tasks. Our key contributions are summarized as follows:

1. We propose a scalable and annotation-free vision-language model, fVLM, for CT image interpretation, which demonstrates strong scaling capabilities to meet a wide range of clinical diagnostic needs.
2. We address the vision-language misalignment issues of VLMs by employing a fine-grained anatomy-level contrastive learning framework.
3. We introduce a dual false negative reduction module to alleviate the adverse effects of false negatives in both normal and abnormal samples.
4. Extensive experiments on a large-scale in-house dataset as well as two public benchmarks demonstrate the advantages of fVLM over the state-of-the-art counterparts.

2 Related Work

2.1 Medical Vision-Language Pre-training

Existing medical vision-language pre-training (Med-VLP) methods primarily focus on 2D images depicting a single body part, notably chest X-rays (CXR). Most of them learn transferable representations by aligning the medical scans and corresponding reports with contrastive loss Zhang et al. (2022); Boecking et al. (2022); Tiu et al. (2022); Huang et al. (2023); Zhou et al. (2023); Zhang et al. (2023b); Lin et al. (2023); Liu et al. (2023b); Bannur et al. (2023); Cheng et al. (2023); Liu et al. (2023a); Lin et al. (2023); Sun et al. (2024); Lu et al. (2024); Christensen et al. (2024). In particular, MedKLIP Wu et al. (2023) and KAD Zhang et al. (2023c) utilize medical domain knowledge to enhance the textual information extraction, thereby improving the contextual understanding of radiology reports. Imitate Liu et al. (2023b) derives multi-level visual features from CXR images and separately aligns these features with descriptive and conclusive text in hierarchical medical reports. Given the paucity of paired image-text data in the medical domain, several studies have investigated data-efficient Med-VLP. Notably, MedCLIP Wang et al. (2022b) and PTUnifier Chen et al. (2023) use unpaired CXR images and reports for multimodal pre-training. Pairaug Xie et al. (2024) designs a pairwise augmentation approach that scales up the training data by manipulating existing image-report pairs or generating entirely new cases. Beyond inspecting a single body part, recent studies have expanded the scope of VLP to encompass broader anatomical structures within high-detail 3D CT images Cao et al. (2024); Hamamci et al. (2024); Bai et al. (2024); Lin et al. (2024); Blankemeier et al. (2024), enabling more comprehensive diagnostic support in clinical practice. Specifically, BIUD Cao et al. (2024) and CT-CLIP Hamamci et al. (2024) align chest CT volumes and radiology reports. Merlin Blankemeier et al. (2024) focuses on abdomen scenarios and incorporates structured electronic health record (EHR) data as additional supervision.

While existing Med-VLP studies have demonstrated decent performance, they predominantly employ a global alignment scheme that contrasts entire images and reports Zhang et al. (2022); Tiu et al. (2022), overlooking the local similarities or disparities between image patches and report pieces. This oversight can result in a misalignment problem Müller et al. (2022), constraining the model to a coarse-grained understanding and limiting its capacity to capture fine-grained, clinically relevant details.

2.2 Fine-grained Alignment in Med-VLP

To address the misalignment challenge, GLoRIA Huang et al. (2021), LoVT Müller et al. (2022) and MGCA Wang et al. (2022a) integrate global contrastive learning with a local alignment technique. They leverage a cross-attention mechanism to implicitly learn fine-grained correspondences between image regions and report sentences within each sample. However, while this implicit local

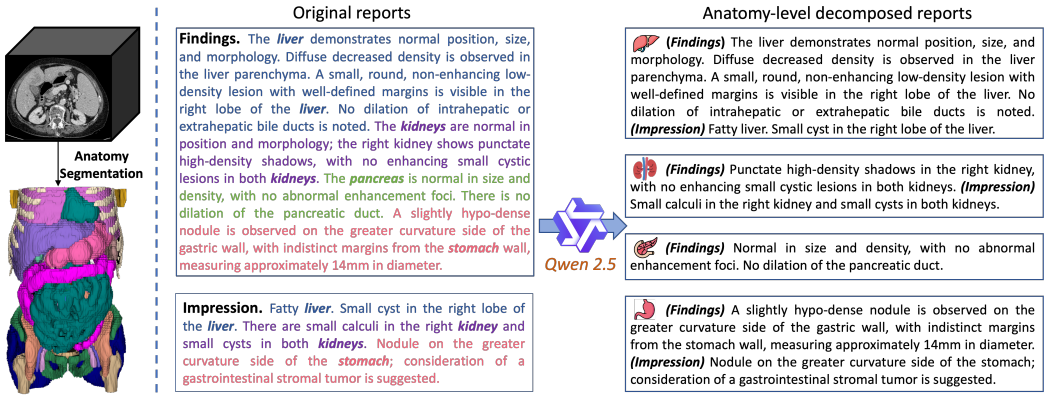

Figure 2: Illustration of CT anatomy parsing (left) and diagnostic report decomposition (right).

alignment has demonstrated effectiveness for 2D CXR data, we argue that its applicability to 3D CT volumes may be limited due to the dramatically higher data complexity. Specifically, compared to 2D CXR images that involve only a few anatomical anatomies Li et al. (2024b), 3D CT scans typically encompass hundreds of anatomical structures and provide detailed, volumetric views of the human body Wasserthal et al. (2023). This increased imaging complexity enables a deeper analysis of intricate medical conditions while concurrently yielding more extensive and nuanced radiology reports that delineate wide-ranging anatomical features and clinical findings Udare et al. (2022); Blankemeier et al. (2024). Given these distinctions, the endeavor to learn local alignments implicitly, which is already prone to be sensitive to hyper-parameters and difficult to train Müller et al. (2022), becomes exceedingly intractable in CT scenarios.

3 Method

3.1 Data Pre-processing

Anatomy parsing. We utilize Totalsegmentator to generate detailed anatomical structure masks for 104 regions within CT scans Wasserthal et al. (2023), encompassing organs, bones, muscles, and vessels, as illustrated in Fig. 2. Subsequently, we group these 104 regions into 36 major anatomies to align with the granularity of descriptions in clinical reports, as detailed in Appendix Tab. 6. This grouping is necessary because CT diagnosis reports often lack precise localization of the lesion areas Li et al. (2024a). For instance, the lung is segmented into five distinct lobes in Totalsegmentator Wasserthal et al. (2023), while a report might merely state "lung inflammation" without specifying which lobe is affected. This ambiguity presents a significant challenge in precisely extracting corresponding diagnostic descriptions for each lobe from the report. Furthermore, even when the lesion locations are reported in some cases, the probability of anomalies occurring at a specific fine-grained anatomical site (*i.e.*, right middle lobe) is considerably low, leading to an overwhelming imbalance between normal and abnormal samples for that anatomical structure. As a result, most mini-batches may consist entirely of normal samples, which may skew the training process and impair the model's diagnostic capability. Overall, anatomical grouping entails a trade-off among analytical granularity, image-text consistency, and data balance.

Report decomposition. As depicted in Fig. 2, we decompose raw CT diagnostic reports according to the grouped anatomies. To reduce the complexity, we employ a divide-and-conquer strategy, executing the decomposition process for the *findings* and *impression* sections of each report independently, followed by an integration of extracted anatomy-level descriptions. Our approach is delineated in the following three steps. First, we design a prompt (see Appendix Fig. 6) and employ the LLM, Qwen 2.5 Bai et al. (2023), to identify all anatomies mentioned in both sections. Notably, we found that when one section lacks explicit references to some anatomies but instead mentions their anatomical sub-structures or uses medical terminology as referents, the LLM may fail to recognize these anatomies due to insufficient domain knowledge. To mitigate these potential omissions, we employ a complementary string-matching strategy. For instance, the inclusion of terms such

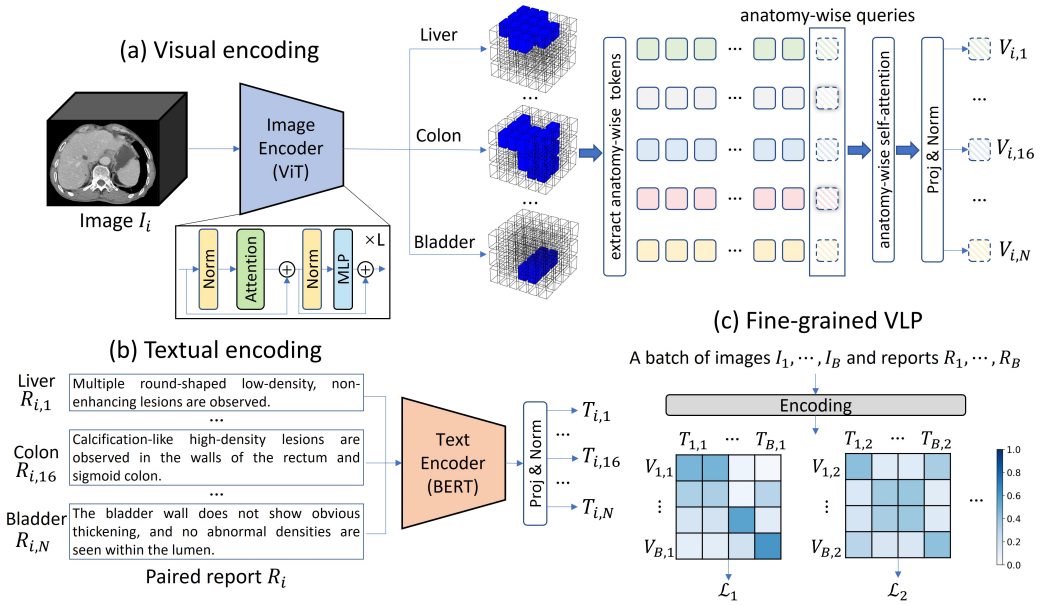

Figure 3: Framework of fVLM. (a) Visual encoding. We input a CT volume I_i into the image encoder and extract corresponding visual tokens for each anatomy. We then append an anatomy-specific query token to the extracted visual tokens of each anatomy. These query tokens are subsequently updated through self-attention, constituting the visual representations of their respective anatomies. N is the number of anatomies. (b) Textual encoding. We decompose the paired report R_i into anatomy-wise descriptions and feed them separately into the text decoder to obtain anatomy-specific textual representation. (c) Fine-grained VLP. We perform local alignment for each individual anatomy across different CT scans. L_j denotes the contrastive loss computed for the *j*-th anatomy.

as "*jejunum*", "*ileum*", or "*duodenum*" in the section will prompt the recognition of "*small intestine*". Second, we use the LLM to extract anatomy-specific descriptions from both sections, with the prompt detailed in Appendix Fig. 7. Lastly, a simple post-processing is performed to integrate the anatomy-level descriptions extracted from these two sections. Specifically, for each anatomy mentioned in both sections, we concatenate the extracted *findings* content with its corresponding *impression* description. In instances where the anatomy appears in only one section, we supplement the absent component with a *"null"* string before concatenation. If one anatomy is not mentioned in either section, we default its description to *"{anatomy} shows no significant abnormalities."* based on established clinical practice.

3.2 Fine-grained contrastive pre-training

Our approach is grounded in the CLIP architecture Radford et al. (2021), which aligns visual and linguistic modalities through contrastive learning of positive and negative pairs. Following Bai et al. (2024); Cao et al. (2024); Lu et al. (2024), we adopt vision transformer (ViT) Dosovitskiy et al. (2020) and BERT Devlin et al. (2018) as the image and text encoder, respectively. Given a CT volume $I_i \in \mathbb{R}^{1\times D\times H\times W}$, where D, H and W represent the inter-slice, spatial height and width dimensions respectively, the vision encoder transforms the input into a compact visual embedding $\mathcal{F}_i \in \mathbb{R}^{c\times d\times h\times w}$. For each anatomy, we utilize its segmentation mask $M_{i,j} \in \{0,1\}^{D\times H\times W}$, where 0 represents the background and 1 denotes the foreground, to guide the construction of anatomy-specific visual representations. Specifically, we begin by partitioning $M_{i,j}$ into non-overlapping patches of size $\frac{D}{d} \times \frac{H}{h} \times \frac{W}{w}$. Each patch spatially corresponds to a visual token in $\mathcal{F}_i$. Then, we locate the patches that contain foreground elements of $M_{i,j}$ and extract their associated tokens as the visual descriptors of the *j*-th anatomy. Next, we append a learnable anatomy-wise query token to these extracted tokens and update it via a self-attention layer. Finally, the updated query token is fed into a linear projection layer followed by L2-normalization to generate anatomy-wise

visual representation $\boldsymbol{V}_{i,j}$. Given the irregular sizes of CT images between patients, we employ RandomCrop to facilitate the construction of mini-batches. It is important to note that anatomies truncated by the cropping operation will be overlooked to maintain the integrity of anatomical visual content during contrastive alignment. The absence of this visual information could include critical diagnostic cues, potentially resulting in alignment failures.

Given the image's associated report R_i, we decompose it into discrete descriptions $R_{i,j}$ for each anatomy, as detailed in Sec. 3.1. Then, we employ the text encoder to transform $R_{i,j}$ into anatomy-specific textual embeddings $\boldsymbol{T}_{i,j}$. For a mini-batch of images $\{I_1, \cdots, I_B\}$ and reports $\{R_i, \cdots, R_B\}$, we calculate the softmax-normalized image-to-text and text-to-image similarity as:

$$\boldsymbol{p}^{i2t}_{i,j,k} = \frac{e^{\langle \boldsymbol{V}_{i,j}, \boldsymbol{T}_{k,j} \rangle / \tau}}{\sum_{k'=1}^{N_j} e^{\langle \boldsymbol{V}_{i,j}, \boldsymbol{T}_{k',j} \rangle / \tau}}, \quad \boldsymbol{p}^{t2i}_{i,j,k} = \frac{e^{\langle \boldsymbol{T}_{i,j}, \boldsymbol{V}_{k,j} \rangle / \tau}}{\sum_{k'=1}^{N_j} e^{\langle \boldsymbol{T}_{i,j}, \boldsymbol{V}_{k',j} \rangle / \tau}} \tag{1}$$

where j denotes anatomy index, N_j is the number of structurally complete samples for the *j*-th anatomy after RandomCrop, $\langle a, b \rangle$ refers to the cosine similarity between vectors a and b, τ is a learnable temperature parameter. The total loss is computed as:

$$L_{itc} = \frac{1}{2} \left(\sum_{j=1}^{T} \frac{1}{N_j} \sum_{i=1}^{N_j} \left(\mathrm{H}(\boldsymbol{y}^{i2t}_{i,j},\ \boldsymbol{p}^{i2t}_{i,j}) + \mathrm{H}(\boldsymbol{y}^{t2i}_{i,j},\ \boldsymbol{p}^{t2i}_{i,j}) \right) \right) \tag{2}$$

in which T is the number of anatomy categories, and H is cross-entropy loss. $\boldsymbol{y}^{i2t}_{i,j}$ and $\boldsymbol{y}^{t2i}_{i,j}$ denote ground-truth one-hot similarity, where negative pairs have a probability of 0 and the positive pair has a probability of 1.

3.3 Reducing false negatives in image-report pairs

The core of contrastive-based VLP lies in instance-level pairing, which brings together the vision and language modalities of the same instance while distancing different instances. However, there are often complex semantic relationships between different instances (patients) in medical contexts Hamamci et al. (2024). For example, patients diagnosed as normal are semantically consistent and abnormal samples with the same pathologies also exhibit high semantic similarities. These semantically similar samples constitute false negatives when they co-occur within the same mini-batch during contrastive pre-training, and inadvertently increasing their distances could degrade the diagnostic accuracy of medical VLMs. To address this issue, we propose a dual false negative reduction (FNR) approach that goes beyond instance-level pairing and pursues a more comprehensive understanding of the semantic landscape in medical imaging.

When performing global contrastive learning between entire images and reports Hamamci et al. (2024), a patient sample is diagnosed as normal only if all scanned anatomies are free of abnormalities. Under this definition, the proportion of normal samples is notably low (*e.g.*, 0.2% in MedVL-CT69K). However, in our fine-grained framework, the number of normal cases increases substantially (refer to Appendix Fig. 8) due to the more granular definition of normality at the anatomy level: although a CT examination reveals abnormalities in specific anatomical structures, those unaffected anatomies can still be considered normal based on established clinical protocols. This substantial increase in normal samples leads to a proliferation of false negatives in our fine-grained contrastive learning framework. Moreover, in contrast to the relatively fixed template-style descriptions for entirely normal images Cao et al. (2024), we observe considerable variability in the descriptions for normal cases of each anatomy. As a result, how to identify and cope with these massive normal samples poses a critical challenge in unlocking the full potential of our method. We address this issue by leveraging the inherently hierarchical structure of CT reports Hamamci et al. (2024); Blankemeier et al. (2024). Specifically, the *findings* section of a report outlines all observations derived from the image, including the appearance of anatomical structures, any abnormalities such as masses or lesions, and the conditions of various anatomical components. Meanwhile, the *impression* section consolidates the abnormal observations into a concise summary, offering standard diagnostic conclusions and highlighting potential diseases. Based on this prior, we empirically annotate anatomies not mentioned in the *impression* section as normal. We then correct $\boldsymbol{y}^{i2t}_{i,j,k}$ and $\boldsymbol{y}^{t2i}_{i,j,k}$ to 1 if the *i*-th and *k*-th patients are both normal in terms of the *j*-th anatomy. Moreover, to stabilize model training, we normalize $\boldsymbol{y}^{i2t}_{i,j}$ and $\boldsymbol{y}^{i2t}_{i,j}$ so that their sums equal 1.

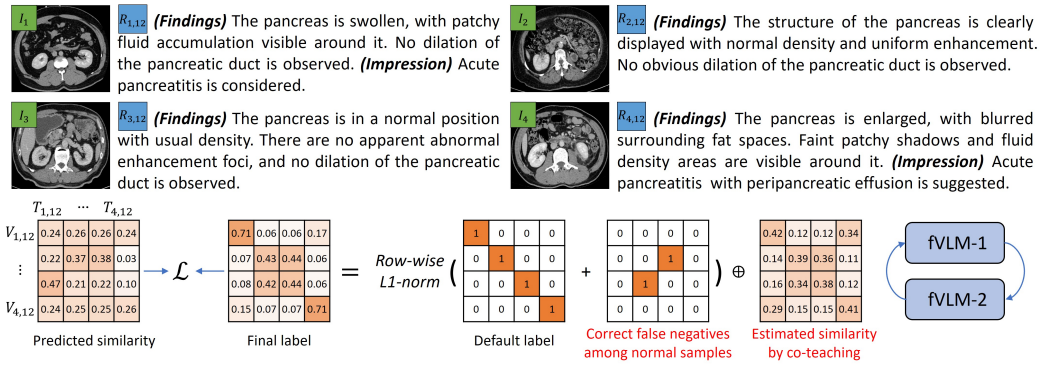

Figure 4: Illustration of the proposed dual false negative reduction approach. $V_{i,12}$ and $T_{i,12}$ represent pancreas-specific visual and textual features from the *i*-th sample, respectively. On one hand, we identify those samples not mentioned in the *impression* section of reports as normal and correct the corresponding labels for these semantically consistent samples to 1 in the label matrix. On the other hand, we further incorporate the estimated image-text similarities into the label matrix, aiming to capture potential semantic relationships between different samples and thereby enhance the model's semantic comprehension. Notably, to mitigate error accumulation in this process, we propose a co-teaching strategy, wherein two fVLMs are trained alternately and the image-text similarities employed by one model are estimated from the other.

Furthermore, due to the narrowed abnormality space from the entire body to specific anatomical regions, the abnormal samples in our fine-grained framework typically exhibit higher semantic similarity compared to those in global contrastive learning methods. For instance, although two patients exhibit significant overall differences, their pancreas may manifest the same pathology as described as follows: $R_{1,12}$: *"The pancreas is swollen, with patchy fluid accumulation visible around it. Acute pancreatitis is considered"* and $R_{2,12}$: *"The pancreas is enlarged, and fluid density shadows are visible around it. Acute pancreatitis with peripancreatic fluid collection is suggested."* Here, the subscript 12 denotes the index of the pancreas in all involved anatomies. In this scenario, pushing away the visual features $V_{1,12}$ from the textual features $T_{2,12}$ is unreasonable and potentially compromises the model's capability in pancreatitis diagnosis. To accommodate this heightened inter-sample similarity, we propose a bootstrapping strategy that utilizes the similarity scores $\boldsymbol{p}^{i2t}$ and $\boldsymbol{p}^{t2i}$ predicted by the model itself to dynamically correct the target label during contrastive pre-training. However, these predicted similarity scores may be biased. Further incorporating them into model training could cause error accumulation and ultimately result in significant performance degradation. To tackle this, we propose a co-teaching training framework that alternately trains two fVLMs, where the image-text similarity scores predicted by one model are used to correct the contrastive learning target of the other model:

$$\begin{aligned} \boldsymbol{y}^{i2t} &= \alpha \boldsymbol{y}^{i2t} + (1-\alpha)\boldsymbol{p}^{i2t\prime}, \quad \boldsymbol{y}^{i2t\prime} = \alpha \boldsymbol{y}^{i2t\prime} + (1-\alpha)\boldsymbol{p}^{i2t} \\ \boldsymbol{y}^{t2i} &= \alpha \boldsymbol{y}^{t2i} + (1-\alpha)\boldsymbol{p}^{t2i\prime}, \quad \boldsymbol{y}^{t2i\prime} = \alpha \boldsymbol{y}^{t2i\prime} + (1-\alpha)\boldsymbol{p}^{t2i} \end{aligned} \tag{3}$$

Here $\alpha \in [0, 1]$ is a free parameter and we empirically set it to 0.5 in this work. $\boldsymbol{p}^{i2t\prime}$ and $\boldsymbol{p}^{t2i\prime}$ are predicted image-to-text and text-to-image similarities from another model. To reduce the risk of concurrent errors arising from both models for the same image-text pair, we enhance their diversity by employing different model initialization, data iteration sequences and augmentations. Fig. 4 exemplifies the calculation of the final labels.

4 Experiments

4.1 Experimental Setup

Dataset. In this study, we curate MedVL-CT69K, a large-scale CT dataset comprising 272,124 CT scans from 69,086 unique patients and their associated reports. Each patient consists of a non-contrast CT scan and contrast-enhanced CT scans, which include one or more of the following

Table 1: Zero-shot performance comparison on the MedVL-CT69K dataset. The best and second-best zero-shot results are highlighted in **bold** and underlined.

	Method	AUC	ACC	Spec	Sens	F1	Prec
Supervised	Baseline	73.3	69.1	76.2	62.0	79.4	17.6
	CT-VocabFine	76.7	72.2	76.1	68.2	81.6	20.3
	CT-LiPro	76.5	70.9	76.8	65.1	81.3	19.3
Zero-shot	CLIP Radford et al. (2021)	68.4	66.7	68.0	65.5	76.0	18.0
	LOVT Müller et al. (2022)	69.4	65.4	60.1	70.8	70.9	15.2
	MGCA Wang et al. (2022a)	70.1	66.4	64.5	68.3	73.9	16.0
	Imitate Liu et al. (2023b)	70.6	67.9	66.6	69.2	75.4	17.9
	ASG Li et al. (2024a)	70.1	67.7	67.4	68.0	75.9	18.8
	CT-GLIP Lin et al. (2024)	69.3	66.9	63.1	70.6	74.2	18.1
	BIUD Cao et al. (2024)	71.4	69.2	69.0	69.3	76.6	18.7
	Merlin Blankemeier et al. (2024)	71.9	69.5	69.7	69.2	77.0	18.1
	Ours	**81.3**	**76.2**	**76.5**	**75.8**	**82.2**	**21.1**

phases: arterial, venous, and delayed. We randomly split the dataset into training, validation and test sets of 64,476, 1,151, and 3,459 patients, respectively. The validation and test sets are annotated with 36 and 54 diseases by expert radiologists. A detailed distribution of these diseases is provided in Appendix Tab. 9 and Tab. 10. Additionally, we conduct experiments on two benchmarks, CT-RATE Hamamci et al. (2024) and Rad-ChestCT Draelos et al. (2021). Following Hamamci et al. (2024), we train fVLM on the training set of CT-RATE and use its test set and the whole Rad-ChestCT dataset for internal and external evaluations, respectively. To the best of our knowledge, CT-RATE is the only publicly available CT dataset that includes complete radiology reports to date. The details regarding these two datasets can be found in Hamamci et al. (2024) and Draelos et al. (2021).

Evaluation metrics. We compare the performance of different pre-training methods on zero-shot abnormality detection and downstream report-generation tasks. For the zero-shot experiments, following Hamamci et al. (2024), we adopt the area under the ROC curve (AUC), balanced accuracy (ACC), specificity (Spec), sensibility (Spec), precision (Prec) and weighted F1-score as the metrics. For the report-generation task, we employ both diagnostic metrics and natural language generation metrics for model evaluation. To facilitate the calculation of diagnostic metrics, we develop a high-performing text classifier to identify abnormalities in generated radiology reports. A detailed exposition of the classifier's training and evaluation is provided in Appendix A.1.

Implementation details are available in Appendix A.2.

4.2 Zero-shot Abnormality Detection

Through the extensive MedVL-CT69K dataset, we compare the zero-shot abnormality detection performance of different methods on 54 diseases across 15 anatomies. The results are presented in Tab. 1. It can be seen that our method outperforms all counterparts by a large margin. Specifically, it suppresses CLIP Radford et al. (2021) by 12.9 points on AUC and 9.5 points on ACC. Furthermore, compared to the second-best competitor, Merlin Blankemeier et al. (2024), our method achieves absolute gains of 9.4 points on AUC and 6.7 points on ACC. Notably, we observe that LOVT Müller et al. (2022) and MGCA Wang et al. (2022a) exhibit marginal performance improvements over CLIP, which underscores the significant limitations of implicit local alignment methodologies in CT imaging scenarios. We enumerate the detection performance of our model for each abnormality in Appendix Tab. 11.

Tab. 3 exhibits the performance comparison with the current state-of-the-art method (*i.e.*, CT-CLIP) on the CT-RATE and Rad-ChestCT benchmarks. In the zero-shot setting, our method demonstrates significant improvements over CT-CLIP, achieving absolute AUC gains of 7.4% and 4.8% in the internal and external evaluations, respectively. Notably, the zero-shot performance of our model even outperforms the outcomes of CT-VocabFine and CT-LiPro that are both derived from CT-CLIP through supervised fine-tuning. To be specific, in the internal test set, our approach exceeds CT-VocabFine and CT-LiPro by 2.3 and 3.7 points on F1-score. In the external test set, it surpasses

Table 2: Performance comparison on the downstream report-generation task using the MedVL-CT69K dataset. 'IN' means initialization with ImageNet supervised weights, while all other methods are trained with our dataset. 'SP' denotes the supervised baseline model.

Encoder	Init	ACC	GREEN	BLEU-1	BLEU-2	BLEU-3	BLEU-4	METEOR	ROUGE-L	CIDEr
Frozen	IN	51.3	34.0	47.4	**32.2**	**25.5**	**21.2**	28.1	44.3	10.6
	SP	55.8	25.9	48.3	26.3	18.0	12.8	30.8	40.6	6.6
	MAE	50.7	21.6	49.0	27.1	18.6	13.1	30.5	41.6	6.1
	CLIP	57.3	33.4	49.7	28.8	20.7	15.5	31.0	42.2	9.6
	BIUD	58.4	33.7	47.1	30.4	23.4	18.9	29.1	44.2	13.9
	Merlin	58.8	34.2	49.5	31.4	23.9	19.0	30.0	43.8	14.3
	Ours	**61.5**	**37.2**	**50.7**	**32.2**	24.5	19.6	**31.3**	**45.1**	**14.9**
Fine-tuning	IN	58.0	33.4	49.4	29.8	21.9	16.9	30.4	43.6	10.0
	SP	60.6	35.5	49.9	30.7	22.9	17.9	30.6	43.4	11.7
	MAE	54.4	29.4	49.0	27.1	18.6	15.1	30.5	42.5	8.8
	CLIP	62.0	37.6	49.9	31.9	24.3	19.5	30.7	44.7	14.3
	BIUD	62.6	38.8	50.2	31.7	24.0	19.0	30.9	44.7	13.8
	Merlin	63.0	39.2	50.7	33.3	25.8	20.9	31.1	46.0	**17.2**
	Ours	**64.5**	**40.2**	**52.2**	**34.5**	**26.8**	**21.9**	**31.6**	**46.4**	17.1

Table 3: Performance comparison on the CT-RATE and Rad-ChestCT benchmarks. Here, CT-CLIP refers to the CLIP model trained on the CT-RATE dataset, as named in the original paper. The best and second-best zero-shot results are highlighted in **bold** and underlined.

Dataset	Metric	Supervised			Zero-shot			
		Baseline	CT-VocabFine	CT-LiPro	CT-CLIP	BIUD	Merlin	Ours
Internal validation (CT-RATE)	AUC	60.3	75.0	75.1	70.4	71.3	72.8	**77.8**
	ACC	58.1	69.2	67.6	65.1	68.1	67.2	**71.8**
	F1	63.2	72.8	71.4	69.1	71.6	70.9	**75.1**
	Prec	24.0	34.2	33.1	30.6	33.8	33.7	**37.9**
	Spec	-	-	-	-	68.6	66.8	**71.7**
	Sens	-	-	-	-	67.3	70.1	**72.8**
External validation (Rad-ChestCT)	AUC	54.1	64.9	64.7	63.2	62.9	64.4	**68.0**
	ACC	53.9	62.2	62.5	59.9	60.6	61.9	**64.7**
	F1	58.7	66.5	66.8	64.8	65.2	66.3	**68.8**
	Prec	28.7	35.9	35.3	33.9	33.7	34.8	**37.4**
	Spec	-	-	-	-	60.2	61.7	**64.6**
	Sens	-	-	-	-	59.6	61.0	**64.6**

these two models by 2.3 and 2.0 points on F1-score. We provide the decomposed anatomy-wise descriptions of the CT-RATE dataset in the supplementary material, which will be released to catalyze the advancement of fine-grained CT imaging analysis within the research community.

To further assess the clinical utility of our method, we conduct a reader study to compare our method with three board-certified radiologists. Please refer to Appendix A.3 for detailed results and discussions.

4.3 Radiology Report Generation

To assess the transfer abilities of VLMs, we conduct experiments on the downstream task of radiology report generation using the MedVL-CT69K dataset. For these experiments, we integrate each pre-trained image encoder with a BERT-base text decoder for whole report generation. The generation process is optimized using the language modeling loss Devlin et al. (2018).

Tab. 2 presents the experimental results in both frozen and fine-tuning protocols, where the frozen protocol keeps the pre-trained image encoder fixed, while the fine-tuning protocol allows the entire model to be updated during training. It demonstrates that vision-language pre-trained models outperform those with purely visual pre-training, underscoring the benefits of aligning visual and textual features into a unified representation space for the report generation task. Notably, in the frozen regime, our method significantly outperforms CLIP by 4.2 points on ACC and 3.8 points on GREEN Ostmeier et al. (2024). While the performance gap attenuates in the fine-tuning protocol, our method still surpasses CLIP by a clear margin, achieving a 2.5-point improvement on ACC and

Table 4: Effect of our proposed modules. CLIP serves as the baseline.

FGA	FNCN	CoT	AUC	ACC
			70.9	69.3
✓			76.0	74.0
✓	✓		78.7	75.3
✓		✓	77.5	74.6
✓	✓	✓	79.8	75.9

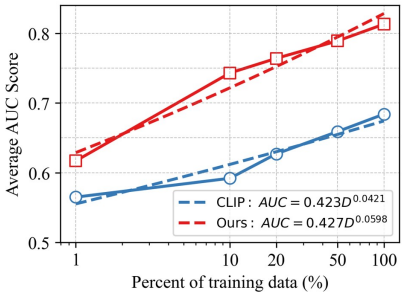

Figure 5: Scaling laws of CLIP and our method.

and a 2.6-point improvement on GREEN. Although the results have demonstrated the superiority of our approach, we argue that directly employing the fine-grained alignment model for whole report generation may not unleash its full power due to the granularity mismatch issue. We will explore a potentially more effective strategy of generating anatomy-wise diagnostic reports in our future work.

4.4 Analysis of Our Framework

Ablation study. We investigate the impact of three modules on the performance of fVLM on the validation set of MedVL-CT69K, including **f**ine-**g**rained **a**lignment (FGA), **f**alse **n**egatives **c**orrection between **n**ormals (FNCN) and **co**-**t**eaching strategy (CoT). As shown in Tab. 4, each enhancement component contributes to the improvement of the model's performance. Notably, the FGA and FNCN contribute the largest performance gains. The combination of them leads to an overall improvement of 7.8 points on AUC and 6.0 points on ACC. Furthermore, in Appendix A.4, we demonstrate that applying CoT to correct contrastive learning labels yields superior results compared to using either the training model or the momentum model.

Scaling law. In Fig. 5, we compute the data scaling law curves to assess how the performance of CLIP and our method improves as the volume of training data increases. It can be seen that our approach consistently outperforms CLIP across multiple data scales, exhibiting superior data efficiency.

Visualization analysis. The visualization results and discussions can be found in Appendix A.5

5 Conclusion

In this paper, we have presented fVLM, a fine-grained vision-language pre-training method for CT data. Our proposed methodology explicitly aligns discrete anatomical structures in CT scans with their corresponding descriptions in diagnostic reports, thereby addressing the misalignment issue of CLIP and its existing variants that contrast entire images and reports. Extensive experiments, including quantitative abnormality detection and report generation tasks as well as qualitative visualization analysis, demonstrate the superiority of fVLM.

Limitations and future work. The implementation of our fine-grained alignment methodology necessitates localizing anatomical structures in CT images and decomposing diagnostic reports into anatomy-wise sub-descriptions. This data processing step entails additional resource consumption and time commitment. For future work, we plan to investigate anatomy-wise report generation to fully unleash the potential of fVLM on this application.

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A APPENDIX

{*findings or impression*}

You are a professional radiologist. Please determine if the anatomy ({*anatomy*}) is mentioned in this CT image report. Please answer directly with "Yes" or "No".

Figure 6: Prompt used to judge if an anatomy is mentioned in the "Findings" or "Impression" section of a clinical report.

{*findings or impression*}

You are a professional radiologist. Please extract the descriptive information about the specific anatomy ({*anatomy*}) from this CT image diagnostic report. Please follow these guidelines:

Precise extraction: Extract the descriptive information directly related to {*anatomy*} from the report.
Specify anatomical details: If the report mentions specific areas, parts, or anatomical details of {*anatomy*}, make sure to include this information in the description. This could include affected areas, normal structures, or any notable features.
Concise and clear: Directly extract the report content, avoiding unnecessary explanations or background.
Format requirement: Please provide the information in the format "{*anatomy*}: descriptive information", ensuring to use {*anatomy*} as the unified prefix for the item. Even if the anatomy has multiple independent parts or multiple lateral characteristics, it should be treated and described as a whole, returning only one comprehensive piece of information about that anatomy.

Figure 7: Prompt used to extract anatomy-specific description from the "Findings" or "Impression" section of a clinical report. Notably, we do not obtain the descriptions for all anatomies in a single query; rather, we strategically query the LLM for each anatomy individually. This approach significantly simplifies the complexity of description extraction and greatly enhances the quality of the extracted descriptions.

A.1 DETAILS ABOUT THE TEXT CLASSIFIER

We utilize the annotated validation and test sets of MedVL-CT69K to develop a text classifier that identifies 54 abnormalities in the generated radiology reports. To achieve this, we first merge these two sets and then re-split them into new training and validation sets using a 2:1 ratio. Afterwards, we train the classifier, which consists of a BERT-base encoder and a classification head, using the reports and corresponding disease labels form the training set. A binary cross-entropy loss is used to supervise the model training. Tab. 7 shows the precision, recall, and F1 scores of the text classifier across 54 abnormalities on the validation set. Notably, the model achieves an impressive average F1 score of 0.95. This high performance substantiates its reliability as a tool for assessing the diagnostic accuracy of report generation models.

A.2 IMPLEMENTATION DETAILS

For the abdominal MedVL-CT69K dataset, we reformat all CT scans so that the first axis points from inferior to superior, the second from posterior to anterior, and the third from left to right. We then resample the in-plane axial images to 1mm resolution and the out-of-plane slice thickness to 5mm spacing using trilinear interpolation. We map the Hounsfield unit range -300:400 to the range 0:1, clipping values that fall outside of this range. We use ViT-base Dosovitskiy et al. (2020), initialized with MAE ImageNet-1K pre-trained weights He et al. (2022), as the image encoder. The patch size is set to 16, 16, 32 along the axial, coronal, and sagittal axes, respectively. A pre-trained BERT-base Devlin et al. (2018) model is used as the text encoder. We train fVLM with an Adam optimizer. The learning rate linearly increases to 1e-4 in the first epoch and then decreases to 1e-6 with a cosine decay scheduler. The model undergoes training for 20 epochs on 4 A100 GPUs, with a batch size of 48. During model training, we apply RandomCrop and RandomFlip on the fly. The cropping size is set to 96, 256, and 384 along the axial, coronal, and sagittal axes, respectively. Notably,

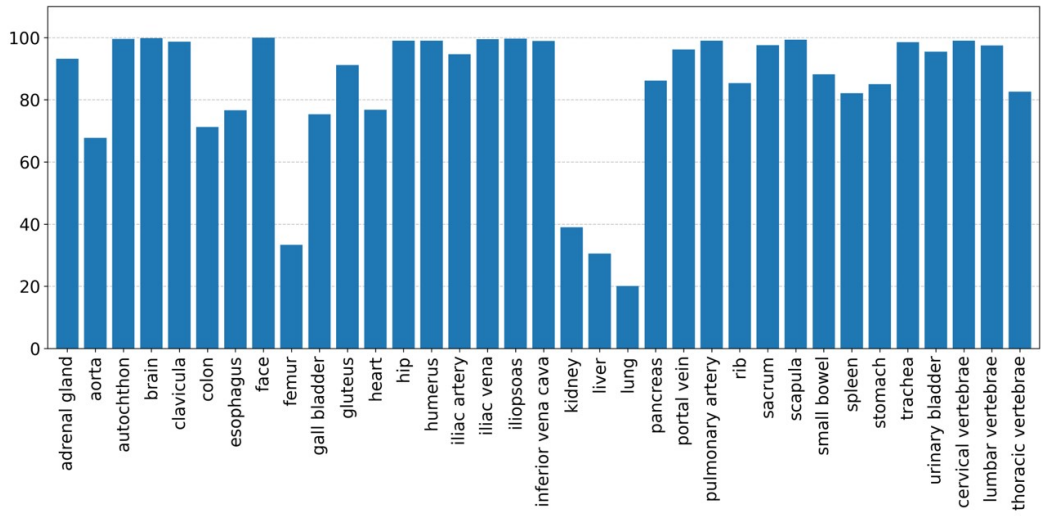

Figure 8: Percentage of normal samples for each anatomy.

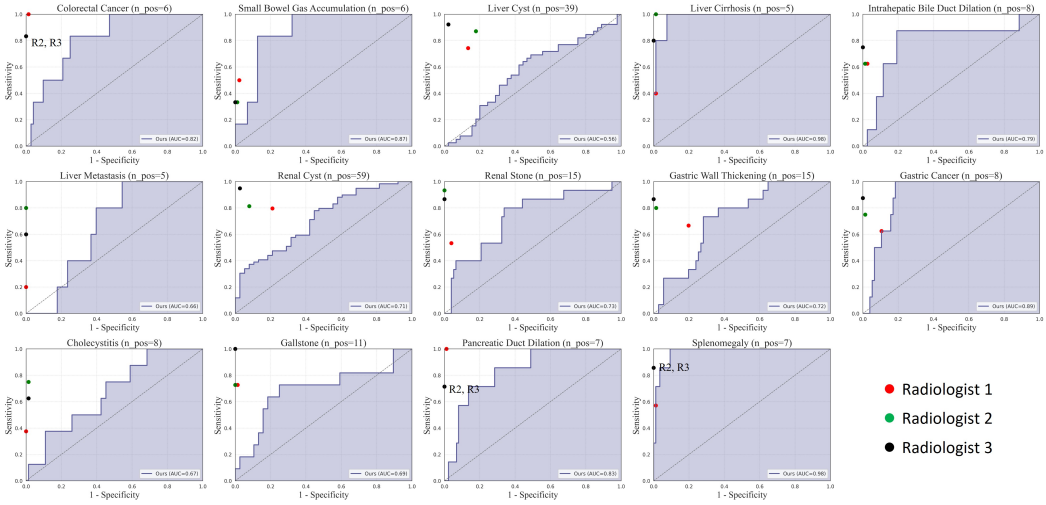

Figure 9: Performance comparison between our method and three radiologists. "n_pos" denotes the number of positive samples of each abnormality.

we observe that if a completely random cropping strategy is used, larger anatomies are more likely to be incomplete after cropping and consequently excluded from the loss calculation. This would introduce a data bias and potentially compromise the model's performance. To address this issue, we employ a uniform sampling strategy to randomly select an anatomy that must be completely included in the cropped image region. For the chest CT-RATE dataset, we apply the same image pre-processing as CT-CLIP Hamamci et al. (2024) to ensure a fair comparison with the competitors. In our co-teaching approach, we iteratively train two fVLMs, alternating between them after each iteration. We initiate a burn-in stage of 5 epochs to allow both models to establish a baseline level of performance. After that, we leverage each model to generate soft labels for its counterpart.

A.3 Reader Study

To further validate our method's efficacy, we conduct a reader study to compare our approach with three board-certified radiologists. For this experiment, we randomly select 100 patients from the test set of MedVL-CT69K. Fig. 9 shows the results. Although our method has demonstrated sig-

Table 5: Performance of fVLM when using different models to correct contrastive labels.

	Baseline	Model self	Momentum	CoT
AUC	78.7	73.3	78.8	79.8
ACC	75.3	71.4	75.5	75.9

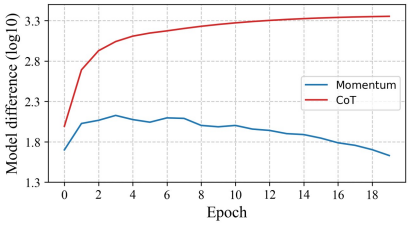

Figure 10: Difference between training model and label correction model.

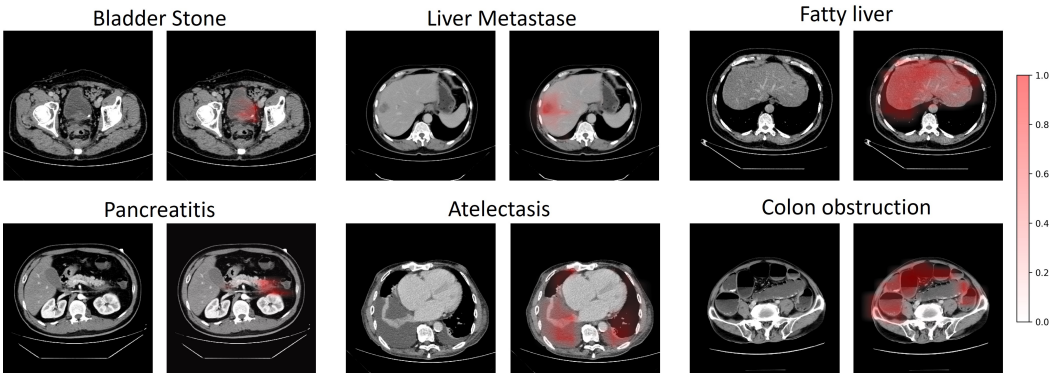

Figure 11: Visual activation maps of our model in diagnosing multiple diseases.

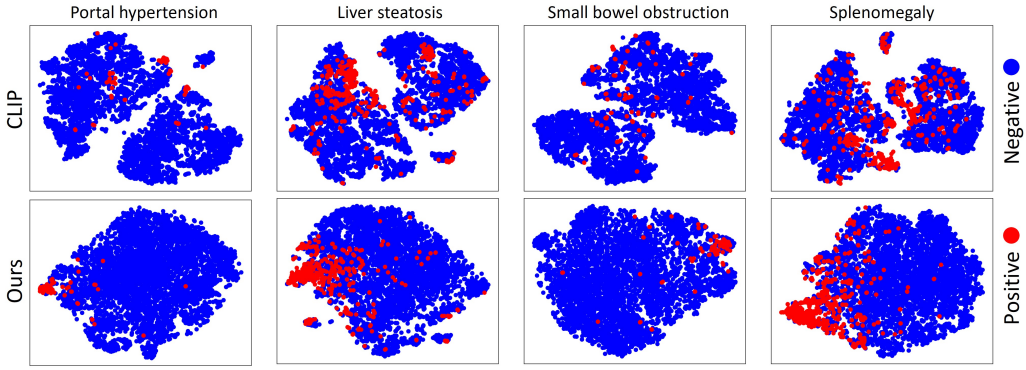

Figure 12: T-SNE visualization of visual embeddings for various abnormalities.

nificant improvements over previous approaches, there remains a noticeable performance gap compared to professional radiologists overall. However, for some diseases such as liver cirrhosis and splenomegaly, our method achieves comparable diagnostic accuracy to radiologists.

A.4 Further Ablation Analysis

In Tab. 5, we compare the performance of fVLM when employing different models to correct contrastive learning labels during pre-training. It can be seen that utilizing the training model itself for label correction leads to a significant performance degradation, which could be attributed to the error accumulation issue. Moreover, the proposed CoT strategy yields greater performance gains compared to the momentum model. To explore this, we measure the difference between training model and label correction model by calculating the Euclidean distance of their parameters, as illustrated in Fig. 10. It can be observed that the momentum model, updated through exponential moving average, exhibit minimal discrepancy with the training model. This suggests they may produce similar predictions, potentially leading to error accumulation in the label correction process. In contrast, the iteratively trained models in our proposed CoT framework exhibit considerable distinctness, leading to diverse predictions and reducing the risk of error accumulation.

A.5 VISUALIZATION

We qualitatively assess the alignment efficacy of our proposed method through visualization in Fig. 11. The heatmaps illustrates the correlation between anatomy-specific visual tokens and the textual embedding of abnormality. We observe high activation in specific affected areas for both localized lesions (*e.g.*, bladder stone) and diffuse abnormalities (*e.g.*, fatty liver). The results demonstrate the model's capacity to precisely localize pathological changes across a spectrum of conditions. Fig. 12 illustrates the distribution of visual embedding for a diverse array of abnormalities. In contrast to CLIP, our method exhibits more compact embedding clusters among positive cases of each abnormality. These findings demonstrate the improved semantic understanding and diagnostic interpretability of our fVLM.

Table 6: Anatomy grouping.

Anatomical System	Anatomy	Grouped Anatomy
Organs	Face	Face
	Brain	Brain
	Esophagus	Esophagus
	Trachea	Trachea
	Lung upper lobe left Lung lower lobe left Lung upper lobe right Lung middle lobe right Lung lower lobe right	Lung
	Heart myocardium Heart atrium left Heart atrium right Heart ventricle left Heart ventricle right	Heart
	Adrenal gland right Adrenal gland left	Adrenal gland
	Kidney right Kidney left	Kidney
	Stomach	Stomach
	Liver	Liver
	Gall bladder	Gall bladder
	Pancreas	Pancreas
	Spleen	Spleen
	Colon	Colon
	Small bowel Duodenum	Small bowel
	Urinary bladder	Urinary bladder
Vessels	Aorta	Aorta
	Inferior vena cava	Inferior vena cava
	Portal vein and splenic vein	Portal vein and splenic vein
	Pulmonary artery	Pulmonary artery
	Iliac artery left Iliac artery right	Iliac artery
	Iliac vena left Iliac vena right	Iliac vena
Bones	Vertebrae L1-L4	Lumbar vertebrae
	Vertebrae T1-T12	Thoracic vertebrae
	Vertebrae C1-C7	Cervical vertebrae
	Rib left 1-12 Rib right 1-12	Rib
	Humerus left Humerus right	Humerus
	Scapula left Scapula right	Scapula
	Clavicula left Clavicula right	Clavicula
	Femur left Femur right	Femur
	Hip left Hip right	Hip
	Sacrum	Sacrum
Muscles	Gluteus maximus left Gluteus maximus right Gluteus medius left Gluteus medius right Gluteus minimus left Gluteus minimus right	Gluteus
	Iliopsoas left Iliopsoas right	Iliopsoas
	Autochthon left Autochthon right	Autochthon

Table 7: Performance of text classifier.

Anatomical organ	Abnormality	Precision	Recall	F1-score
Adrenal gland	Thickening	1.00	0.97	0.99
	Nodule	1.00	0.96	0.98
Bladder	Diverticulum	0.97	0.94	0.96
	Stones	1.00	1.00	1.00
Colon	Gas	0.84	0.79	0.81
	Effusion	0.81	0.71	0.75
	Obstruction	0.86	1.00	0.92
	Diverticulum	0.97	1.00	0.98
	Colorectal Cancer	0.97	0.95	0.96
	Rectal Cancer	1.00	0.95	0.97
	Appendicitis	1.00	1.00	1.00
	Appendicolith	0.89	0.96	0.92
Esophagus	Hiatal Hernia	0.74	1.00	0.85
	Varicose Veins	1.00	1.00	1.00
Gallbladder	Cholecystitis	0.99	1.00	0.99
	Gallstone	1.00	1.00	1.00
	Adenomyomatosis	0.92	0.92	0.92
Heart	Cardiomegaly	1.00	0.95	0.97
	Pericardial Effusion	1.00	1.00	1.00
Kidney	Atrophy	0.97	0.88	0.92
	Cyst	0.97	0.96	0.97
	Hydronephrosis	0.88	1.00	0.94
	Calculi	0.99	0.98	0.99
Liver	Steatosis	0.99	1.00	0.99
	Glisson's Capsule Effusion	0.85	0.89	0.87
	Metastase	0.90	0.95	0.92
	Intrahepatic Bile Duct Dilatation	0.96	0.97	0.97
	Cancer	1.00	1.00	1.00
	Cyst	0.99	0.99	0.99
	Abscess	0.91	0.95	0.93
	Cirrhosis	1.00	1.00	1.00
Lung	Atelectasis	0.96	0.98	0.97
	Bronchiectasis	0.97	0.9	0.93
	Emphysema	1.00	0.96	0.98
	Pneumonia	0.98	0.96	0.97
	Pleural effusion	0.98	1.00	0.99
Pancreas	Pancreatic cancer	1.00	0.89	0.94
	Atrophy	1.00	0.82	0.90
	Pancreatitis	1.00	1.00	1.00
	Pancreatic duct dilatation	0.98	0.91	0.95
	Steatosis	0.97	0.87	0.92
Portal vein	Hypertension	1.00	0.91	0.95
	Thrombosis	0.74	0.74	0.74
Small Intestine	Gas	0.89	0.93	0.91
	Effusion	0.89	0.92	0.91
	Obstruction	0.93	0.93	0.93
	Diverticulum	0.97	1.00	0.98
	Intussusception	0.93	0.90	0.92
Spleen	Hemangioma	1.00	0.97	0.87
	Infarction	0.95	0.97	0.96
	Splenomegaly	1.00	0.99	1.00
Stomach	Gastric wall thickening	0.96	0.96	0.96
	Stomach cancer	1.00	0.97	0.99
Sacrum	Osteitis	0.97	1.00	0.99
Average		0.95	0.95	0.95

Table 8: The distribution of 54 tested abnormalities in the train set. We employ the well-developed text classifier to automatically extract abnormality labels from radiology reports for each sample.

Anatomy	Anatomy count	Abnormality	Abnormality count
Adrenal gland	63915	Thickening	3037
		Nodule	3687
Bladder	62182	Diverticulum	283
		Stones	109
Colon	62054	Gas	2173
		Effusion	975
		Obstruction	436
		Diverticulum	1623
		Colorectal Cancer	817
		Rectal Cancer	858
		Appendicitis	1623
		Appendicolith	1119
Esophagus	2636	Hiatal Hernia	184
		Varicose Veins	609
Gallbladder	63407	Cholecystitis	3935
		Gallstone	5500
		Adenomyomatosis	1246
Heart	3701	Cardiomegaly	316
		Pericardial Effusion	1067
Kidney	63618	Atrophy	921
		Cyst	27019
		Hydronephrosis	1140
		Calculi	5356
Liver	63690	Steatosis	4872
		Glisson's Capsule Effusion	915
		Metastase	2403
		Intrahepatic Bile Duct Dilatation	6093
		Cancer	888
		Cyst	21710
		Abscess	239
		Cirrhosis	1772
Lung	6598	Atelectasis	1988
		Bronchiectasis	781
		Emphysema	190
		Pneumonia	1463
		Pleural effusion	4665
Pancreas	63627	Pancreatic cancer	933
		Atrophy	942
		Pancreatitis	1035
		Pancreatic duct dilatation	2697
		Steatosis	846
Portal vein	63855	Hypertension	1149
		Thrombosis	760
Small Intestine	62419	Gas	2906
		Effusion	2326
		Obstruction	1174
		Diverticulum	2352
		Intussusception	168
Spleen	63749	Hemangioma	718
		Infarction	374
		Splenomegaly	1732
Stomach	63682	Gastric wall thickening	2871
		Stomach cancer	1064
Sacrum	62055	Osteiti	246

Table 9: The distribution of 36 annotated abnormalities in the validation set.

Anatomy	Anatomy count	Abnormality	Abnormality count
Adrenal gland	1149	Thickening	62
		Nodule	79
Colon	1127	Gas	29
		Effusion	13
		Obstruction	5
		Colorectal Cancer	10
		Rectal Cancer	16
		Appendicitis	5
Gallbladder	1054	Cholecystitis	73
		Gallstone	127
		Adenomyomatosis	35
Kidney	1148	Atrophy	16
		Cyst	492
		Hydronephrosis	14
		Calculi	104
Liver	1146	Steatosis	97
		Glisson's Capsule Effusion	20
		Metastase	40
		Intrahepatic Bile Duct Dilatation	132
		Cancer	10
		Cyst	381
		Cirrhosis	30
Pancreas	1149	Pancreatic cancer	5
		Atrophy	16
		Pancreatitis	26
		Pancreatic duct dilatation	49
Portal vein	1150	Hypertension	18
		Thrombosis	10
Small Intestine	1131	Gas	34
		Effusion	25
		Obstruction	8
Spleen	1140	Hemangioma	12
		Infarction	8
		Splenomegaly	35
Stomach	1150	Gastric wall thickening	61
		Stomach cancer	20

Table 10: The distribution of 54 annotated abnormalities in the test set.

Anatomy	Anatomy count	Abnormality	Abnormality count
Adrenal gland	3418	Thickening	96
		Nodule	87
Bladder	3243	Diverticulum	21
		Stones	28
Colon	3213	Gas	129
		Effusion	50
		Obstruction	17
		Diverticulum	104
		Colorectal Cancer	96
		Rectal Cancer	73
		Appendicitis	19
		Appendicolith	74
Esophagus	105	Hiatal Hernia	10
		Varicose Veins	78
Gallbladder	3134	Cholecystitis	246
		Gallstone	355
		Adenomyomatosis	60
Heart	234	Cardiomegaly	20
		Pericardial Effusion	77
Kidney	3313	Atrophy	37
		Cyst	1646
		Hydronephrosis	87
		Calculi	408
Liver	3281	Steatosis	263
		Glisson's Capsule Effusion	68
		Metastase	122
		Intrahepatic Bile Duct Dilatation	264
		Cancer	61
		Cyst	1264
		Abscess	12
		Cirrhosis	188
Lung	126	Atelectasis	70
		Bronchiectasis	18
		Emphysema	10
		Pneumonia	72
		Pleural effusion	94
Pancreas	3328	Pancreatic cancer	29
		Atrophy	37
		Pancreatitis	77
		Pancreatic duct dilatation	94
		Steatosis	45
Portal vein	3410	Hypertension	54
		Thrombosis	55
Small Intestine	3248	Gas	188
		Effusion	142
		Obstruction	61
		Diverticulum	113
		Intussusception	10
Spleen	3352	Hemangioma	47
		Infarction	22
		Splenomegaly	353
Stomach	3373	Gastric wall thickening	206
		Stomach cancer	117
Sacrum	3242	Osteiti	17

Table 11: Detailed zero-shot performance of our method on each abnormality.

Anatomy	Abnormality	AUC	ACC	Spec	Sens
Adrenal gland	Thickening	64.6	62.1	64.8	59.4
	Nodule	66.8	64.8	63.0	66.7
Bladder	Diverticulum	85.9	77.8	74.6	81.0
	Stones	82.0	75.7	80.0	71.4
Colon	Gas Accumulation	88.7	80.8	78.6	82.9
	Effusion	87.6	80.4	78.7	82.0
	Obstruction	99.5	98.6	97.2	100
	Diverticulum	71.7	68.7	65.3	72.1
	Colorectal Cancer	72.6	64.6	65.6	63.5
	Rectal Cancer	85.4	77.0	82.8	71.2
	Appendicitis	74.9	71.9	70.2	73.7
	Appendicolith	65.7	63.1	62.6	63.5
Esophagus	Hiatal Hernia	97.7	92.6	95.1	90
	Varicose Veins	98.8	97.9	97.1	98.7
Gallbladder	Cholecystitis	67.3	62.7	61.1	64.2
	Gallstone	64.6	61.8	58.3	65.4
	Adenomyomatosis	62.6	61.0	57.0	65.0
Heart	Cardiomegaly	95.1	88.7	87.3	90.0
	Pericardial Effusion	76.5	74.4	64.4	84.4
Kidney	Atrophy	96.0	91.5	91.1	91.9
	Cyst	68.6	63.1	64.3	61.8
	Hydronephrosis	75.7	69.5	78.1	60.9
	Calculi	57.9	56.6	56.4	56.9
Liver	Steatosis	93.3	85.1	84.6	85.6
	Glisson's Capsule Effusion	86.5	78.9	82.7	75.0
	Metastase	78.8	71.6	70.3	73.0
	Intrahepatic Bile Duct Dilatation	76.8	70.8	68.2	73.5
	Cancer	84.9	79.1	77.8	80.3
	Cyst	62.9	59.4	61.4	57.3
	Abscess	81.8	79.5	75.7	83.3
	Cirrhosis	94.7	88.5	87.5	89.4
Lung	Atelectasis	94.8	89.4	89.4	89.3
	Bronchiectasis	81.6	74.1	76.0	72.2
	Emphysema	75.0	69.3	68.6	70.0
	Pneumonia	72.8	69.0	79.8	58.2
	Pleural Effusion	86.7	81.3	80.5	82.0
Pancreas	Pancreatic Cancer	87.0	79.7	80.2	79.3
	Atrophy	86.4	77.3	76.3	78.4
	Pancreatitis	91.0	87.6	93.3	81.8
	Pancreatic Duct Dilatation	77.2	70.9	75.8	66.0
	Steatosis	84.9	75.7	78.1	73.3
Portal vein	Hypertension	96.8	92.2	95.5	88.9
	Thrombosis	96.6	91.8	90.8	92.7
Small Intestine	Gas Accumulation	84.1	77.2	84.7	69.7
	Effusion	81.5	74.2	72.4	76.1
	Obstruction	95.2	90.5	92.6	88.5
	Diverticulum	73.0	67.1	65.1	69.0
	Intussusception	76.5	72.4	78.0	66.7
Spleen	Hemangioma	63.8	60.6	59.5	61.7
	Infarction	89.7	86.2	90.6	81.8
	Splenomegaly	92.4	84.8	83.8	85.8
Stomach	Gastric Wall Thickening	69.6	65.7	62.5	68.9
	Gastric Cancer	78.7	72.0	73.1	70.9
Sacrum	Osteiti	87.5	85.8	83.3	88.2
Average		81.3	76.2	76.5	75.8