Med-UniC: Unifying Cross-Lingual Medical Vision-Language Pre-Training by Diminishing Bias (Supplementary Material)

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1 Appendix Overview

In the supplementary material section, we first discuss the social impact and limitations of Med-UniC framework. Then, we introduce the details of the pre-training stage, including cross-lingual MLM pre-training and VLP for Med-UniC. Then we present the detailed configurations of several downstream tasks. Next, we conduct some additional experimental analysis.

2 Discussion

Social impact Our Med-UniC framework presents an innovative solution for unifying CXR images and corresponding medical reports from diverse communities that use different languages, thereby addressing the data shortage in the medical VLP domain. Further investigations reveal that existing VLP models exhibit biased performance across various linguistic communities, even when pre-trained on cross-lingual data. However, Med-UniC effectively minimizes this bias, enhancing performance not only in cross-lingual tasks but also in uni-modal tasks. In essence, our work offers more than just a strategy for integrating data from different sources; it shines a light on the significant issue of community bias in cross-lingual VLP, calling for more fair and equitable practices in this field.

Limitation Our research primarily concentrates on cross-lingual medical VLP, limiting the number of languages, medical images, and reports included due to the current lack of public datasets. We've conducted comprehensive experiments involving uni-modal visual and vision-language tasks, but have not ventured into uni-modal language tasks like report generation. Looking ahead, we aim to expand our work to include more languages in the medical VLP and take on more challenging tasks, such as zero-shot guided segmentation or object detection. This area of our work, thus, acknowledges room for further development and exploration.

Future work Exploring these methods on diverse modality medical data such as electrocardiograms paired with clinical monitor records is an interesting future direction [**?**]. Furthermore, the alignment of different modality data can be viewed as a data fusion task, a commonly addressed issue in physics [**? ? ? ?**], or recommendation system [**?**] .

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3 Implementation details for Pre-Training

3.1 Implementation for Cross-lingual MLM

Medical Report Pre-processing We prepare the cross-lingual pre-training corpus from the medical reports of MIMIC (En) [?] and PadChest (Sp) [?]. Specifically, we concatenate the findings and impression to form English medical reports for MIMIC. As for PadChest, we treat their radiology reports as Spanish reports. Examples of these reports can be seen in Fig 1 and Fig 2. To create the MLM corpus, we combine all the reports and shuffle them at the report-level.

MLM Pre-training Setup To obtain cross-lingual medical LM, we train the cross-linguistic encoder with the combined corpus using an Adam optimizer and adopt a linear warm-up scheduler. Specifically, the learning rate is 5e-4, and the learning rate linearly increases from 0 to the peak value with a linear warm-up. Additionally, the max length for input tokens is 256. The MLM process is conducted on 8 V100 GPUs and pre-trained within 15 epochs. To save GPU memory and speed up training, we adopt automatic mixed-precision FP16. The details of cross-lingual MLM are shown in Tab 1.

Table 1: Hyper-parameters of Cross-lingual MLM

Hyperparameters	
Training epochs	15
Total Batch size	1024
Number of GPUs	8
Gradient Accumulation	16
Maximum Sequence Length	256
Learning Rate	5e-4
Learning Rate Optimizer	Adam
Schedule	Linear Warm-up
Warm-up Proportion	10%
Adam Epsilon	1e-8
Masked Rate	0.15
FP16	True

Table 2: Hyper-parameters of VLP

Hyperparameters	
Pre-training epochs	50
Batch size per GPU	128
Number of GPUs	16
Gradient Accumulation	2
Maximum Sequence Length	256
Learning Rate	4e-5
Learning Rate Optimizer	AdamW
schedule	CosineAnnealing
Weight Decay	5e-2
FP16	True
Frozen Linguistic Encoder Layers	9
λ	5.1e-3
VL Alignment Dimension	512
CTR Embedding Dimension	1024

3.2 Implementation for Vision-language Pre-training

Model Architecture Following the same framework as CLIP [?], we utilize ResNet-50 [?], ViT-B/16 and ViT-L/32 [?] as our visual encoder, and we further pre-train CXR-BERT [?] via cross-lingual masked language modelling to obtain the linguistic encoder. Moreover, the input resolution of visual encoder is 256×256, and the input token length of the linguistic encoder is 256. The final image and text features are projected to the same dimension, which is 512 as [?], followed by batch normalization before interaction. The dimension of cross-lingual text alignment regularization (CTR) is set to 1024. More senstivity analysis can be found in Sec 5.5.

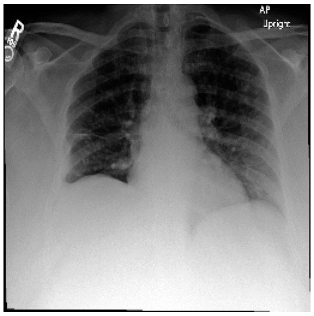
Image Data Pre-processing The original CXR images from the MIMIC-CXR and PadChest datasets [? ?] are resized to 256×256 and randomly cropped to 224×224, following the procedure in [? ? ?]. All images are normalized to the range $[0, 1]$. For data augmentation during pre-training, we apply horizontal flip, random rotation in the range $[0°, 180°]$, and auto contrast using the PyTorch vision library[1]. The English and Spanish CXR image examples and its corresponding reports are depicted in Fig 1 and Fig 2, respectively.

Vision-language Pre-training Setup The detailed hyperparameters of vision-language pre-training for Med-UniC are shown in Tab 2. We use a cosine annealing scheduler for the adjustment of the learning rate. The pre-training step is conducted by V100 GPUs. To save GPU memory and speed up training, we also adopt automatic mixed-precision FP16.

4 Configurations for downstream Tasks

This section provides a detailed introduction to all downstream tasks and presents the data split information for each task. The data split details are presented in Tab 3.

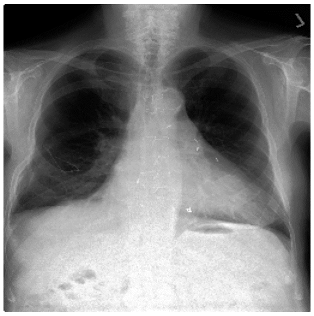
[1] https://pytorch.org/vision/stable/transforms.htmls



(a) CXR image example 1 from MIMIC dataset

Subject ID: 10000935
Study ID: 56164612
Report:
Lung volumes are low The heart size is normal.
The mediastinal and hilar contours are unremarkable.
New nodular opacities are clustered within the left upper lobe, and to a lesser extent, within the right upper lobe.
……
Findings are compatible with metastases, as was noted in the lung bases on the subsequent CT of the abdomen and pelvis performed later the same day.

(b) CXR report example 1 from MIMIC dataset



(c) CXR image example 2 from MIMIC dataset

Subject ID: 10002430
Study ID: 58911492
Report:
The lung volumes are normal.
Mild cardiomegaly which is stable.
Normal hilar and mediastinal structures.
……
Status post CABG with aligned median sternotomy wires and normal location of surgical clips.
Status post right lung surgery with surgical material seen.
Mild cardiomegaly No evidence of pneumonia

(d) CXR report example 2 from MIMIC dataset

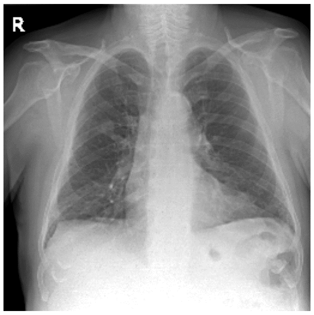
Figure 1: CXR dataset examples from MIMIC-CXR[?].

Table 3: Data Split Details, '/' indicates that no training/validation data is required in the zero-shot classification task.

Task	Dataset	Split	Train	Valid	Test
Linear Classification	CheXpert [?]	[?]	186,027	5,000	202
	RSNA [?]	[? ?]	16,010	5,337	5,337
	COVIDx [?]	[? ?]	23988	5998	400
Semantic Segmentation	RSNA [?]	[? ?]	16,010	5,337	5,337
	SIIM [?]	[? ?]	8,433	1,807	1,807
Object Detection	RSNA [?]	[? ?]	16,010	5,337	5,337
	Object-CXR [?]	[?]	6,400	1,600	1,000
Zero-shot Classification	CXP500 [?]	[?]	/	/	500
	PDC [?]	[?]	/	/	1000

Medical Image Linear Classification We explain the setting of linear classification tasks, including CheXpert [?], RSNA [?], and COVIDx [?]. We utilize ResNet-50, ViT-B/16 and ViT-L/32 as our visual backbone and fine-tune the linear layer with 50 epochs using early stop, with the same learning rate of 5e-4 and the default batch size is 8. We leverage the AdamW optimizer to schedule the learning rate, with the β_1 of 0.9, the β_2 of 0.999, and the weight decay rate of 1e-6. All the linear classification tasks are conducted on a V100 GPU with 32GB memory.

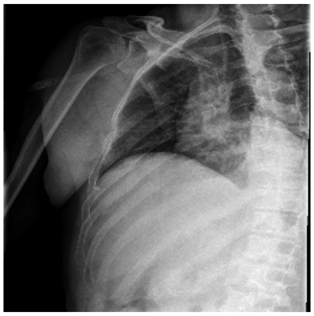
Medical Image Semantic Segmentation For the segmentation tasks RSNA and SIIM [?], we first adopt the ResNet-50 as the visual backbone and train the segmentation network on a 32G V100 GPU. We leverage early stopping to train the tasks for 50 and 100 epochs. We adapt 5e-4 as the learning rate , 1e-8 as the weight decay and 4 as the default batch size. We also employ AdamW as the optimizer



Study ID: 216840111366964013217898866992011329134906098
Report:
Nodul proyect lsd 1 4 cm contorn parcial bien defin cit tac torac.
Patron intersticial con probabl are panalizacion bibasal probabl fibrosis pulmon.

(a) CXR image example 1 from PadChest dataset

(b) CXR image example 1 from PadChest dataset



Study ID: 216840111366964013515091760022012318080539431
Report:
Fractur arcos costal lateral derech cuart quint sext septim.
Condensacion subsegmentari lii descart aspiracion sobreinfeccion respiratori.
Pinzamient sen costofren izquierd.

(c) CXR image example 2 from PadChest dataset

(d) CXR image example 2 from PadChest dataset

Figure 2: CXR dataset examples from PadChest [**?**].

and set the β_1 and β_2 as 0.9 and 0.999, respectively. For the ViT-B/16 and ViT-L/32 backbones, we set the training configurations following [**? ?**].

Medical Image Object Detection The Object Detection tasks RSNA and Object-CXR [**?**] are conducted on 1 V100 GPU. We use the grid search to find the optimal batch size as shown in Tab **??**. Specifically, we also adapt AdamW as our optimizer with the learning rate of 5e-4, weight decay of 1e-6, β_1, β_2 of 0.9 and 0.999, batch size of 4. The IOU and NMS thresholds are [0.4, 0.45, 0.5, 0.55,0.6, 0.65, 0.7, 0.75] and 0.5, respectively. We use ResNet-50 as the visual encoder of Med-UinC for fair comparisons with other baselines.

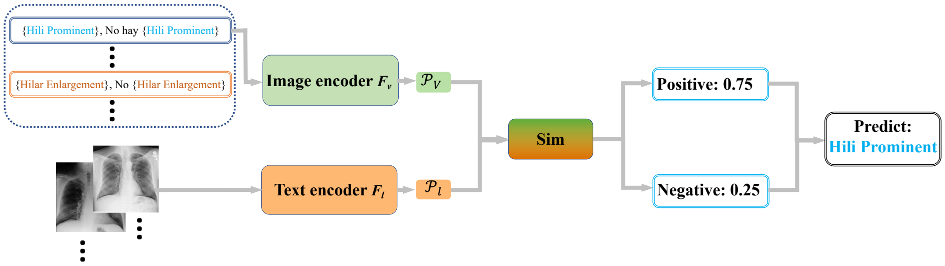


Figure 3: An example of Med-UniC zero-shot pipeline. Blue and orange denote Spanish and English prompts, respectively.

Zero-shot Task The original image undergoes a two-step process. Firstly, it is resized to dimensions of 256 × 256 and then center cropped to 224 × 224. Subsequently, all pixel values are normalized within the range of $[0, 1]$, following [**? ?**]. The resulting resized image is then passed through an image encoder to generate an image embedding . Concurrently, the prompts are inputted into a text encoder to obtain a text embeddings. To evaluate the classification, we measure the cosine similarity between the image and text embeddings for each prompt associated with a specific class. This is

Table 4: Comparisons of different backbones on medical image segmentation tasks. Best results of each setting are in boldface.

	RSNA			SIIM		
Backbone	1%	10%	100%	1%	10%	100%
ResNet-50	72.6	74.4	76.7	56.7	62.2	64.4
ViT-B/16	**75.6**	76.6	77.9	62.1	67.3	71.5
ViT-L/32	74.4	**77.5**	**78.7**	**64.5**	**68.7**	**73.3**

computed using the equation:

$$\text{sim}(\text{img}, \text{prompt}) = \mathcal{P}_v(\mathbf{v}_{e,i})^T \mathcal{P}_l(\mathbf{l}_{e,i}) \tag{1}$$

where $\mathbf{v}_{e,i}$ and $\mathbf{l}_{e,i}$ are image and text embeddings from visual and linguistic encoders, respectively. $\mathcal{P}_v$ and $\mathcal{P}_l$ are visual and linguistic projectors. The classification outcome is determined based on the comparison of cosine similarities. If the cosine similarity between the image embedding and the positive prompt (e.g., *disease*) exceeds the cosine similarity between the image embedding and the corresponding negative prompt (e.g., *No disease*), the outcome is considered positive. Conversely, if the reverse is true, the outcome is negative. The pipeline is detailed in Fig 3. To compute the performance metrics, the macro AUC score and F1 score, we calculate these scores for each category individually and then average them across all categories.

5 Additional Experimental Analysis

5.1 Tokenization Analysis of Cross-lingual Medical LM

Input Spanish report:

'infitr alveor ambos camp pulmonar predomini derech bibasal sin grand cambi relacion rx previ 11 03 2017 . derram pleural bilateral . catet venos con extrem proyect vcs .'

Tokens of CXR-BERT tokenizer:

['inf', '##itr', 'alve', '##or', 'amb', '##os', 'camp', 'pulmon', '##ar', 'predom', '##ini', 'dere', '##ch', 'bibas', '##al', 'sin', 'grand', 'camb', '##i', 'rel', '##aci', '##on', 'rx', 'prev', '##i', '11', '03', '2017', '.', 'der', '##ram', 'pleural', 'bilateral', '.', 'cat', '##et', 'veno', '##s', 'con', 'extrem', 'pro', '##ye', '##ct', 'vc', '##s', '.']

Tokens of Cross-lingual medical LM tokenizer:

['infitr', 'alveor', 'amb', '##os', 'camp', 'pulmonar', 'predomini', 'derech', 'bibasal', 'sin', 'grand', 'cambi', 'relacion', 'rx', 'previ', '11', '03', '2017', '.', 'derram', 'pleural', 'bilateral', '.', 'catet', 'venos', 'con', 'extrem', 'proyect', 'vcs', '.']

Figure 4: Tokenization visualization of one report sample from PadChest dataset. Blue tokens represent tokenized words in the Spanish medical vocabulary of cross-lingual medical LM.

In this section, we visualize the tokenization results of one random selected Spanish report generated by CXR-BERT and Cross-lingual Medical LM' tokenizers, respectively. As shown in Fig 4, compared with CXR-BERT, Cross-lingual Medical LM's tokenizer can handle the Spanish sentence correctly and give a tokenized scheme without loss of Spanish words' semantics. However, CXR-BERT's tokenizer uses tokens from its English medical vocabulary may deteriorate the original Spanish semantics. The visualization results demonstrate the importance of building a cross-lingual lexicon from Spanish medical reports.

5.2 Medical Image Segmentation with ViT Backbone

In this section, we adopt the ViT-B/16 and ViT-L/32 as the visual encoder of Med-UniC to compare with ResNet-50 for medical image segmentation tasks on RSNA and SIIM datasets. As shown in Tab 4, surprisingly, the ViT-B/16 backbone has noticeable improvement compared with the ResNet-50 backbone, especially for SIIM. Additionally, the ViT-L/32 backbone shows better results than ViT-B/16 in most settings, indicating that larger visual backbone can further improve the performance of Med-UniC. We attribute this enhancement from the ViT backbone to the global attention capability of the transformer-based visual encoder on segmentation [**?**].

Table 5: Ablation Study on CTR. Best results of each setting are in boldface, and the '-' denotes mAP values smaller than 1%.

	COVIDx(ACC)			RSNA(Dice)			Object CXR(mAP)		
Backbone	1%	10%	100%	1%	10%	100%	1%	10%	100%
$\mathcal{L}_{CTR}$	**76.5**	**89.0**	**92.8**	**72.6**	**74.4**	**76.7**	**6.6**	**13.3**	**21.6**
$\mathcal{L}_{CTR}$ (w/o $\mathcal{L}_{TF}$)	74.9	86.2	92.3	72.2	72.9	74.4	-	12.3	19.9
$\mathcal{L}_{CTR}$ (w/o $\mathcal{L}_{TT}$)	75.8	87.4	92.5	71.6	73.5	75.6	4.5	12.9	20.5

Table 6: Ablation Study on VLP data, The best results for each setting are highlighted in bold, and the '-' denotes mAP values smaller than 1%. Methods with $\star$ leverage disease-level annotations. † denotes that Med-UniC only pre-trained on MIMIC dataset (En). Best results of each setting are in boldface.

	COVIDx(ACC)			RSNA(Dice)			Object CXR(mAP)		
Backbone	1%	10%	100%	1%	10%	100%	1%	10%	100%
ConVIRT[**?**]	67.3	77.8	89.0	55.0	67.4	67.5	-	8.6	15.9
GLoRIA-MIMIC[**?**]	66.5	80.5	88.8	60.3	68.7	68.3	-	8.9	16.6
MGCA* [**?**]	74.5	85.2	90.3	63.0	68.3	69.8	-	12.1	19.2
MedKLIP* [**?**]	72.0	83.5	90.5	66.2	69.4	71.9	-	7.1	11.6
Med-UniC (En)†	74.7	85.5	91.3	70.4	71.2	73.5	3.4	12.5	19.5
Med-UniC	**76.5**	**89.0**	**92.8**	**72.6**	**74.4**	**76.7**	**6.6**	**13.3**	**21.6**

5.3 Ablation Study on Cross-lingual Text Alignment Regularization

In this part, we explore the influence of each sub-component belonging to Cross-lingual Text Alignment Regularization $\mathcal{L}_{CTR}$, including text-feature alignment $\mathcal{L}_{TF}$ and text-to-text alignment $\mathcal{L}_{TT}$. As shown in Tab 5, reducing $\mathcal{L}_{TT}$ or $\mathcal{L}_{TF}$ can both lead to performance drop. Specifically, removing $\mathcal{L}_{TF}$ shows worse results than removing $\mathcal{L}_{TT}$ on most of settings, demonstrating the importance of learning cross-lingual invariance and reducing the languages bias through $\mathcal{L}_{TF}$.

5.4 Med-UniC Pre-training on Uni-lingual data

On the basis of Med-UniC paradigm, we further study the performance of only using the uni-lingual MIMIC dataset for pre-training. The ablation results are shown in Tab 6, which reveals that although using uni-lingual data to pre-train Med-UniC causes performance drop, compared to other baselines, our framework can also bring benefits. We attribute this to the self-supervised vision alignment (SSV) to learn more exhaustive visual representation and text-to-text alignment to keep in-modal consistency.

Table 7: Dimension Analysis of Projector $\mathcal{P}_d$. Best results of each setting are in boldface.

	COVIDx(ACC)			RSNA(Dice)			Object CXR(mAP)		
Dimension	1%	10%	100%	1%	10%	100%	1%	10%	100%
512	75.5	87.9	92.2	72.4	73.8	74.5	3.8	12.9	20.8
1024	**76.5**	**89.0**	**92.8**	72.6	**74.4**	**76.7**	**6.6**	**13.3**	21.6
2048	75.9	88.7	92.5	**73.1**	74.2	76.5	4.6	13.1	**22.5**

5.5 Embedding Dimension Analysis of Text Alignment Projector $\mathcal{P}_d$

In this section, we investigate the impact of output dimension D' from text alignment projector $\mathcal{P}_d$, since D' determines the size of cross-correlation matrix $\tilde{\mathbf{Z}}_e$ for text-feature alignment. We experiment with linear classification, segmentation and object detection, respectively. Tab 7 shows the corresponding results with different dimensions. When the dimension size is 1024, it can achieve better results on most of the experimental settings. Hence, we take $D' = 1024$ as our default setting during the pre-training.