DiRA: Discriminative, Restorative, and Adversarial Learning for Self-supervised Medical Image Analysis

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Abstract

Discriminative learning, restorative learning, and adversarial learning have proven beneficial for self-supervised learning schemes in computer vision and medical imaging. Existing efforts, however, omit their synergistic effects on each other in a ternary setup, which, we envision, can significantly benefit deep semantic representation learning. To realize this vision, we have developed DiRA, the first framework that unites discriminative, restorative, and adversarial learning in a unified manner to collaboratively glean complementary visual information from unlabeled medical images for fine-grained semantic representation learning. Our extensive experiments demonstrate that DiRA (1) encourages collaborative learning among three learning ingredients, resulting in more generalizable representation across organs, diseases, and modalities; (2) outperforms fully supervised ImageNet models and increases robustness in small data regimes, reducing annotation cost across multiple medical imaging applications; (3) learns fine-grained semantic representation, facilitating accurate lesion localization with only image-level annotation; and (4) enhances state-of-the-art restorative approaches, revealing that DiRA is a general mechanism for unified representation learning. All code and pretrained models are available at \url{https://github.com/JLiangLab/DiRA}.

1. Introduction

Self-supervised learning (SSL) aims to learn generalizable representations without using any expert annotation. The representation learning approaches in the SSL paradigm can be categorized into three main groups: (1) discriminative learning, which utilizes encoders to cluster instances of the same (pseudo) class and distinguish instances from different (pseudo) classes; (2) restorative learning, which utilizes generative models to reconstruct original images from their distorted versions; and (3) adversarial learning, which utilizes adversary models to enhance restorative learning. In computer vision, discriminative SSL approaches, especially contrastive learning \cite{chen2020simple, he2020momentum, kiros2014uniter, oord2018representation, chen2020improved, oord2018neural, chen2020self, chen2021exploring, he2020momentum}, currently offer state-of-the-art (SOTA) performance, surpassing standard supervised ImageNet models in some tasks. In medical imaging, however, restorative SSL methods \cite{park2021self, liang2021unified, liang2021self, prota2021contrastive, zhou2021medical} compared to discriminative approaches \cite{ahn2021self, zhang2021self} presently reach a new height in performance. Naturally, we contemplate: What contributes to the popularity differences between discriminative and restorative methods in computer vision and in medical imaging? Furthermore, from our extensive literature review, we have discovered that no SSL method simultaneously employs all three learning ingredients. Our proposed DiRA, a novel SSL framework, unites discriminative, restorative, and adversarial learning in a unified manner to collaboratively glean complementary visual information from unlabeled data for fine-grained semantic representation learning.

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a single framework to foster collaborative learning for deep semantic representation, yielding more powerful models for a broad range of applications? In seeking answers to the two questions, we have gained the following insights.

Computer vision and medical imaging tasks embrace the spirit of evil in opposite ways, originating from the marked differences between photographic and medical images. Photographic images, particularly those in ImageNet, have large foreground objects with apparent discriminative parts, residing in varying backgrounds (e.g., zebra and daisy images in Fig. 2). Thus, object recognition tasks in photographic images are primarily based on high-level features, while medical tasks demand holistic fine-grained discriminative features captured throughout images.

According to our systematical analysis, we have gained the following understandings: (1) discriminative learning excels in capturing high-level (global) discriminative features, (2) restorative learning is good at conserving fine-grained details embedded in local image regions, and (3) adversarial learning consolidates restoration by conserving more fine-grained details. Putting these understandings and fundamental differences between photographic and medical images together would explain why restorative learning is preferred in medical imaging while discriminative learning is preferred in computer vision. More importantly, we have acquired a new and intriguing insight into trio of discriminative, restorative, and adversarial learning to excavate effective features required for medical recognition tasks—not only high-level anatomical representations but also fine-grained discriminative cues embedded in the local parts of medical images.

Based on the insights above, we have designed a novel self-supervised learning framework, called DiRA, by uniting discriminative learning, restorative learning, and adversarial learning in a unified manner to glean complementary visual information from unlabeled medical images. Our extensive experiments demonstrate that (1) DiRA encourages collaborative learning among three learning components, resulting in more generalizable representation across organs, diseases, and modalities (see Fig. 4); (2) DiRA outperforms fully supervised ImageNet models and increases robustness in small data regimes, thereby reducing annotation cost in medical imaging (Tab. 1 and Tab. 2); (3) DiRA learns fine-grained representations, facilitating more accurate lesion localization with only image-level annotations (Fig. 5); and (4) DiRA enhances SOTA restorative approaches, showing that DiRA is a general framework for unified representation learning (Tab. 3).

In summary, we make the following contributions:

- The insights that we have gained into the synergy of discriminative, restorative, and adversarial learning in a ternary setup, realizing a new paradigm of collaborative learning for SSL.
- The first self-supervised learning framework that seamlessly unites discriminative, restorative, and adversarial learning in a unified manner, setting a new SOTA for SSL in medical imaging.
- A thorough and insightful set of experiments that demonstrate not only DiRA’s generalizability but also its potential to take a fundamental step towards developing universal representations for medical imaging.

2. Related works

Discriminative self-supervised learning. Discriminative methods can be divided into class-level and instance-level discrimination. Class-level discrimination methods [7, 8, 17, 22, 35, 54] group images based on certain criteria, assign a pseudo label to each group, and train a model to discriminate the images based on their pseudo labels, such as rotation degrees [22] and cluster assignments [7, 8, 54].
On the other hand, *instance-level* discrimination methods [8, 12, 13, 15, 21, 24, 27, 34, 44, 48, 52, 53] treat each image as a distinct class, and maximize the similarity of representations derived from different views of the same image, seeking to learn transformation invariant representations. *Instance-level* discriminative learning has been investigated in various forms, including contrastive learning [12, 14, 27, 49], asymmetric networks [15, 24], and redundancy reduction [21, 53]. However, both *class-level* and *instance-level* approaches in discriminative learning have shown failures in tasks that require finer-grained features [47, 50, 51]. Our DiRA addresses this limitation by incorporating restorative and adversarial learning, which not only improves discriminative learning but also yields fine-grained representations required for medical imaging tasks.

**Restorative and adversarial self-supervised learning.** The key objective for a restorative method is to faithfully reconstruct the distribution of data [36, 48]. In the SSL context, multiple pretext tasks are formulated to reconstruct the perturbed images using generative models [33, 37, 45]. The advance of GANs [23] has led to a new line of research in unsupervised learning, using adversarial learning to generate transferable representations [18, 19]. While recent works [11, 18] have demonstrated impressive results by employing large-scale generative models, it remains unclear to what extent generative models can encapsulate high-level structures. Our DiRA alleviates this limitation by bringing the advantages of discriminative learning into generative models. Through discriminating image samples, generative models are encouraged to capture global discriminative representations rather than superficial representations, leading to a more pronounced embedding space.

**Self-supervised learning in medical imaging.** Due to the lack of large annotated datasets, SSL created substantial interest in medical imaging. Motivated by the success in computer vision, recent discriminative methods concentrate on instance-level discrimination. A comprehensive benchmarking study in [29] evaluated the efficacy of existing instance discrimination methods pre-trained on ImageNet for diverse medical tasks. Several other works adjusted contrastive-based methods on medical images [3, 9, 56]. A large body of work, on the other hand, focuses on restorative approaches, which can be categorized into restorative only [10, 57], restorative and adversarial [43], and discriminative and restorative [36, 30, 55]. Among these groups, the most recent study on TransVW [25, 26] demonstrated superiority by combining discriminative and restorative components into a single SSL framework. DiRA distinguishes itself from all previous works by demonstrating two key advances: (1) employing discriminative, restorative, and adversarial learning simultaneously in a unified framework; and (2) providing a general representation learning framework that is compatible with existing discriminative and restorative methods, regardless of their objective functions.

### 3. DiRA framework

As shown in Fig. 3, DiRA is a SSL framework comprised of three key components: (1) Discrimination (Di) that aims to learn high-level discriminative representations, (2) Restoration (R) that aims to enforce the model to conserve fine-grained information about the image by focusing on more localized visual patterns, and (3) Adversary (A) that aims to further improve feature learning through the restoration component. By integrating these components into a unified framework, DiRA captures comprehensive information from images, providing more powerful representations for various downstream tasks. In the following, we first introduce each component by abstracting a common paradigm and then describe the joint training loss.

#### 3.1. Discriminative learning

Discriminative learning can be thought of as training an encoder to maximize agreement between instances of the same (pseudo) class in the latent space via a discriminative loss. As illustrated in Fig. 3, the discriminator branch is comprised of two twin backbone networks $f_\theta$ and $f_\xi$, and projection heads $h_\theta$ and $h_\xi$. $f_\theta$ is a regular encoder, while...
can be a momentum encoder [24, 27] or share weights with \( f_\theta \) [15, 26, 53]. Given two patches \( x_1 \) and \( x_2 \), which are cropped from the same image or different images, we first apply an augmentation function \( T(\cdot) \) on them. The two augmented patches are then processed by \( f_\theta \) and \( f_\xi \) to generate latent features \( y_1 = f_\theta(T(x_1)) \) and \( y_2 = f_\xi(T(x_2)) \). The projection heads \( h_\theta \) and \( h_\xi \) projects the latent features to a unit sphere and output projections \( z_1 = h_\theta(y_1) \) and \( z_2 = h_\xi(y_2) \). The discriminator’s objective is to maximize the similarity between the embedding vectors obtained from two samples of the same (pseudo) class:

\[
\mathcal{L}_{\text{disc}} = \ell(z_1, z_2)
\]  

where \( \ell(z_1, z_2) \) is the similarity/distance function that measures compatibility between \( z_1 \) and \( z_2 \). DiRA is a general framework that allows various choices of discrimination tasks without any constraint. As such, the declaration of class might range from considering every single image as a class (instance discrimination) to clustering images based on a similarity metric (cluster discrimination). Accordingly, \( x_1 \) and \( x_2 \) can be two views of the same image or two samples from the same cluster. Based on the nature of the discrimination task, the instantiation of \( \mathcal{L}_{\text{disc}} \) can be cross-entropy [22, 26, 35, 58], contrastive [3, 8, 12, 27], redundancy reduction [21, 53], etc.

### 3.2. Restorative learning

Our restorative learning branch aims to enhance discrimination learning by leveraging fine-grained visual information. As shown in Fig. 3, the restoration branch is comprise of an encoder \( f_\theta \) and decoder \( g_\theta \), where encoder \( f_\theta \) is shared with the discrimination branch. Given the input sample \( x_1 \) distorted by \( T \), the \( f_\theta \) and \( g_\theta \) aims to map the distorted sample back to the original one, i.e., \( f_\theta, g_\theta : (x, T) \rightarrow x \). \( f_\theta \) and \( g_\theta \) are trained by minimizing the distance between the original sample and the restored one at pixel-level:

\[
\mathcal{L}_{\text{res}} = \mathbb{E}_x \text{dist}(x_1, x'_1)
\]  

where \( x'_1 = g_\theta(f_\theta(T(x_1))) \) denotes the restored image. \( \text{dist}(x_1, x'_1) \) presents the distance function that measures similarity between \( x_1 \) and \( x'_1 \), such as \( L_1 \) or \( L_2 \).

### 3.3. Adversarial learning

Adversarial learning aims to reinforce \( f_\theta \) by measuring how realistic the restored images are. As such, the adversarial discriminator \( D_\phi \) is formulated to distinguish (discriminate) the set of training images from the set of synthesized images, guiding encoder \( f_\theta \) to capture more informative features from images so that \( g_\theta \) can reproduce the original images effectively. Therefore, the encoder \( f_\theta \) and decoder \( g_\theta \) play a minimax game with adversarial discriminator \( D_\phi \), and are optimized jointly with an adversarial loss [6, 36]:

\[
\mathcal{L}_{\text{adv}} = \mathbb{E}_x [\log D_\phi(x_1)] + \mathbb{E}_x [\log(1 - D_\phi(x'_1))]
\]

### 3.4. Joint training

Finally, the combined objective for the proposed DiRA framework becomes:

\[
\mathcal{L} = \lambda_{\text{disc}} \ast \mathcal{L}_{\text{disc}} + \lambda_{\text{res}} \ast \mathcal{L}_{\text{res}} + \lambda_{\text{adv}} \ast \mathcal{L}_{\text{adv}}
\]

where \( \lambda_{\text{disc}}, \lambda_{\text{res}}, \) and \( \lambda_{\text{adv}} \) are multiplication factors that determine the relative importance of different losses. Through our unified training scheme, DiRA learns a representation that preserves fine-grained details within the samples while being discriminative among the image classes. In particular, the formulation of \( \mathcal{L}_{\text{disc}} \) encourages the model to capture high-level discriminative features. Moreover, \( \mathcal{L}_{\text{res}} \) forces the model to encode fine-grained information from the images by focusing on pixel-level visual patterns. This results in more descriptive feature embeddings that elevate the discrimination task. Finally, \( \mathcal{L}_{\text{adv}} \) elevates restoration based learning through capturing more informative features.

### 4. Implementations details

#### 4.1. Pre-training protocol

DiRA is a general framework that is compatible with existing self-supervised discriminative and restorative methods, regardless of their objective functions. To assess the effectiveness of our framework, we adapt recent SOTA 2D and 3D self-supervised methods into DiRA, as described in the following. The pretrained models with DiRA are identified as DiRA subscripted by the original method name.

**2D image pretraining settings.** We apply DiRA to MoCo-v2 [14], Barlow Twins [53], and SimSiam [15] for 2D image self-supervised learning. All DiRA models are pretrained from scratch on the training set of ChestX-ray14 [46] dataset. For each of these three discrimination tasks [14,15,53], we follow the original methods in the formulation of \( \mathcal{L}_{\text{disc}} \), projection head architecture, and hyper-parameters settings. Furthermore, we optimize the encoder and decoder networks \( f_\theta \) and \( g_\theta \) following the optimization setups in [14, 15, 53]. For all methods, we employ a 2D U-Net [38] with a standard ResNet-50 [28] backbone as the \( f_\theta \) and \( g_\theta \). We adopt mean square error (MSE) as the \( \mathcal{L}_{\text{res}} \). The adversarial discriminator network \( D_\phi \) consists of four convolutional layers with the kernel size of \( 3 \times 3 \) [37], trained using the Adam optimizer with a learning rate of \( 2e-4 \) and \( (\beta_1, \beta_2) = (0.5, 0.999) \). We use batch size 256 distributed across 4 Nvidia V100 GPUs. \( \lambda_{\text{res}}, \lambda_{\text{adv}}, \lambda_{\text{disc}} \) are empirically set to 10, 0.001, and 1, respectively. Input images are first randomly cropped and resized to \( 224 \times 224 \); the image augmentation function \( T(\cdot) \) includes random horizontal flipping, color jittering, and Gaussian blurring. Additionally, we apply cutout [16, 37] and shuffling [10] to make the restoration task more challenging. More details are provided in the Appendix.
3D volume pretraining settings. We apply DiRA to TransVW [26], the SOTA method for 3D self-supervised learning in medical imaging. We adapt TransVW in DiRA by adding an adversarial discriminator \( D_\phi \) into its training scheme. For fair comparisons, we follow the publicly available TransVW code for setting instance discrimination and restoration tasks. Moreover, similar to publicly released TransVW, DiRA models are pre-trained from scratch using 623 chest CT scans in the LUNA [40] dataset. We use 3D U-Net [20] as the encoder-decoder network and a classification head including fully-connected layers. The adversarial discriminator \( D_\phi \) includes four convolutional blocks with the kernel size \( 3 \times 3 \times 3 \), \( \lambda_{\text{re}} \), \( \lambda_{\text{adv}} \), \( \lambda_{\text{dis}} \) are empirically set to 100, 1, and 1, respectively. \( f_\theta \), \( g_\theta \), and \( D_\phi \) are optimized for 200 epochs using Adam with a learning rate of 1e-3 and batch size of 8. More details are provided in the Appendix.

4.2. Transfer learning protocol

Target tasks and datasets. We evaluate the effectiveness of DiRA's representations in transfer learning to a diverse suite of 9 common but challenging 2D and 3D medical imaging tasks, including: ChestX-ray14, CheXpert [31], SIIM-ACR [1], and NIH Montgomery [32] for 2D models, and LUNA, PE-CAD [41], LiDC-IDRI [2], LiTS [5], and BraTS [4] for 3D models (see Appendix for dataset details). These tasks encompass various label structures (multi-label classification and pixel-level segmentation), diseases (brain tumors and thoracic diseases, such as lung nodules, pulmonary emboli, and pneumothorax), organs (lung, liver, brain), and modalities (X-ray, CT, MRI). Moreover, these tasks contain many hallmark challenges encountered when working with medical images, such as imbalanced classes, limited data, and small-scanning areas for the pathology of interest [3, 29]. We use the official data split of these datasets when available; otherwise, we randomly divide the data into 80%/20% for training/testing.

Fine-tuning settings. We transfer the pre-trained (1) encoder \( f_\theta \) to the classification tasks, and (2) encoder and decoder \( f_\theta \) and \( g_\theta \) to segmentation tasks. We evaluated the generalization of DiRA representations by fine-tuning all the parameters of downstream models. We use the AUC (area under the ROC curve), and the IoU (Intersection over Union) and Dice coefficient for evaluating classification and segmentation performances, respectively. Following [29], we strive to optimize each downstream task with the best performing hyperparameters (details in Appendix). We employ the early-stop mechanism using 10% of the training data as the validation set to avoid over-fitting. We run each method ten times on each downstream task and report the average, standard deviation, and statistical analysis based on an independent two-sample \( t \)-test.

5. Results

We conduct extensive experiments to better understand not only the properties of our framework but also its generalizability across 9 downstream tasks. Through the following groups of experiments, we establish that DiRA (1) enriches existing discriminative approaches, capturing a more diverse visual representation that generalizes better to different tasks; (2) addresses the annotation scarcity challenge in medical imaging, providing an annotation-efficient solution for medical imaging; (3) learns fine-grained features, facilitating more accurate lesion localization with only image-level annotation; and (4) improves SOTA restorative approaches, demonstrating that DiRA is a general framework for united representation learning.

5.1. DiRA enriches discriminative learning

Experimental setup: To study the flexibility and efficacy of our proposed self-supervised framework, we apply DiRA to three recent SOTA self-supervised methods with diverse discrimination objectives: MoCo-v2, Barlow Twins, and SimSiam. To evaluate the quality of our learned representations and ascertain the generality of our findings, we follow [29] and consider a broader range of four target tasks, covering classification (ChestX-Ray14 and CheXpert) and...
Table 1. Transfer learning under different downstream label fractions: DiRA models combat overfitting in low data regimes and provide stronger representations for downstream tasks with limited annotated data. For each downstream task, we report the average performance over multiple runs. (7) shows the improvement of DiRA models compared with the underlying discriminative method.

![Table 1](image_url)

**Figure 5. Visualization of Grad-CAM heatmaps** for (a) MoCo-v2 vs. DiRA_{MoCo-v2}, (b) Barlow Twins vs. DiRA_{Barlow Twins}, and (c) SimSiam vs. DiRA_{SimSiam}. Ground truth bounding box annotations are shown in black. Training with DiRA leads to improvements in weakly-supervised disease localization. While both DiRA and underlying models predict the correct disease label on the test images, DiRA models capture the diseased locations more precisely than the baselines which attune to larger regions of the image (e.g. (c), second row) or provide inaccurate localization with no overlap with the ground truth (e.g. (b), second row).

**Results:** As seen in Fig. 4, utilizing our DiRA framework consistently enhances its underlying discriminative method across all tasks (1) ChestX-ray14, (2) CheXpert, (3) SIIM-ACR, and (4) NIH Montgomery. Compared with the original methods, DiRA_{MoCo-v2} showed increased performance by 0.76%, 1.17%, 1.35%, and 0.21%, respectively; Similarly, DiRA_{Barlow Twins} showed increased performance by 0.43%, 0.60%, 0.16%, and 0.03%; Finally, DiRA_{SimSiam} showed increased performance by 0.82%, 2.22%, 1.18%, and 0.45%. These results imply that DiRA is a comprehensive representation learning framework that encourages existing self-supervised instance discriminative approaches to retain more fine-grained information from images, enriching their visual representation and allowing them to generalize to different medical tasks more effectively.

5.2. DiRA improves robustness to small data regimes

**Experimental setup:** We investigate the robustness of representations learned with DiRA in small data regimes to determine if the learned representation can serve as a proper foundation for fine-tuning. We randomly select 1%, 25%, and 50% of training data from ChestX-ray14, CheXpert, and Montgomery, and fine-tune the self-supervised pre-trained models on these training-data subsets.

**Results:** As shown in Tab. 1, our DiRA pre-trained models outperform their counterparts’ original methods in all subsets, 1%, 25%, and 50%, across ChestX-ray14, CheXpert, and Montgomery. In particular, the average of improvement for MoCo-v2 and SimSiam across all three downstream tasks in each underlying subset garnering: (1) 5.6 % and 7% when using 1%, (2) 2.9 % and 1.3% when using 25%, and (3) 2.2 % and 1% when using 50%. As seen in 1%, DiRA outperforms its counterparts MoCo-v2 and SimSiam by a large margin, demonstrating our framework’s potential for combating overfitting in extreme low data regimes. Although the Barlow Twins is more resistant to low data regimes than the previous two approaches, DiRA still improves its performance by 0.5%, 0.5%, and 0.6% on average across all three datasets when using 1%, 25%, and 50% of labeled data, respectively. In summary, our results in the low-data regimes demonstrate our framework’s superiority for providing more robust and transferable repre-
Table 2. Comparison with fully-supervised transfer learning: DiRA models outperform fully-supervised pre-trained models on ImageNet and ChestX-ray14 in three downstream tasks. The best methods are bolded while the second best are underlined. ↑ and * present the statistically significant (p < 0.05) improvement compared with supervised ImageNet and ChestX-ray14 baselines, respectively, while * and ** presents the statistically equivalent performances accordingly. For supervised ChestX-ray14 model, transfer learning to ChestX-ray14 is not applicable since pre-training and downstream tasks are the same, denoted by ‘-’.

| Method          | Pretraining Dataset | Classification [AUC (%)] | Segmentation [Dice (%)] |
|-----------------|---------------------|--------------------------|-------------------------|
|                 |                     | ChestX-ray14            | CheXpert                | SIIM-ACR     | Montgomery   |
| Random          | -                   | 80.31±0.10              | 86.62±0.15              | 67.54±0.60  | 97.53±0.36  |
| Supervised      | ImageNet            | 81.70±0.15              | 87.17±0.22              | 67.93±1.45  | 98.19±0.13  |
| DiRA_{MoCo-v2}  | ChestX-ray14        | 81.12±0.17              | 87.59±0.28              | 69.24±0.41  | 98.24±0.09  |
| DiRA_{Barlow}   | ChestX-ray14        | 80.88±0.30              | 87.50±0.27              | 69.87±0.68  | 98.16±0.06  |
| DiRA_{SimSiam}  | ChestX-ray14        | 80.44±0.29              | 86.04±0.43              | 68.76±0.69  | 98.17±0.11  |

5.3. DiRA improves weakly-supervised localization

Experimental setup: We investigate our DiRA framework in a weakly supervised setting, comparing its applicability for localizing chest pathology to underlying discriminative methods. Given this goal, we follow [46] and use the ChestX-ray14 dataset, which contains bounding box annotations for approximately 1,000 images. For training, we initialize models with our DiRA pre-trained models, and train downstream models using only image-level disease labels. Following [39, 46], bounding boxes are only used as ground truth to evaluate disease localization accuracy in the testing phase. To generate heatmaps, we leverage Grad-CAM [39]. Heatmaps indicate the spatial location of a particular thoracic disease.

Results: As seen in Fig. 5, our framework learns more fine-grained representations, enabling it to localize diseases more accurately. In particular, heatmaps generated by MoCo-v2, Barlow Twins, and SimSiam models are highly variable, whereas DiRA models consistently achieve more robust and accurate localization results over each corresponding original method. Through the production of more interpretable activation maps, our DiRA framework demonstrates possible clinical potential for post-hoc interpretation by radiologists. Quantitative disease localization results are provided in the Appendix.

5.4. DiRA outperforms fully-supervised baselines

Experimental setup: Following the recent transfer learning benchmark in medical imaging [29], we compare the transferability of DiRA models, pre-trained solely on unlabeled images from ChestX-ray14, with two fully-supervised representation learning approaches: (1) supervised ImageNet model, the most common transfer learning pipeline in medical imaging and (2) supervised model pre-trained on ChestX-ray14, the upper-bound in-domain transfer learning baseline. The supervised baselines benefit from the same encoder as DiRA, namely ResNet-50. We fine-tune all pre-trained models for 4 distinct medical applications ranging from target tasks on the source dataset to the tasks with comparatively significant domain-shifts in terms of data distribution and disease/object of interest.

Results: As shown in Tab. 2, DiRA models achieve significantly better or on-par performance compared with both supervised ImageNet and ChestX-ray14 models across four downstream tasks. In particular, DiRA_{MoCo-v2} and DiRA_{Barlow} outperform both supervised baselines in CheXpert, SIIM-ACR, and Montgomery, respectively. Moreover, DiRA_{SimSiam} outperforms the supervised ImageNet and the ChestX-ray14 pre-trained models in SIIM-ACR and Montgomery, respectively. These results indicate that our framework, with zero annotated data, is capable of providing more generic features for different medical tasks.

5.5. DiRA sets a new state-of-the-art for self-supervised learning in 3D medical imaging

Experimental setup: We further investigate the effectiveness of our framework for enhancing restorative representation learning by applying DiRA to TransVW [26], the state-of-the-art SSL approach for 3D medical imaging. We select TransVW as representative of restorative self-supervised methods because it shows superior performance over discriminative [42, 58], restorative only [10, 57], and restora-
Table 4. Ablation study on different components of DiRA: We study the impact of each component of DiRA, including discrimination, restoration, and adversary, in four downstream tasks. Adding restorative learning ($L_{res}$) to discriminative learning leads to consistent performance improvements. Furthermore, equipping models with adversarial learning ($L_{adv}$) yields performance boosts across all tasks.

| Base            | Pretraining dataset | $L_{dis}$ | $L_{res}$ | $L_{adv}$ |
|-----------------|---------------------|-----------|-----------|-----------|
| MoCo-v2         | ChestX-ray14        | ✓         | ×         | ×         |
|                 |                     | 80.36±0.26 | 86.42±0.42 | 67.89±1.14 |
| Barlow Twins    | ChestX-ray14        | ✓         | ✓         | ×         |
|                 |                     | 80.72±0.29 | 86.86±0.37 | 68.16±1.07 |
| SimSiam         | ChestX-ray14        | ✓         | ✓         | ✓         |
|                 |                     | 81.12±0.17 | 87.59±0.28 | 69.24±0.41 |
|                 |                     | 80.45±0.29 | 86.90±0.62 | 69.71±0.34 |
|                 |                     | 80.86±0.16 | 87.44±0.33 | 69.83±0.29 |
|                 |                     | 80.88±0.30 | 87.50±0.27 | 69.87±0.68 |
|                 |                     | 79.62±0.34 | 83.82±0.94 | 67.58±1.89 |
|                 |                     | 79.41±0.42 | 84.45±0.46 | 68.35±1.16 |
|                 |                     | 80.44±0.29 | 86.04±0.43 | 68.76±0.69 |

The performance of all methods in four downstream tasks.

The performance of all methods in four downstream tasks.

7. Conclusion and discussion

We propose DiRA, the first SSL framework that unites discriminative, restorative, and adversarial learning in a unified manner. The key contribution of our DiRA arises from the insights that we have gained into the synergy of these three SSL approaches for collaborative learning. Given DiRA’s generalizability, we envisage it will take a fundamental step towards developing universal representations for medical imaging. Our DiRA achieves remarkable performance gains, though we fixed the restorative learning tasks in all experiments when examining various formulations of discriminative learning. In the future, examining various choices of restoration tasks and searching for optimal collaborative learning strategies may lead to even stronger representations for medical imaging. In this paper, we have focused on medical imaging, but we envision that DiRA can also offer outstanding performance for vision tasks that demand fine-grained details.

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