Alternating Cross-attention Vision-Language Model for Efficient Learning with Medical Image and Report without Curation

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Abstract
Recent advances in vision-language pre-training have demonstrated astounding performances in diverse vision-language tasks, shedding a light on the long-standing problems of a comprehensive understanding of both visual and textual concepts in artificial intelligence research. However, there has been limited success in the application of vision-language pre-training in the medical domain, as the current vision-language models and learning strategies for photographic images and captions are not optimal to process the medical data which are usually insufficient in the amount and the diversity, which impedes successful learning of joint vision-language concepts. In this study, we introduce MAX-VL, a model tailored for efficient vision-language pre-training in the medical domain. We experimentally demonstrated that the pre-trained MAX-VL model outperforms the current state-of-the-art vision language models in various vision-language tasks. We also suggested the clinical utility for the diagnosis of newly emerging diseases and human error detection as well as showed the widespread applicability of the model in different domain data.
Introduction

Deep learning has witnessed dramatic advances in vision and language models in recent years, coming closer to human-level intelligence in the fields including the medical domain. However, the successes have been confined within each modality, unlike the human perception being able to be shared between the vision and language concepts. Building the model that can correlate the visual and language concepts has been a long-standing topic of research in the field of artificial intelligence (AI)\(^1\). Recently, vision-language pre-training, the paradigm of training on a large corpus of image-text pairs aiming to learn shared concepts between images and texts, has attained astounding performance in downstream tasks requiring both visual and language understanding such as image-text retrieval, vision question answering (VQA), visual grounding, and has changed the landscape of the multi-modal vision-language research, yielding a great number of studies in past years\(^2\text{-}^8\).

The rapid advances of VLP have been indebted to the introduction of vision transformer (ViT)\(^9\), which processes the images as a set of small patches similar to those of several words for a sentence with the transformer model\(^10\) for language. Thanks to the intrinsic similarities between the ways of processing an image or sentences with the self-attention mechanism of the transformer, direct attention between the image patches and words are possible, facilitating more straightforward cross-attention between modalities. The recent works have demonstrated that the transformer-based vision-language models obtained with the web-scale image and text data pairs have the generic capability for multiple downstream vision-language tasks\(^2\text{-}^4,11\text{-}14\). Compared with individual models specialized for each task and modality, the vision-language models pre-trained with massive data exhibited superior performances along with the amortization of training cost, enabling to push the limit of model capacity for both domains to reach human-level performances.
In the medical domain, there remain unmet needs for the vision-language model that can directly learn from the medical images and reports. Currently, uncurated medical data, for instance, radiograph image and report pairs are already abundant in hospitals, but the absence of manual annotation to discrete label for traditional supervised learning impedes the utilization of those uncurated image and text pairs to build a robust model. Therefore, making the model learn directly from the uncurated image-report pairs will greatly increase the usability of data, and thereby enable to develop the robust model that can efficiently adapt to various downstream tasks. Nevertheless, there exist only a few studies about the vision-language pre-training in the medical domain\textsuperscript{15,16}, where the pairs of image and sentence are frequently used as the form of radiographs, pathology slides, and corresponding reports.

Directly introducing the vision-language model devised for the general domain to the medical domain may result in suboptimal performance due to the different characteristics between the two domains. Compared with the photographic images and captions where billion-scale image-text pairs can be utilized with web crawling\textsuperscript{2,11}, the amount of image-text pairs for the medical images are often not sufficient to enable learning a firm relation between visual semantics and textual concept. Furthermore, the diversities between the different images and reports are often subtle. For radiographs as an example, the standardized imaging protocols make them consistent in anatomical patterns, and the abnormal findings in radiographs are usually subtly different in appearance\textsuperscript{17}. Likewise, the medical reports usually take the confined words and the sentence structures for better workflow, producing the formatted patterns of words in a sentence except for some keywords to describe the key findings. The capability to discriminate those subtle differences is required for the model tailored for the medical domain. Finally, the relative importance and the uniqueness of the words in a medical report differs more, and those words should be more exact than a caption for a photographic image. For example, given the caption "The boys are playing on the ground", the word "boy" can be substituted with "children" or "kids", while not altering the meaning. Like-
wise, the word "playing" can be substituted with "romping", and the "ground" with "field". On the other hand, given the medical report "No pleural effusion or pneumothorax is observed", the keywords "pleural effusion" or "pneumothorax", which represent the key concepts of the report, are unique and hard to be substituted\textsuperscript{16}.

To take into consideration of the intrinsic properties of images and reports of the medical domain, we proposed a model dubbed Medical Alternating X-attention Vision-Language (MAX-VL), leveraging the key components to be tailored for the medical data. We have experimentally demonstrated that these key components are indispensable to attain optimal performance, and also shown that the MAX-VL model outperforms the other state-of-the-art vision-language pre-trained models as well as shows versatility to adapt to the wide range of downstream tasks and data in the medical domain (Fig. 1A). In addition, we also scrutinized the clinical usefulness of the model in the simulation for diverse human-made errors that can be disastrous and even life-threatening once occurred as well as in the application for newly emerging disease given a highly data-limited setting. In addition to the quantitative measures, we performed a qualitative analysis on the MAX-VL model by visualizing the cross-attention between images and words, providing a transparent interpretation of the model’s behavior. Finally, we extended our model to real clinical data of another domain, abdominal radiograph, to demonstrate the wide applicability of the proposed model.

Results

Overview of the proposed model For vision-language problems, most contemporary models can be categorized into two architectures: single stream and dual stream architectures\textsuperscript{18}. The single stream architecture refers to the model that concatenates visual ad text features from the uni-modal encoders and processes them with a single multi-modal transformer encoder equipped with the self-attention. It is parameter efficient, but is often not pertinent for the joint vision-language
Figure 1: (A) The proposed MAX-VL model is pre-trained with an uncurated image-report corpus, and can be utilized for a variety of downstream medical vision and language tasks, also allowing the efficient adaptation to medical data on a different domain. (B) The overview of the model architecture and the learning objectives of the MAX-VL model. MIM, masked image modeling; ITM, image-text-matching; MLM, masked language modeling; EMA, exponential moving average.

understanding tasks like VQA, owing to the missing components to learn fusing visual and text representation. While, for the dual stream model, the visual and text representations are not con-
catenated but separately fed into the multi-modal transformer layers. In addition to the intra-modal self-attention, cross-modal attention is used to enable explicit multi-modal interaction to achieve a higher performance as well as joint visual-language understanding, while usually requiring more computational overheads. In our work, the model was developed based on the dual stream architecture, as we aim to develop a versatile model that can adapt to multiple downstream tasks including those requiring joint vision-language understanding. More detailed descriptions are provided in Supplementary Fig. 1.

Fig. 1B illustrates the overall architecture and the learning objectives of the proposed MAX-VL model. Like the vision-language models based on the cross-attention\(^3,19\), it deploys the cross-attention between image and text for vision-language understanding. However, different from the existing models, it uses an alternating fusion encoder that alternatively processes both image-to-text and text-to-image fusions with \(X\)-shaped cross attention. The contrastive learning between image and text, which aims to increase the similarity of image and text features after the uni-modal encoders, enforces the vision and text encoders to embed the image and text features into the same embedding spaces (Fig. 2A). This enables the modality agnostic learning approach, which makes the model have a better understanding of the relationship between the modalities through more efficient data utilization by alternately using the given image-text pair as key/value and query (Fig. 2B and C). When not leveraging the contrastive learning to align image and text features, the model cannot be trained at all as suggested in Table 1. Furthermore, since both the fused image features and text features are obtained from the two alternating pathways, the downstream tasks requiring either the fused image or text representation can all be performed, as well as enabling the self-ensemble of both pathways to improve performance (Fig. 2D). When ablating either the parameter sharing of fusion encoder by using two separate fusion encoders for image-to-text and text-to-image pathways or self-ensemble of both pathways, the model performances were sub-optimal, as shown in the ablation study (Table 1).
To learn the correlation between the visual semantics and text concepts, the commonly adopted learning objectives include contrastive learning, image-text matching (ITM), and masked language modeling (MLM). Along with these objectives, we utilized masked image modeling (MIM) which serves a similar purpose to MLM which enables the model to learn the intra-modal knowledge by having it complete the imperfect sample. As the MLM and MIM are done with fused text and image features in our model, these can be regarded as image-aided text completion and
Table 1: Ablation study of the key components for MAX-VL model.

| Method                              | Image-to-report | Report-to-image |
|-------------------------------------|-----------------|-----------------|
|                                     | R@1  | R@5  | R@10 | R@1  | R@5  | R@10 |
| w/o Alternating fusion encoder      | 59.0 (0.4) | 88.4 (0.6) | 95.0 (0.4) | 60.0 (0.4) | 88.7 (0.3) | 94.7 (0.2) |
| w/o Ensemble (text only)            | 60.6 (1.4) | 89.6 (0.3) | 95.5 (0.2) | 63.2 (0.5) | 90.4 (0.4) | 95.0 (0.2) |
| w/o Ensemble (vision only)          | 59.1 (1.2) | 89.0 (0.2) | 95.5 (0.2) | 61.2 (0.2) | 89.7 (0.2) | 95.0 (0.2) |
| w/o Contrastive learning            | 7.7 (0.9) | 15.6 (1.0) | 23.2 (0.8) | 6.3 (1.1) | 14.3 (1.3) | 22.2 (1.1) |
| w/o Masked language modeling        | 50.8 (0.9) | 83.3 (0.5) | 92.5 (0.4) | 52.0 (1.5) | 84.7 (0.5) | 92.1 (0.2) |
| w/o Masked image modeling           | 58.9 (0.4) | 87.8 (0.7) | 94.3 (0.2) | 60.3 (0.7) | 88.6 (0.3) | 94.0 (0.0) |
| w/o Knowledge distillation          | 46.4 (0.9) | 80.0 (0.6) | 89.8 (0.6) | 47.6 (0.3) | 81.1 (0.2) | 89.1 (0.0) |
| w/o Hard negative mining            | 58.0 (1.4) | 88.8 (0.3) | 95.0 (0.3) | 58.3 (1.3) | 89.0 (0.4) | 94.4 (0.2) |
| w/o Medical keyword weighting       | 60.7 (1.1) | 89.1 (0.7) | 95.2 (0.2) | 62.5 (0.4) | 89.6 (0.2) | 94.7 (0.6) |
| **Proposed**                        | **61.3 (1.4)** | **89.8 (0.2)** | **95.5 (0.2)** | **63.2 (0.2)** | **90.5 (0.3)** | **95.0 (0.2)** |

All experiments are performed with three different random seeds, and the means (standard deviations) are provided.

text-aided image completion tasks, respectively, again enforcing the joint understanding of vision and language concepts. As suggested in Table 1, the absence of any objective significantly drops the performance, suggesting the distinct roles of each component for model performance. For a detailed description of the model architecture and learning objectives, refer to the Method section.

To strengthen the discrimination ability of the model for subtle differences between data, which is demanded in the medical domain, we have made use of several additional components, momentum distillation, hard negative mining, and medical keyword weighting. Momentum distillation is a kind of knowledge distillation, a learning method of training the student network under the guidance of the pre-built teacher network that is slowly updated by the student. The teacher-student distillation enables the model to learn the dark knowledge between the discrete label, under the continuity assumption and clustering assumption20. This is suitable for the medical domain where the similarity between data is high, and therefore the negative samples should be treated differently according to their similarity to the positive pair for better discrimination ability. Secondly, we employed hard negative mining, a learning strategy that samples ”difficult” negative samples with high probability, to enforce the model to attend more to and learn more from the
fine-grained details of the samples. Finally, the medical keyword weighting strategy is adopted to assign a higher probability of masking for medical terms during the MLM to account for the different importance of each word in the medical reports. Specifically, we masked a word included in the Medical Subject Headings (MeSH) terms with higher probability, such as "Lung" or "Pneumonia", as it contains key semantic meaning in reports. By having the model predict those MeSH terms more frequently than others, it can get a better understanding of important semantics within images and reports. As provided in Table 1, ablating any of these components leads to suboptimal performances.

Performances of the proposed model on downstream tasks Next, we compared the MAX-VL with the existing vision-language models by assessing the model performances for various downstream tasks. For the retrieval and report generation, we used an open-sourced CXR dataset (MIMIC-CXR) containing 91,685 image-report pairs. Since we used ITM loss as one of the learning objectives, the zero-shot retrieval was possible with the pre-trained MAX-VL (Supplementary Fig. 2A). For report generation, the pre-trained model was fine-tuned with an autoregressive language modeling objective instead of MLM, along with other learning objectives. In detail, the model was trained to predict the next words given the previous sequence of words for the sentence by employing the casual mask to enforce autoregressive generation during the training (Supplementary Fig. 2B). For inference, the [CLS] token denoting the start of the sentence is given to the model, and the word next to this [CLS] token is predicted. The predicted word is then appended to the input sequence, and this step repeats until the [SEP] token, denoting the end of the sentence, is generated. Furthermore, to scrutinize the model’s ability to process a challenging task requiring joint vision-language understanding, we experimented on the VQA task with the VQA-RAD dataset containing 3,515 pairs of the question-answer on 315 images. We fine-tuned the pre-trained MAX-VL model for VQA by deeming the answering task as answer generation, instead of multi-answer classification (Supplementary Fig. 2C).
Table 2: Comparison of zero-shot retrieval performances of MAX-VL with other vision-language models.

| Method   | Image-to-report | Report-to-image |
|----------|-----------------|-----------------|
|          | R@1  | R@5  | R@10 | R@1  | R@5  | R@10 |
| w/o VLP  | 29.4 (12.5) | 67.3 (8.2) | 86.0 (0.4) | 28.8 (14.3) | 67.4 (11.6) | 86.0 (0.2) |
| MedViLL  | 54.2 (1.2) | 86.1 (0.7) | 93.8 (0.3) | 55.5 (0.7) | 85.0 (0.3) | 92.8 (0.3) |
| ALBEF    | 52.6 (1.2) | 84.8 (0.5) | 91.5 (0.4) | 53.7 (1.1) | 85.2 (0.1) | 90.8 (0.1) |
| TCL      | 24.8 (0.4) | 59.1 (1.1) | 75.6 (1.3) | 20.9 (1.0) | 54.8 (1.5) | 72.3 (1.4) |
| Proposed | 61.3 (1.4) | 89.8 (0.2) | 95.5 (0.2) | 63.2 (0.2) | 90.5 (0.3) | 95.0 (0.2) |

All experiments are performed with three different random seeds, and the means (standard deviations) are provided. * Results from the paper.

Table 3: Comparison of report generation performances of MAX-VL with other vision-language models.

| Method   | Clinical evaluation |
|----------|---------------------|
|          | BLEU-4  | METEOR  | ROUGE-L | CIDEr | Accuracy | Precision | Recall |
| w/o VLP  | 0.041 (0.002) | 0.082 (0.009) | 0.175 (0.009) | 0.046 (0.001) | 67.9 (0.3) | 54.1 (0.2) | 38.3 (6.5) |
| MedViLL  | 0.023 (0.001) | 0.109 (0.002) | 0.136 (0.001) | 0.009 (0.002) | 71.1 (0.5) | 58.0 (0.7) | 53.3 (0.9) |
| ALBEF    | 0.058 (0.006) | 0.112 (0.001) | 0.197 (0.001) | 0.082 (0.005) | 73.7 (0.4) | 62.3 (0.5) | 57.4 (0.8) |
| TCL      | 0.056 (0.002) | 0.112 (0.001) | 0.196 (0.001) | 0.079 (0.007) | 73.3 (0.3) | 61.7 (0.3) | 57.1 (0.9) |
| CoCa     | 0.040 (0.002) | 0.092 (0.001) | 0.169 (0.003) | 0.052 (0.004) | 71.5 (0.3) | 58.8 (0.1) | 54.5 (2.1) |
| Proposed | 0.060 (0.003) | 0.114 (0.001) | 0.200 (0.001) | 0.086 (0.004) | 73.5 (0.3) | 62.0 (0.5) | 57.5 (0.4) |

All experiments are performed with three different random seeds, and the means (standard deviations) are provided.

Table 2 provides the comparison of retrieval performances between the MAX-VL and other vision-language models. The MAX-VL substantially outperformed the current state-of-the-art medical vision-language model as well as the models for photographic image and text. For report generation, the MAX-VL provided overall better performances, both in terms of the evaluation metrics for the text generation in NLP (BLEU-n, ROUGE-L, METEOR, and CIDEr) and the clinical accuracy of generated report assessed with CheXpert labeler (Table 3). An example of the comparison between the ground truth and generated reports for an image is suggested in Supplementary Fig. 2A. For VQA, the MAX-VL model outperformed all other models not only for the question specific to chest radiographs but also for the questions regarding all imaging modal-
Table 4: Comparison of VQA performances of MAX-VL with other vision-language models.

| Methods                  | All  | Chest |
|--------------------------|------|-------|
|                          | Open | Closed | Open | Closed |
| No VLP                   | 36.0 (6.3) | 65.5 (2.6) | 0.0 (0.0) | 51.7 (0.0) |
| MedViLL\textsuperscript{15\*} | 59.7 | 78.2 | 60.8 | 78.3 |
| MEVF\textsuperscript{25\*}    | 40.7 | 74.1 | - | - |
| PubMedCLIP-MEVEF\textsuperscript{26\*} | 48.6 | 78.1 | - | - |
| PubMedCLIP-QCR\textsuperscript{26\*} | 60.1 | 80.0 | - | - |
| ALBEF\textsuperscript{3}    | 60.0 (0.6) | 78.2 (1.2) | 60.9 (1.0) | 80.7 (4.1) |
| TCL\textsuperscript{19}     | 59.0 (4.0) | 79.0 (1.3) | 62.1 (3.4) | 78.7 (1.0) |
| Proposed                 | \textbf{66.7 (2.3)} | \textbf{80.1 (0.8)} | \textbf{67.8 (2.0)} | \textbf{84.5 (1.7)} |

All experiments are performed with three different random seeds, and the means (standard deviations) are provided. * Results from the paper.

The superiority of the performances was prominent for the open-ended cases that can be considered to be more challenging than the close-ended ones, probably due to our implementation of VQA as an answer generation problem (Table 4).

Utility of vision-language pre-training for emerging disease One important merit of the vision-language pre-training is that the model can obtain a joint understanding of visual semantics and textual concepts. Considering that the human reader usually interprets newly encountered findings in an image with already learned language concepts, it is expected that a comprehensive understanding of vision and language will provide more efficient adaptation to downstream tasks like classification, compared with merely learning the semantic features via self-supervised learning.

Therefore, we hypothesized that the vision-language pre-trained model will exhibit fine-tune performance superior to the self-supervised model especially in terms of the generalization ability, given the limited data availability. To simulate the data-limited setting, we fine-tuned the visual encoder of MAX-VL and other self-supervised models using a highly limited number of COVID-19 data containing only 181 COVID-19 and 276 non-COVID-19 images (Supplementary Fig. 2D). Then, we evaluated the generalization ability of the model to the external validation dataset from
Table 5: Comparison of classification performance for COVID-19 in the highly data limited setting.

| Methods      | AUC       | Accuracy | Precision | Recall  |
|--------------|-----------|----------|-----------|---------|
| No pretrain  | 0.693 (0.121) | 37.4 (0.4) | 37.4 (0.0) | 100.0 (0.0) |
| SimCLR       | 0.788 (0.092) | 77.0 (5.1) | 74.9 (13.2) | 60.1 (7.7) |
| DINO         | 0.842 (0.026) | 79.3 (2.7) | 76.1 (7.9)  | 65.8 (2.6)  |
| SimMIM       | 0.748 (0.081) | 44.6 (6.5) | 40.2 (2.8) | 99.5 (0.5) |
| Proposed     | 0.882 (0.030) | 80.5 (5.3) | 71.6 (8.1) | 80.5 (2.9) |

All experiments are performed with three different random seeds, and the means (standard deviations) are provided.

three hospitals labeled by board-certified radiologists, containing 660 COVID-19 and 1,117 non-COVID-19 images. For details of the datasets, refer to the Method section.

As shown in Table 5, the vision-language pre-trained MAX-VL showed generalization performances superior to those pre-trained with the contemporary self-supervised learning methods as well as the baseline without pre-training, indicating its utility for prompt development of a robust model with an extremely small number of data, given a newly emerging disease.

Verification of image-text binding via qualitative analysis of cross attention To provide a transparent interpretation of the model’s behavior, we performed qualitative analysis using the Grad-CAM\textsuperscript{35} visualization for the fusion encoder’s cross-attention, as suggested in the ALBEF\textsuperscript{3}, as depicted in the exemplified cases of Fig 3. Without any supervision for the region-word correlations, the MAX-VL model correctly focuses on the regions related to each word, demonstrating its ability to understand the relationship between the semantics of the image and the textual concept. Notably, the model not only grounds the important clinical findings ("Consolidation", "Congestion", "Pacemaker"), but also understand the location ("Mediastinal", "Cardiac") and the relationship ("Left ... Upper").
Figure 3: (A-B) Exemplified cases of the Grad-CAM visualization of the cross-attention maps corresponding to each word. The MAX-VL model not only grounds the important clinical findings (“Consolidation”, “Congestion”, “Pacemaker”), but also understand the location (“Mediastinal”, “Cardiac”) and the relationship (“Left ... Upper”).

Clinical application for human error detection In clinics, several human errors like right-left orientation confusion or patient-report misregistration rarely occur but may lead to devastating results. As our MAX-VL has a comprehensive understanding of visual semantics and textual concepts, we assessed whether it can detect and correct human errors in sentences. For detection of an error, we hypothesized that the image-report matching score may be altered if the error occurs, as the resulting erroneous report may not be matched to the given image. We simulated the human errors by generating errors with 1% probability, mimicking the critical human-made errors in clinics.
Figure 4: (A) Example for the detection and correction of the right-left orientation error. Notably, other than the wrong words, it also changes another word (“enlargement”) to another (“widening”) without significantly changing the meaning. (B) Example for the detection of the patient-report mismatching error, and the model’s suggestion for the correct matching report. AUC, area under the receiver operating characteristics curve. Experiments are performed with three random seeds and means \(\pm\) standard deviations are provided.

First, the word “right” was changed to “left” and vice versa, to emulate the right-left orientation confusion, and we evaluated whether the model can detect and correct the wrong word automatically. As shown in Fig. 4A, the pre-trained MAX-VL can detect the right-left orientation error with the AUC of 0.759 \(\pm\) 0.067, without any supervision. In addition, thanks to the image-aided MLM in pre-training objectives, it can correct erroneous reports by substituting wrong words (red text) into correct ones (green text) referring to the image, when masking each word within a sentence one by one and predicting it. Interestingly, the model sometimes substituted other words (“enlargement” to “widening”) as shown in the green text of Fig 5, which does not significantly
alter the overall meaning of the sentence.

Next, given a radiograph image, the original report was substituted with an unmatched report with a probability of 1% to emulate the misregistration error. We evaluate whether the model can detect the misregistration and suggest the matching report for the image. As shown in Figure 9, the model can accurately detect the misregistration with an AUC of $0.981 \pm 0.025$, and successfully suggested the exactly matching report or those with semantically identical meaning as in the exemplified case (Fig. 4B).

**Application to real clinical data in different domain** To investigate the widespread applicability, we extended our work to the domain of abdominal radiographs. A total of 8,201 abdominal radiograph image-text pairs were collected from two hospitals (Chung Ang University Hospital [CAUH] and Chungnam University Hospital [CNUH]) were used for the vision-language pre-training on abdominal radiographs, and the other 235 images collected from a separated group of patients were utilized as the validation dataset. We initialized the model with pre-trained weights from chest radiographs, as there exist common semantics between the chest and abdominal radiographs albeit different in the field of view. The clinical accuracy of the generated reports was evaluated whether or not the model found out and mentioned the important clinical findings in the generated report, given an abdominal radiograph.

As provided in Table 6, the quality of the report generated by the MAX-VL model was good in terms of both the metrics for generated sentences in NLP and the clinical accuracy. The example for a comparison between the real and generated reports for a given image is suggested in Supplementary Fig. 2B. The performances of the vision-language pre-trained model were significantly better than those without, showing the necessity of the vision-language pre-training for a comprehensive understanding of images and texts regardless of the downstream tasks. The direct training
Table 6: Report generation performances of the MAX-VL model for abdominal radiographs.

| Methods     | BLEU-4   | METEOR   | ROUGE-L  | CIDEr    | Accuracy | Precision | Recall  |
|-------------|----------|----------|----------|----------|----------|-----------|---------|
| w/o VLP     | 0.593 (0.002) | 0.381 (0.001) | 0.746 (0.001) | 5.549 (0.001) | 76.9 (0.2) | 0.0 (0.0) | 0.0 (0.0) |
| Proposed    | 0.612 (0.004) | 0.454 (0.007) | 0.787 (0.009) | 6.067 (0.040) | 90.1 (0.6) | 86.9 (4.5) | 67.4 (5.2) |

All experiments are performed with three different random seeds, and the means (standard deviations) are provided.

of the model for report generation without the vision-language pre-training was unsuccessful, resulting in non-discriminative repetition of the same report for all images.

**Discussion**

Recently, deep learning-based AI models have achieved astonishing progress in an increasing range of tasks but their successes have been confined to narrow domains, throwing a doubt that something fundamental is still unaccounted. For example, the state-of-the-art classification model still could not learn to correlate the visual semantics to the textual concept, which is trivial to humans in the perspective of cognitive science. This discrepancy between the cognition of AI models and humans has given a rise to a new learning paradigm, the vision-language pre-training.

Different from the traditional supervised learning in which the visual recognition learning is tackled with the manually annotated image-label pair, the uncurated image-text pair is given to the model in the learning process of vision-language pre-training. The merit of vision-language pre-training is that the vision-language model can learn rich semantics with the broad coverage of visual concepts from the free-form text instead of discrete labels that provide dense but confined visual concept\(^\text{36}\). By learning the broad visual semantics along with the corresponding textual concepts, the model can easily attain good performances in a variety of downstream tasks, ranging from retrieval to text generation. Nevertheless, there remains the unsolved problem that the image-text pair, albeit offers broad coverage of visual concepts, generally lacks the powerful discrim-
inative ability compared with the dense label for traditional supervised learning. Consequently, billion-scale image-text data are usually required to train a robust vision-language model as shown in the study of CLIP\textsuperscript{11} and ALIGN\textsuperscript{2}, which is extremely difficult to obtain for the medical domain.

To cope with the problem, we leveraged several methods to maximally exploit the supervisory signal from each data. Given an image-text pair, we utilized the alternating fusion pathways, namely image-to-text and text-to-image fusions, enabling the model to learn once from image-guided text and once from text-guided image understandings. In our approach, this was possible thanks to the contrastive learning between the features after the uni-modal encoder that induces the image and text features to be aligned in the same embedding space before the fusion. Furthermore, the two methods, knowledge distillation, and hard negative mining were utilized during the training. The knowledge distillation enables the model to learn the dark knowledge between the positive and negative samples, by not treating all negative sample uniformly but according to their similarities to the positive sample. Hard negative mining, which draws a similar negative sample with a high probability, also enforces the model to learn more about the discrimination between the similar data. Combined, these two methods improve the discrimination ability to relatively small variation between the samples in the medical domain. Finally, to account for the importance of the unique medical terms, the medical keyword weighting that applies more weights to the clinically important expressions was utilized during the MLM. With these components, the proposed MAX-VL model could surpass the contemporary medical deep learning model as well as the state-of-the-art vision-language model for photographic images and captions in various downstream tasks.

We further investigated the utility of our MAX-VL model in diverse clinical applications. In clinics, critical human-made error, like orientation confusion and misregistration, rarely occurs but can lead to disastrous result. Although contemporary AI-based CAD models provide excel-
lent detection performances to detect abnormalities within an image, they cannot find the error in the medical report describing the image, as they do not have the ability for a joint understanding of image and text. Meanwhile, our MAX-VL model can successfully detect the errors with high accuracy, and even automatically corrects them or retrieves the matching pair without any supervision. In addition, compared with the other contemporary self-supervised learning approaches, the generalization ability of the vision-language pre-trained model was superior, given the extremely data-limited setting. This result suggests that the visual and textual concepts that the model learned through vision-language pre-training can be shared irrespective of disease entities, and can be efficiently utilized for the newly emerging disease like COVID-19 in 2020, especially in the early stage of the outbreak when the data availability matters most.

Our study has several limitations. First, since the form of the medical report for chest radiograph is not standardized, the generated reports are arbitrary and different from the original report in details, albeit containing semantically similar meaning (Supplementary Fig. 2). This results in relatively low scores for the natural language evaluation metrics, compared with those reported for the photographic images and caption pairs in previous works. Further study is warranted using the other imaging modality in which the structured report form is widely adopted. Second, although our method enables the vision-language learning with uncurated image-report data stored in each institutional database, the dependency on pre-built image-report paired data can be regarded as a limitation. For photographic images and captions, an automated web crawling algorithm can be used to build a billion-scale data corpus, but this is not feasible for the medical image and report.

Nevertheless, given the emergence of the vision-language models, we have demonstrated that vision-language pre-training can be effectively applied to the medical domain with our MAX-VL introduced for the medical domain. We also investigated the clinically useful application in
a real-world setting, like error detection, correction, and the fast adaptation to newly emerging diseases, which may lead to improved clinical practice. Considering the general configuration of image-report pairs in the medical imaging modalities other than radiograph, we believe that our method possesses broad applicability in the field of medical imaging.

**Methods**

**Details of model architecture** Our medical alternating cross-attention vision-language (MAX-VL) model follows the structure general structure of the dual stream cross-attention based vision-language models\(^3,^{12,19,38}\), but different in the multi-modal fusion encoder that alternates between the image-to-text and text-to-image cross-attention. This fusion encoder is shared between two pathways, namely image-to-text and text-to-image fusion, enabling more efficient utilization of data pairs. In our experiment, using separate fusion encoders for each pathway meaningfully dropped the performance, suggesting the benefit of the shared encoder for efficient data utilization (Table 1). An input image \(I\) is encoded to the sequence of patch embeddings \(\{p_{cls}, p_1, ..., p_N\}\) by the image encoder, where \(p_{cls}\) denotes the [CLS] token embedding. Likewise, an input text \(T\) is transformed to the sequence of word embeddings \(\{w_{cls}, w_1, ..., w_M\}\), where \(w_{cls}\) is the [CLS] token that also means the start of the sequence and \(w_M\) is the [SEP] token to represent the end of the sentence. With the alternating multi-modal fusion encoder, the patch embeddings fuse with the word embeddings to yield the fused patch embeddings \(\{u_{cls}, u_1, ..., u_N\}\) using the cross-attention, and vice versa for the fused word embeddings \(\{v_{cls}, v_1, ..., v_M\}\), making use of a \(X\)-shaped cross attention between the modalities.

**Details of pre-training objectives** Our MAX-VL model is trained with four learning objectives: Contrastive learning for cross- and intra-modal alignment, masked language modeling (MLM) for image-guided text completion, masked image modeling (MIM) for text-guided image completion,
and image-text matching (ITM).

**Contrastive Learning for Cross- and Intra-modal Alignment** The cross-modal contrastive learning aims to align the image and text features in the same embedding space, after the uni-modal encoders before the fusion. Specifically, it pulls the positive image-text pair together while pushing the unmatched pair apart. Given the encoded embeddings $p_{cls}$ and $w_{cls}$ of $[CLS]$ tokens of image $I$ and text $T$, similarity function $sim(I, T)$ and $sim(T, I)$ can be defined as:

$$sim(I, T) = h_I(p_{cls})^\top h_T(w_{cls}), \quad sim(T, I) = h_T(w_{cls})^\top h_I(p_{cls})$$

(1)

where $h_I$ and $h_T$ denote linear projector with normalization layer for image and text features.

Then, the normalized image-to-text and text-to-image similarities of each image-text pair are calculated as:

$$s_{i2t} = \frac{\exp \left( \frac{sim(I, T_m)}{\tau} \right)}{\sum_{m=1}^{M} \exp \left( \frac{sim(I, T_m)}{\tau} \right)}, \quad s_{t2i} = \frac{\exp \left( \frac{sim(T, I_n)}{\tau} \right)}{\sum_{n=1}^{N} \exp \left( \frac{sim(T, I_n)}{\tau} \right)}$$

(2)

where $\tau$ denotes the temperature parameter.

Meanwhile, intra-modal contrastive learning aims to teach model the semantic differences between positive and negative samples within the modality. Similar to cross-modal contrast learn-
ing, the normalized image-to-image and text-to-text similarities can be defined as:

\[
s_{i2t} = \frac{\exp \left( \frac{\text{sim}(I, I_n)}{\tau} \right)}{\sum_{n=1}^{N} \exp \left( \frac{\text{sim}(I, I_n)}{\tau} \right)}, \quad s_{t2t} = \frac{\exp \left( \frac{\text{sim}(T, T_m)}{\tau} \right)}{\sum_{m=1}^{M} \exp \left( \frac{\text{sim}(T, T_m)}{\tau} \right)}
\]

(3)

where \( \tau \) is the same temperature parameter used in the cross-modal contrastive learning.

Consequently, given the one-hot label similarity \( y \), the cross-modal contrastive loss \( L_{CMC} \), intra-modal contrastive loss \( L_{IMC} \) and overall contrastive loss \( L_{\text{contrastive}} \) can be defined as the cross-entropy loss \( H \):

\[
L_{CMC} = \frac{1}{2} \left[ H(y_{i2t}, s_{i2t}) + H(y_{t2t}, s_{t2t}) \right]
\]

(4)

\[
L_{IMC} = \frac{1}{2} \left[ H(y_{i2t}, s_{i2t}) + H(y_{t2t}, s_{t2t}) \right]
\]

(5)

\[
L_{\text{contrastive}} = L_{CMC} + L_{IMC}
\]

(6)

Inspired by the recent contrastive learning approaches\(^{39}\), we have the image and text queues to store the most recent \( Q \) samples from the momentum encoder for each modality. In our experiments, the que size \( Q \) was 49,152.
As the feature similarities can be calculated between image and text with the above objectives, these similarities can also be utilized in hard negative mining for ITM, by sampling the negative pair with high similarity more frequently.

Additionally, this learning objective enables the alternating fusion encoder to process both image-to-text and text-to-image fusion, which seems to be unreasonable at first glance as the same key, query and value weights are shared between different modalities, by aligning the image patch and the word features in the same embedding space. In our experiments, ablating the contrastive learning objective substantially degraded the performance, showing that this aligning process is essential for the learning alternating fusion encoder shared between the modalities (Table 1).

0.0.1 Masked Language Modeling for Image-guided Text Completion

Masked Language Modeling (MLM) is a commonly adopted learning objective to obtain language understanding to predict the ground truth of the masked word tokens $w_{mask}$ from other unmasked word tokens and in our model, with the aid of the corresponding image. In detail, the word tokens are masked out with a probability of 15% and replaced with the [MASK] token with 80%, the random word token with 10% and the unchanged original token with 10% probabilities. Let the masked text as $T_{mask}$, the prediction for [MASK] tokens after fusion encoder as $p^{mask}(I, T_{mask})$, and the ground truth for each word tokens as $y_{w}^{mask}$, the MLM loss in our model can be defined with cross-entropy loss $H$:

$$L_{MLM} = H(y_{w}^{mask}, p^{mask}(I, T_{mask}))$$  \hspace{1cm} (7)
As the predictions for the \texttt{[MASK]} token come from the multi-modal fusion encoder which fuses the image representation into text tokens, our MLM task can be considered as an image-aided masked text token prediction. Consequently, the model comes to understand the joint image-text representation and their relationship.

\subsection*{0.0.2 Masked Image Modeling for Text-guided Image Completion}

Similar to MLM, we also employed masked image modeling (MIM) to enable the model to learn the comprehensive image-text joint understanding, performing the task of text-guided masked area completion. Specifically, instead of directly predicting the pixel values of masked image patches, we utilized the distilled online token prediction method proposed in the study of iBOT\textsuperscript{41}. Given an image $I$, image patch tokens $\{x_{cls}, x_1, ..., x_N\}$ are blockwisely masked with a random mask $M = \{m_1, ..., m_N\} \in \{0, 1\}^N$ with masking ratio $r$ by substituting image token $x$ with the mask token \texttt{[MASK]}, where $m_i = 1$ indicates the masked patch tokens, making a masked image $I^{\text{mask}}$. For the set of masked patch tokens $x_{\text{masked}} \triangleq \{x_i | m_i = 1\}$, the model learn to match its prediction for masked patch token after fusion encoder $p^{\text{mask}}(T, I^{\text{mask}})$ to the label $y^{\text{mask}}_p$, referring to both the unmasked image area and the corresponding text. Similar to the iBOT that uses the momentum teacher as an online tokenizer instead of the offline discrete tokenizer like BEiT\textsuperscript{42}, the labels for masked patch tokens were generated by the momentum teacher parameterized by $\hat{\theta}$. Consequently, the learning objective of the model parameterized by $\theta$ can be defined as:

\[
L_{\text{MIM}} = H(y^{\text{mask}}_p, p^{\text{mask}}(T, I^{\text{mask}})) = \sum_{i=1}^{N} m_i \cdot P_\theta(x_i) \log P_\theta(x_i)
\]  

(8)
This can be considered as text-aided image completion, which again enforces the model to learn the mutual relationship between image and text representations.

### 0.0.3 Image-Text Matching

Image-text matching directly predicts whether a given image-text pair is matched or unmatched. We utilized the fusion embeddings of two [CLS] tokens obtained from the outputs of image-to-text and text-to-image paths of the fusion encoder, as they both imply the joint representation of the image-text pair. Following the fusion embeddings, we appended the binary classifiers to predict the prediction $c_{itm}(I, T)$ for matching of each image-text pair. Given $y_{itm}$ as the ground truth label for image-text matching, the ITM loss can be defined with cross-entropy loss $H$ as below:

$$L_{ITM} = H(y_{itm}, c_{itm}(I, T))$$ (9)

We additionally employed hard negative mining for ITM, by drawing the samples with high similarity $s_{i2t}$ and $s_{t2i}$ with high probability when sampling negative pair from the batch for a given image or text\(^3\). As the semantically similar negatives can be regarded as hard negatives that only differ in fine-grained detail, this allows the model to get better discrimination capability to catch subtle differences, which is especially important for medical imaging where the differences between images are small owing to the standardized acquisition protocol. With this strategy, the model performances were significantly improved with zero computational overhead.

Combined, the overall pre-training objective $L$ of the MAX-VL is:
\[ L = L_{\text{contrastive}} + L_{\text{MLM}} + L_{\text{MIM}} + L_{\text{ITM}} \] (10)

### 0.0.4 Momentum Distillation

In contrastive learning, some negative samples may also have a similar context to the positive ones and need to be treated differently from the entirely different negative sample. For example, given a radiograph showing the bibasilar opacifications suggesting the sign of pneumonia, other than the exactly matching description "There is newly developed bibasilar opacification suggesting newly developed pneumonia", a report like "There exist lung opacities in both lower lobe suggesting the severe pleural effusion", albeit describing different etiology for opacification and therefore may be regarded as a negative sample, should be penalized differently compared with an entirely unmatching description "Both lung fields are clear and there is no remarkable finding". This matters more in the medical domain, where the differences between the images and reports are smaller than the photographic images and captions and therefore overlapping between the images or reports can be substantial. Similarly, for MLM, there may exist other candidates different from ground truth but have the semantically same meaning like "No remarkable findings" and "No abnormality". However, the binary and one-hot coded labels for contrastive learning and MLM penalize all negative samples without considering their correctness.

Therefore, we employed the momentum teachers, which are gradually updated with exponential moving averaging of updated models, and generated pseudo labels for contrastive learning and MLM. During the training, the model is optimized to match the pseudo labels generated from the momentum teacher by minimizing distillation loss \( L_{\text{dist}} \) as well as the aforementioned overall
loss $L$, with weights $\lambda$ to balance the contributions of momentum distillation as follow:

$$L_{total} = (1 - \lambda) \cdot L + \lambda \cdot L_{dist}$$  \hspace{1cm} (11)$$

**Details for Model for Downstream Tasks** We adapted and assessed the pre-trained VL models for several downstream tasks. Supplementary Fig. 3 illustrates the modification of the pre-trained MAX-VL model for the specific downstream tasks. For retrieval, we could directly evaluate the zero-shot retrieval performances, since the $L_{ITM}$ was included as a component of pre-training objectives (Supplementary Fig. 3A). For report generation, the model was fine-tuned by substituting MLM with the next word prediction, to allow the auto-regressive generation of reports similar to image captioning (Supplementary Fig. 3B). As for the VQA, we deemed VQA as an answer generation instead of multi-answer classification$^{5,24}$, similar to the approach taken in recent works$^{3,19}$. We utilized the BERT$_{base}$ model to fuse the image features and question into fused features and used the six-layered transformer decoder to generate the answer in an auto-regressive manner (Supplementary Fig. 3C). For classification, we utilized the vision encoder of the MAX-VL model, to compare with the same-sized ViT model trained with the existing self-supervised learning approaches (Supplementary Fig. 3D).

**Details of datasets** For the vision-language pre-training with chest radiographs, we utilized the MIMIC-CXR dataset$^{22}$, an open-sourced database containing 377,110 image and report pairs. Among these images, we only utilized the 91,685 anterior-posterior (AP) view images and followed the train, validation, and test sets division provided by a previous study of MedViLL$^{15}$ for the comparison, resulting in 89,395, 759, and 1,531 images for training, validation, and testing, respectively. As the reports of MIMIC-CXR contain several descriptions (e.g. impression, findings,
etc.) that are all redundant in contents, we selected a longer description for each report, as proposed in a previous work\textsuperscript{15}. For VQA, we utilized the VQA-RAD dataset\textsuperscript{23} containing 3,515 question-answer pairs on 315 images, not only for the chest radiographs but also the other medical imaging modalities. Among those question-answer pairs, 3,064 were used for training and 451 for testing.

To investigate the utility of the vision-language pre-trained model on newly emerging disease, we used 181 images of COVID-19 positive cases and 276 normal images from the Brixia\textsuperscript{43} and the NIH dataset\textsuperscript{44} and evaluated the generalization performance of the developed model on the external validation dataset consist of 660 COVID-19 and 1,117 normal images collected from three hospitals(Chungnam National University Hospital [CNUH], Kyungpook National University Hospital [KNUH], Yeungnam University Hospital [YNU] labeled by the board-certified radiologists).

For the experiments on the abdominal radiograph, the inpatient databases of two hospitals were used. In detail, the 5,776 images from the CAUH and the 2,425 images from the CNUH were collected without curation and integrated to make an entire training dataset containing 8,201 images. For the validation, the data containing 235 images from a different patient group are separately collected.

**Implementation details** The image data were pre-processed by cutting margin space as proposed in a previous work\textsuperscript{15}, and underwent Gaussian blurring, normalization, and resized to $224 \times 224$. For the visual encoder, we used the ViT-S/16 model pre-trained on ImageNet and the same visual encoder was used for ALBEF\textsuperscript{3}, TLC\textsuperscript{19} and CoCa\textsuperscript{12}. For MedViLL, the CNN-based visual encoder was utilized for the MedViLL as proposed in the original work\textsuperscript{15}. Similar to the previous vision-language model having cross-attention\textsuperscript{3,19,38}, the first six layers of the uncased BERT\textsubscript{base} model\textsuperscript{10} were used as the text encoder, while the last six layers the BERT\textsubscript{base} were utilized as the fusion encoder. We trained the text tokenizer with the word corpus of the MIMIC-CXR dataset that occur at least once with a vocabulary size of 30,522, and the maximum length of the report was set to 100.
For the vision-language pre-training, an AdamW optimizer with the initial and maximal learning rate of 0.00001 and 0.0001 was used for the 15 epochs including five epochs of the warm-up period, and the batch size was 12. For fine-tuning on each task, we used the different hyperparameters according to the tasks, as suggested in Supplemental Table 1. All experiments were performed using Python version 3.8 and PyTorch library version 1.10 on NVIDIA GeForce RTX 3090.

**Details of evaluation.** For the evaluation of the retrieval performance, we reported the retrieval accuracy at rank 1, 5, and 10 (R@1, R@5, and R@10). As the rank-based retrieval accuracy can differ according to the size of the test datasets, we randomly divided the test dataset into 100 image-report pairs and calculated the retrieval accuracy similar to the study for comparison. This evaluation was performed with 10 different random to obtain reliable results. Unlike the photographic image and caption, there may exist reports that are different in expression but have the semantically same meaning. For example, the reports ”No abnormal findings” and ”Nothing remarkable.” are different in expression, but semantically the same. If the model successfully retrieved either of these reports and if there is nothing remarkable in the radiograph, it should be considered as correct. Therefore, we defined it as a matching pair if they contain exactly the same label classes with CheXpert labeler, and unmatching pair if not. The evaluation of report generation performance was done in two aspects, the metrics to evaluate generated sentences in NLP like BLEU, METEOR, ROUGE-L, and CIDEr, and the metrics for clinical accuracy of the generated reports after labeling them with the CheXpert labeler. To evaluate the clinical accuracy of generated reports for abdominal radiographs, whether or not clinically important findings (e.g. pneumoperitoneum, ileus, etc.) are mentioned in the report generated by the model was assessed by a clinician, referring to both the original report and the image. For VQA, since the model is pre-trained with the chest X-ray dataset, we separately assessed the adaptation capability of the model for all questions and the question regarding the chest radiographs. In addition, following the VQA-RAD paper, the accuracy of the open-ended and closed-form questions are reported separately.
For classification, the area under the receiver operating characteristics curve (AUC) was used as the principal evaluation metric to compare the performances between the models, and the accuracy, precision, and recall were separately reported. All experiments were repeatedly performed with three different random seeds to validate the reproducibility, and the mean and standard deviation are reported.

Ethic committee approval. The abdominal radiograph data collected for this study were ethically approved by the Institutional Review Boards of Chung-Ang University Hospital, Chungnam University Hospital, Kyungpook National University Hospital and Yeungnam University Hospital, and the requirement for informed consent was waived.

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Author Contributions S.P. performed all experiments, wrote the extended code, and prepared the manuscript. E.S.L and J.E.L collected data and provided clinical evaluation. J.C.Y. supervised the project in conception and discussion, and prepared the manuscript.

Competing Interests The authors declare that they have no competing financial interests.

Data Availability Part of data are collected from open-sourced data repositories that are publicly available. The MIMIC-CXR database is available at https://physionet.org/content/mimic-cxr/2.0.0/. The VQA-RAD database is available at https://osf.io/89kps/. The BIMCV data can be found at https://github.com/BIMCV-CSUSP/BIMCV-COVID-19. The normal NIH database is available at https://cloud.google.com/healthcare-api/docs/resources/public-datasets/nih-chest. Other part of data that are used for the external validation of
COVID-19 classification and the experiments for abdominal radiographs are not publicly available due to the patient privacy obligation. Interested users can request the access to these data for research purpose, by contacting the corresponding author J.C.Y (jong.ye@kaist.ac.kr). The data can be shared after the IRB approval and de-identification along with the signed agreement on data transfer and usage. Replies to the initial request will be made within 10 working days. Use of data is limited only to the research purpose, and the redistribution is prohibited.

**Code Availability**  The code is available at the following github repository. [https://github.com/depecher/](https://github.com/depecher/)

**References**

1. Boden, M. A. *Mind as machine: A history of cognitive science* (Oxford University Press, 2008).

2. Jia, C. et al. Scaling up visual and vision-language representation learning with noisy text supervision. In *International Conference on Machine Learning*, 4904–4916 (PMLR, 2021).

3. Li, J. et al. Align before fuse: Vision and language representation learning with momentum distillation. *Advances in neural information processing systems* 34, 9694–9705 (2021).

4. Cho, J., Lei, J., Tan, H. & Bansal, M. Unifying vision-and-language tasks via text generation. In *International Conference on Machine Learning*, 1931–1942 (PMLR, 2021).

5. Chen, Y.-C. et al. Uniter: Universal image-text representation learning. In *European conference on computer vision*, 104–120 (Springer, 2020).
6. Lu, J., Batra, D., Parikh, D. & Lee, S. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. *Advances in neural information processing systems* 32 (2019).

7. Li, X. *et al.* Oscar: Object-semantics aligned pre-training for vision-language tasks. In *European Conference on Computer Vision*, 121–137 (Springer, 2020).

8. Huang, Z., Zeng, Z., Liu, B., Fu, D. & Fu, J. Pixel-bert: Aligning image pixels with text by deep multi-modal transformers. *arXiv preprint arXiv:2004.00849* (2020).

9. Dosovitskiy, A. *et al.* An image is worth 16x16 words: Transformers for image recognition at scale. *arXiv preprint arXiv:2010.11929* (2020).

10. Vaswani, A. *et al.* Attention is all you need. *Advances in neural information processing systems* 30 (2017).

11. Radford, A. *et al.* Learning transferable visual models from natural language supervision. In *International Conference on Machine Learning*, 8748–8763 (PMLR, 2021).

12. Yu, J. *et al.* Coca: Contrastive captioners are image-text foundation models. *arXiv preprint arXiv:2205.01917* (2022).

13. Wang, W., Bao, H., Dong, L. & Wei, F. Vlmo: Unified vision-language pre-training with mixture-of-modality-experts. *arXiv preprint arXiv:2111.02358* (2021).

14. Alayrac, J.-B. *et al.* Flamingo: a visual language model for few-shot learning. *arXiv preprint arXiv:2204.14198* (2022).

15. Moon, J. H., Lee, H., Shin, W. & Choi, E. Multi-modal understanding and generation for medical images and text via vision-language pre-training. *arXiv preprint arXiv:2105.11333* (2021).
16. Yan, B. & Pei, M. Clinical-bert: Vision-language pre-training for radiograph diagnosis and reports generation (2022).

17. Xiang, T. et al. In-painting radiography images for unsupervised anomaly detection. *arXiv preprint arXiv:2111.13495* (2021).

18. Chen, F. et al. Vlp: A survey on vision-language pre-training. *arXiv preprint arXiv:2202.09061* (2022).

19. Yang, J. et al. Vision-language pre-training with triple contrastive learning. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 15671–15680 (2022).

20. Kim, G. Recent deep semi-supervised learning approaches and related works. *arXiv preprint arXiv:2106.11528* (2021).

21. Lowe, H. J. & Barnett, G. O. Understanding and using the medical subject headings (mesh) vocabulary to perform literature searches. *Jama* 271, 1103–1108 (1994).

22. Johnson, A. E. et al. Mimic-cxr, a de-identified publicly available database of chest radiographs with free-text reports. *Scientific data* 6, 1–8 (2019).

23. Lau, J. J., Gayen, S., Ben Abacha, A. & Demner-Fushman, D. A dataset of clinically generated visual questions and answers about radiology images. *Scientific data* 5, 1–10 (2018).

24. Yu, L. et al. Mattnet: Modular attention network for referring expression comprehension. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1307–1315 (2018).

25. Nguyen, B. D. et al. Overcoming data limitation in medical visual question answering. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, 522–530 (Springer, 2019).
26. Eslami, S., de Melo, G. & Meinel, C. Does clip benefit visual question answering in the medical domain as much as it does in the general domain? *arXiv preprint arXiv:2112.13906* (2021).

27. Papineni, K., Roukos, S., Ward, T. & Zhu, W.-J. Bleu: a method for automatic evaluation of machine translation. In *Proceedings of the 40th annual meeting of the Association for Computational Linguistics*, 311–318 (2002).

28. Lin, C.-Y. Rouge: A package for automatic evaluation of summaries. In *Text summarization branches out*, 74–81 (2004).

29. Banerjee, S. & Lavie, A. Meteor: An automatic metric for mt evaluation with improved correlation with human judgments. In *Proceedings of the acl workshop on intrinsic and extrinsic evaluation measures for machine translation and/or summarization*, 65–72 (2005).

30. Vedantam, R., Lawrence Zitnick, C. & Parikh, D. Cider: Consensus-based image description evaluation. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 4566–4575 (2015).

31. Irvin, J. *et al.* Chexpert: A large chest radiograph dataset with uncertainty labels and expert comparison. In *Proceedings of the AAAI conference on artificial intelligence*, vol. 33, 590–597 (2019).

32. Chen, T., Kornblith, S., Norouzi, M. & Hinton, G. A simple framework for contrastive learning of visual representations. In *International conference on machine learning*, 1597–1607 (PMLR, 2020).

33. Caron, M. *et al.* Emerging properties in self-supervised vision transformers. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, 9650–9660 (2021).
34. Xie, Z. et al. Simmim: A simple framework for masked image modeling. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 9653–9663 (2022).

35. Selvaraju, R. R. et al. Grad-cam: Visual explanations from deep networks via gradient-based localization. In *Proceedings of the IEEE international conference on computer vision*, 618–626 (2017).

36. Yang, J. et al. Unified contrastive learning in image-text-label space. In *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, 19163–19173 (2022).

37. Wang, Z. et al. Simvlm: Simple visual language model pretraining with weak supervision. *arXiv preprint arXiv:2108.10904* (2021).

38. Dou, Z.-Y. et al. Coarse-to-fine vision-language pre-training with fusion in the backbone. *arXiv preprint arXiv:2206.07643* (2022).

39. He, K., Fan, H., Wu, Y., Xie, S. & Girshick, R. Momentum contrast for unsupervised visual representation learning. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, 9729–9738 (2020).

40. Devlin, J., Chang, M.-W., Lee, K. & Toutanova, K. Bert: Pre-training of deep bidirectional transformers for language understanding. *arXiv preprint arXiv:1810.04805* (2018).

41. Zhou, J. et al. ibot: Image bert pre-training with online tokenizer. *arXiv preprint arXiv:2111.07832* (2021).

42. Bao, H., Dong, L. & Wei, F. Beit: Bert pre-training of image transformers. *arXiv preprint arXiv:2106.08254* (2021).

43. Signoroni, A. et al. Bs-net: Learning covid-19 pneumonia severity on a large chest x-ray dataset. *Medical Image Analysis* **71**, 102046 (2021).
44. Wang, X. et al. Chestx-ray8: Hospital-scale chest x-ray database and benchmarks on weakly-supervised classification and localization of common thorax diseases. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2097–2106 (2017).