VertFound: Synergizing Semantic and Spatial Understanding for Fine-grained Vertebrae Classification via Foundation Models

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Abstract. Achieving automated vertebrae classification in spine images is a crucial yet challenging task due to the repetitive nature of adjacent vertebrae and limited fields of view (FoV). Different from previous methods that leverage the serial information of vertebrae to optimize classification results, we propose VertFound, a framework that harnesses the inherent adaptability and versatility of foundation models for fine-grained vertebrae classification. Specifically, VertFound designs a vertebral positioning with cross-model synergy (VPS) module that efficiently merges semantic information from CLIP and spatial features from SAM, leading to richer feature representations that capture vertebral spatial relationships. Moreover, a novel Wasserstein loss is designed to minimize disparities between image and text feature distributions by continuously optimizing the transport distance between the two distributions, resulting in a more discriminative alignment capability of CLIP for vertebral classification. Extensive evaluations on our vertebral MRI dataset show VertFound exhibits significant improvements in both identification rate (IDR) and identification accuracy (IRA), which underscores its efficacy and further shows the remarkable potential of foundation models for fine-grained recognition tasks in the medical domain. Our code is available at https://github.com/inhaowu/VertFound.

Keywords: Foundation Models · Merging Models · Fine-grained Classification.

1 Introduction

The automated recognition of vertebrae in spinal images is crucial for a wide range of medical applications, including the diagnosis of spinal disorders, surgical

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* These authors contributed equally to this work. This work is supported by the National Natural Science Foundation of China under Grants 62101607.
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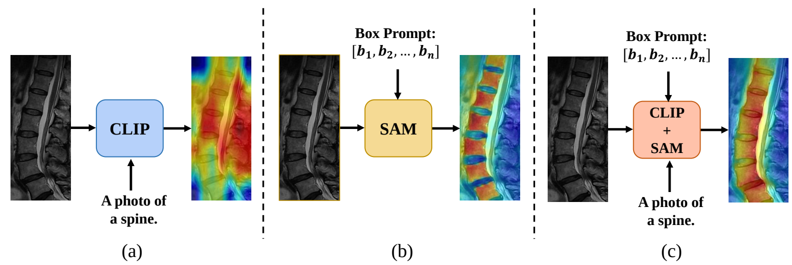


Fig. 1: Illustrations of the individual and combined capabilities of CLIP and SAM for feature representation in spine images. (a) CLIP excels in semantic understanding across the entire image. (b) SAM excels in spatial understanding for precise localization. (c) The merged model obtains features with enhanced local and global information.

planning, and postoperative assessment [1,2]. This process entails not only the precise localization of individual vertebrae but also their subsequent fine-grained classification. Among these tasks, achieving accurate classification poses a great challenge [3], particularly due to the subtle morphological differences among adjacent vertebrae and the constraints arising from arbitrary fields of view (FoV).

Existing methods mainly utilize the spatial relationships of vertebrae to enhance classification results that are aligned with the inherent sequential characteristics of vertebrae. For example, Yang *et al.* [4] enhanced vertebrae classification performance by proposing a message passing scheme to depict the spatial relationship of vertebrae. Wang *et al.* [5] combined key point localization with anatomically-constrained knowledge to facilitate vertebrae classification in CT images. Cui *et al.* [6] introduced a bidirectional relation module to capture the vertebral relationships among vertebrae with a self-attention mechanism. Wu *et al.* [7] designed a sequence loss based on dynamic programming to better preserve the sequential structure of vertebrae. However, the reliance on empirical designs and the scarcity of datasets may limit their robustness to data variability and transferability across different domains.

Recently, large-scale pre-trained foundation models, such as CLIP [8] and SAM [9], have shown remarkable potential with exceptional adaptability and flexibility in the medical domain. For example, Liu *et al.* [10] achieved universal segmentation on partially labeled datasets by leveraging CLIP text embeddings to comprehend the anatomical relationships of different organs and tumors. Lao *et al.* and Qin *et al.* [11,12] introduced different approaches to effectively fuse the different text prompts to enhance the abilities of GLIP [13] for zero-shot lesion detection. Cheng *et al.* and Wang *et al.* [14,15] showed the improved performance of SAM in medical images by introducing additional adapter layers.

However, the use of foundation models in fine-grained vertebrae classification faces considerable challenges due to their deficiencies in effectively exploiting vertebral spatial relationships and their limited discrimination against similar vertebral morphologies. On the one hand, different pre-training objectives endow foundation models with different capabilities in feature representation. As illustrated in Fig.1(a) and (b), contrastive learning-based models such as CLIP excel at capturing high-level semantic information [16], while segmentation models such as SAM excel at capturing low-level spatial details [17]. This disparity indicates that employing a single foundation model might not adequately capture the positional information of vertebrae. On the other hand, foundation models struggle to handle fine-grained classification tasks [18], often lacking the necessary discriminative capacity for the intricate vertebral textures.

To address these challenges, we propose **VertFound**, a framework designed to efficiently synergize the strengths of CLIP and SAM into a unified foundation model for fine-grained vertebrae classification. Firstly, feature extractors from CLIP and SAM are employed to obtain corresponding image-level and region-level features. The proposed vertebral positioning with cross-model synergy (VPS) module then enriches the feature representation by adopting the dot product attention mechanisms. Specifically, VPS utilizes two different attention modules (i.e., CLIP2SAM and SAM2CLIP) to facilitate effective information integration. The CLIP2SAM attention employs image-level features as the queries, while the region-level features serve as both keys and values, which enables local features with global dependencies. Conversely, SAM2CLIP attention employs region-level features as queries and image-level features as keys and values, thereby enriching semantic features with spatial context. This bidirectional attention mechanism amalgamates the strengths of CLIP and SAM, yielding enriched feature representations that encapsulate vertebral spatial relationships. Subsequently, we incorporate textual information as an additional modality input to leverage the image-text alignment capabilities of CLIP for achieving fine-grained classification within vertebral regions. Considering the significant similarities in feature distributions within vertebral images and textual descriptions, we further introduce a Wasserstein loss that transfers contrastive learning into an optimal transport problem by continually optimizing the transport cost between the two distributions. This enables the model to minimize the disparities between the image and text feature distributions and enhance the discriminative alignment capability of CLIP for vertebral classification. Empirical validation underscores the efficacy of VertFound while demonstrating the huge potential of foundation models for fine-grained classification tasks in the medical domain.

2 Methodology

As depicted in Fig.2, VertFound has two main stages. First, CLIP and SAM image encoders are employed to extract image-level and region-level features. The VPS module then combines these features to enhance vertebral position information. In the second stage, fine-grained vertebrae classification is achieved through image-text alignment within CLIP, with an additional Wasserstein loss to improve alignment score discrimination by optimizing the transport distance between image and text feature distributions.

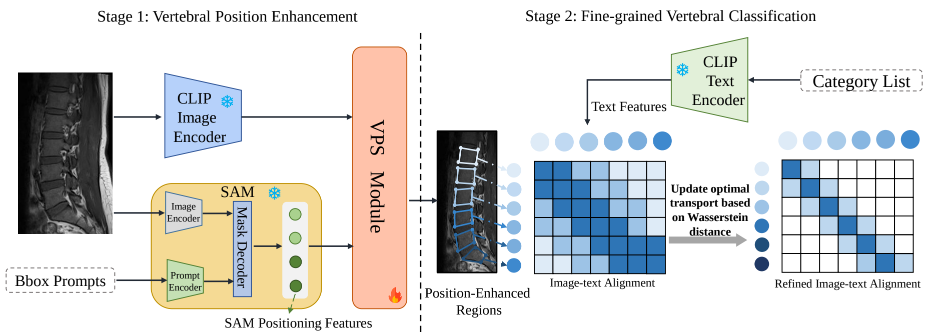


Fig. 2: The two-stage framework of the proposed VertFound. The first stage obtains comprehensive feature representations by employing the VPS module to effectively synergize semantic and spatial features for capturing vertebral position information. The second stage achieves fine-grained vertebrae classification by leveraging image-text alignment within CLIP, while a Wasserstein loss is proposed to enhance the discriminative alignment capability.

2.1 Vertebral Position Enhancement

Image- and Region-Level Feature Extraction Capitalizing on the robust generalization capabilities of foundation models, we directly employ the frozen visual encoders of CLIP and SAM as feature extractors to obtain the corresponding image features at the image-level and region-level. Specifically, we input images I with a shape of $H \times W$ into the vision transformer (ViT) model of CLIP to yield multi-stage features $C_l \in \mathbb{R}^{h,d_c}$ with image-level semantic information, where l represents the l-th stage, h and d_c denote the channels and feature dimensionality, respectively. On the other hand, images combined with their associated annotated box prompts are input into the image encoder and prompt encoders of SAM to produce relevant image and prompt embeddings. The two embeddings are then merged to obtain region-level embeddings $R \in \mathbb{R}^{n,d_s}$ with spatial information, where n represents the number of bounding boxes, d_s denotes feature dimensionality.

Vertebral Positioning with Cross-Model Synergy Module To fully leverage the semantic and spatial knowledge from CLIP and SAM, we propose the **V**ertebral **P**ositioning with Cross-Model **S**ynergy (**VPS**) module that enhances feature representations with more vertebral spatial details. Specifically, as shown in Fig. 3, VPS adopts the dot product attention mechanisms [19] (i.e., SAM2CLIP and CLIP2SAM) to achieve the interactions between global and spatial features. First, CLIP2SAM receives image-level features C_l (e.g., $\{C_{16}, C_{20}, C_{24}\}$) as queries and region-level features R as both keys and values to enrich semantic features with nuanced spatial details:

$$C_l' = \text{softmax}\left(\frac{Q_l K^T}{\sqrt{d}}\right) V \tag{1}$$

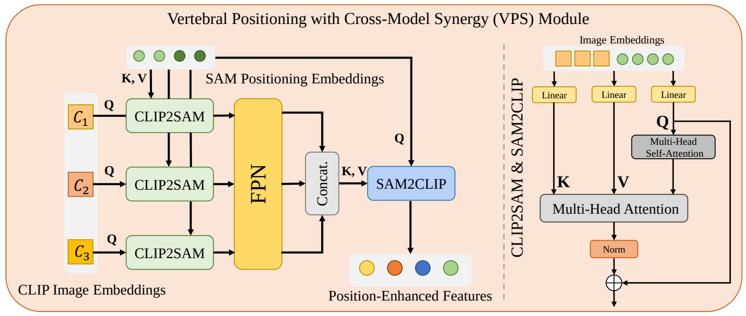


Fig. 3: The paradigm of the VPS module. It employs bidirectional attention mechanisms (i.e., CLIP2SAM and SAM2CLIP) to inherit the advantages of SAM and CLIP and obtain vertebral position-aware features.

$$Q_l = C_l W_q, K = R W_k, V = R W_v \tag{2}$$

where $W_q \in \mathbb{R}^{d_c,d}, W_k \in \mathbb{R}^{d_s,d}$ and $W_v \in \mathbb{R}^{d_s,d}$ are learnable weights, in which d is the dimensionality of the feature space for the queries, keys, and values. Subsequently, a Feature Pyramid Network (FPN) [20] is employed to process C'_l derived from Equation 1 and obtain image-level features $\hat{C} \in \mathbb{R}^{h,d_c}$ with multi-scale information. The refined features $\hat{C}$ are then utilized as keys and values in the SAM2CLIP mechanism, with region-level features R serving as queries, which greatly embeds the spatial understanding with global features. Through the integration of SAM and CLIP, we anticipate that the resultant model will assimilate the representation-level strengths of each, thereby enhancing its understanding of vertebral spatial relationships.

2.2 Fine-grained Vertebral Classification

Region-Text Alignment Beyond learning richer visual representations, we also integrate textual information to harness CLIP's capabilities in image-text alignment for improved vertebral classification. Similar to CLIP, we compute the alignment matrix $S \in \mathbb{R}^{n,m}$ between the refined region features $V \in \mathbb{R}^{n,d_c}$, generated by the VPS, and the text features $T \in \mathbb{R}^{m,d_c}$, extracted from a list of m vertebral categories (e.g., S, L5, L4, ..., C1) by using the text encoder of CLIP. This computation is formulated as follows:

$$S_{ij} = \frac{\phi_v(V)\phi_t(T)^T}{\tau\sqrt{\sum_k \phi_v(V_{ik})^2}\sqrt{\sum_k \phi_t(T_{jk})^2}} \tag{3}$$

Here, ϕ_v and ϕ_t represent different learnable feature projections on image and text features, while τ is a temperature parameter. Based on this, we calculate the cross-entropy loss (CEL) to explicitly push away representations from different image-text pairs while pulling together those that share the same semantics:

$$\mathcal{L}_{CEL} = -\sum_{i=1}^{n}\sum_{j=1}^{m} Y_{ij} \log S_{ij} \tag{4}$$

where $Y \in \{0,1\}^{n,m}$ represents the one-hot vertebral category of the image regions. This approach facilitates precise vertebrae classification by harnessing CLIP's alignment capabilities at the region level.

Wasserstein Loss However, considering the significant similarities between different vertebrae and their corresponding textual descriptions, the image-text alignment score S obtained in Eq. 3 might lack sufficient discrimination for fine-grained vertebral classification. Inspired by the work [21], we propose a Wasserstein loss (WSL) that casts contrastive learning into an *optimal transport problem*. Specifically, we optimize the Wasserstein distance $d_M^\lambda(V,T)$ to reduce the transport cost between two distributions, which results in more discriminative alignment scores for vertebral classification. The calculation of $d_M^\lambda(V,T)$ is formulated as follows:

$$d_M^\lambda(V,T) = \min_{P \in U(V,T)} \sum_{i=1}^{n}\sum_{j=1}^{m} P_{ij} M_{ij} + \frac{1}{\lambda}(-\sum_{i=1}^{n}\sum_{j=1}^{m} P_{ij} \log P_{ij}) \tag{5}$$

where $U(V,T) = \{P \in \mathbb{R}_+^{n,m} \mid P\mathbf{1}_n = V,\ P^T\mathbf{1}_m = T\}$ represents all possible transport matrices; $\mathbf{1}_n$ and $\mathbf{1}_m$ denote the vectors of ones in dimension n and m; λ is the penalty term associated with the distribution P. M_{ij} quantifies the difference between the i^{th} image and the j^{th} text and is defined as:

$$M_{ij} = -\frac{\exp(S_{ij})}{\sum_j \exp(S_{ij})} \tag{6}$$

The Sinkhorn-Knopp algorithm [22] is used to iteratively solve for the optimal solution. As suggested in Eq.5, a smaller $d_M^\lambda(V,T)$ signifies greater similarity among matched image-text pairs while a larger distance indicates a weaker correlation. Therefore, we directly adopt the Wasserstein distance $d_M^\lambda(V,T)$ as the WSL to achieve the fine-grained alignment between image and text:

$$\mathcal{L}_{WSL} = d_M^\lambda(V,T) \tag{7}$$

2.3 Model Optimization

Finally, VertFound employs a dual-loss optimization strategy to enhance the overall vertebrae classification accuracy:

$$\mathcal{L}_{total} = \mathcal{L}_{CEL} + \mathcal{L}_{WSL} \tag{8}$$

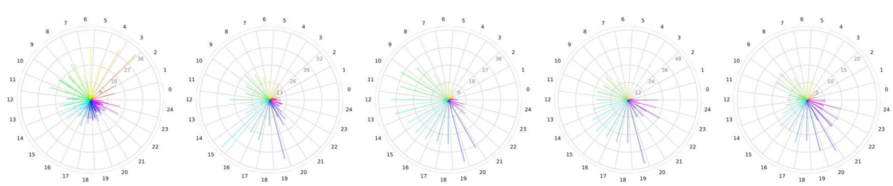
3 Experiment Results

3.1 Datasets and Evaluation Metrics

We evaluate the proposed VertFound on an in-house dataset that contains 1233 2D MRI images from 266 patients with a variety of vertebral appearances and FOVs, and a five-fold cross-validation approach is used for a thorough evaluation. Furthermore, we use identification rate (IDR) and image identification accuracy (IRA) as evaluation metrics. IDR calculates the ratio of vertebrae that are successfully detected, whereas IRA calculates the ratio of images that have all of their vertebrae correctly identified.

3.2 Implementation Details

All input images are resized to 224×224 and 1024×1024 and sent to CLIP and SAM image encoders via frozen ViT-L/14 and ViT-B/16, respectively. During training, the annotated bounding boxes are input to SAM, while in the testing phase the bounding boxes are predicted by a pre-trained detector (YOLOv8). The frozen text encoder of CLIP is employed to extract text features from a total of 25 category names of vertebrae (e.g., S, L5, L4, ... C1). The AdamW optimizer is employed with an initial learning rate of 2.5×10^{-5}, following a warm-up multi-step schedule with weight decay of 0.0001, Adam momentum of 0.9, and batch size of 40. Our methods are implemented in Python using the PyTorch framework and trained on an NVIDIA GTX 1080 Ti GPU. The CEL and WSL are all used for classification optimization, and the loss weights are all empirically set to 1.



(a) wo. CLIP (b) wo. SAM2CLIP (c) wo. CLIP2SAM (d) wo. WSL (e) Full model

Fig. 4: Confusion stars show the classification errors of different ablation studies. Specifically, the circle is divided into 25 regions, each representing a distinct class. Within each region, there are 24 subsections corresponding to the other classes, indicating the number of classification errors for each particular class.

3.3 Results

Comparison with Competing Methods As shown in Table 1, in-depth comparisons with current methods are carried out to evaluate the effectiveness of

Table 1: Comparison with Competing Methods.

Methods	IDR(%)	IRA(%)
DETR [23]	75.58 ± 5.39	46.60 ± 4.26
YOLOv5 [24]	76.46 ± 2.29	54.30 ± 3.27
YOLOv8 [25]	77.21 ± 1.49	55.43 ± 2.46
GLIPv1 [13]	74.31 ± 2.63	47.87 ± 2.19
OWL-ViT [26]	76.68 ± 3.15	54.81 ± 3.56
Ours (VertFound)	**89.05** ± 5.82	**83.73** ± 4.46

Table 2: Ablation study Results.

Methods	IDR(%)	IRA(%)
wo.CLIP	76.31 ± 7.08	64.86 ± 3.62
wo. CLIP2SAM	84.15 ± 2.46	80.18 ± 3.69
wo. SAM2CLIP	61.64 ± 2.12	65.26 ± 4.89
wo. WSL	82.50 ± 4.51	75.97 ± 4.38
Ours (VertFound)	**89.05** ± 5.82	**83.73** ± 4.46

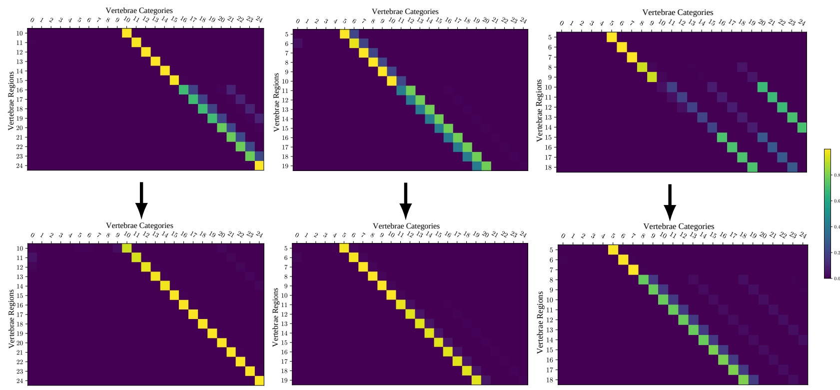
VertFound. All experiments adopt identical experimental settings to ensure fairness and reliability in the comparative evaluation. Our baselines include classical object detection algorithms (i.e., DETR [23], YOLOv5 [24], and YOLOv8 [25]) and recent foundation models (i.e., GLIPv1 [13] and OWL-ViT [26]). VertFound demonstrates superior performance in both IDR and IRA, which underscores its improved capability for fine-grained vertebrae classification.

Ablation Studies We conducted thorough ablation studies to verify the efficacy of the crucial components in VertFound. As presented in Table 2, removing CLIP (relying solely on SAM for classification) results in a noticeable decrease in classification performance. Meanwhile, removing either the CLIP2SAM or SAM2CLIP component in the VPS module also shows a noticeable decrease in both IDR and IRA, which highlights the significance of the aggregation between global and local features for precise vertebral positioning. Besides, the confusion star [27] in Fig.4 vividly illustrates the classification errors arising from different ablation methods. Furthermore, the removal of WSL also leads to a decline in overall performance. Figure 5 further elucidates that the incorporation of WSL optimizes the image-text alignment scores with varying degrees, thereby enhancing the discrimination against fine-grained vertebral features.

4 Conclusion

In this paper, we propose VertFound, which combines semantic and spatial understanding to achieve fine-grained classification of vertebrae. We introduce a novel VPS module that leverages the complementary strengths of CLIP and SAM for enriching vertebral feature representations. A WSL is introduced to enhance the discriminative alignment capability of CLIP for fine-grained vertebrae classification. Empirical validation shows the efficacy of VertFound while demonstrating the remarkable potential of foundation models for fine-grained recognition tasks. In the future, we will extend our experiments to include additional datasets from different sources and modalities to test the generalization capabilities of our method, including 3D MRI and CT scans.

Disclosure of Interests. The authors have no competing interests to declare that are relevant to the content of this article.



(a) Easy case (b) Medium case (c) Hard case

Fig. 5: Different examples show the effectiveness of WSL in improving the discriminative capability of image-text alignment.

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