Curriculum Fine-tuning of Vision Foundation Model for Medical Image Classification Under Label Noise

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Abstract

Deep neural networks have demonstrated remarkable performance in various vision tasks, but their success heavily depends on the quality of the training data. Noisy labels are a critical issue in medical datasets and can significantly degrade model performance. Previous clean sample selection methods have not utilized the well pre-trained features of vision foundation models (VFMs) and assumed that training begins from scratch. In this paper, we propose CUFIT, a curriculum fine-tuning paradigm of VFMs for medical image classification under label noise. Our method is motivated by the fact that linear probing of VFMs is relatively unaffected by noisy samples, as it does not update the feature extractor of the VFM, thus robustly classifying the training samples. Subsequently, curriculum fine-tuning of two adapters is conducted, starting with clean sample selection from the linear probing phase. Our experimental results demonstrate that CUFIT outperforms previous methods across various medical image benchmarks. Specifically, our method surpasses previous baselines by 5.0%, 2.1%, 4.6%, and 5.8% at a 40% noise rate on the HAM10000, APTOS-2019, BloodMnist, and OrgancMnist datasets, respectively. Furthermore, we provide extensive analyses to demonstrate the impact of our method on noisy label detection. For instance, our method shows higher label precision and recall compared to previous approaches. Our work highlights the potential of leveraging VFMs in medical image classification under challenging conditions of noisy labels.

1 Introduction

Deep neural networks have demonstrated remarkable performance across various tasks, including classification, detection, and segmentation [1, 2, 3, 4]. In medical imaging, these neural networks leverage large amounts of labeled data to train models capable of accurately detecting or classifying medical conditions from images such as dermatoscopes, X-rays, MRIs, and CT scans. However, in practical settings, data often contain noisy labels and it is well established that neural networks perform well only when the quality of training data is sufficiently high [5, 6, 7]. Noisy labels occur when the data annotations—the labels assigned to training images—are incorrect or inconsistent. This issue is particularly problematic in medical imaging, where annotating images is more complex compared to natural images [8, 9]. Consequently, improving the robustness of neural networks against noisy labels is a crucial area of research, directly affecting the effectiveness and reliability of medical imaging technologies.

A large number of algorithms have been developed to address the issue of performance degradation caused by noisy samples [5]. In particular, clean sample selection methods, such as MentorNet [10], Co-teaching [11], Co-teaching+ [12], JoCor [13], and CoDis [14], have demonstrated superior performance without requiring modifications to the model architecture or training loss. The core

^{*}Corresponding author: Kyoobin Lee. Our code is available at github.com/gist-ailab/CUFIT.

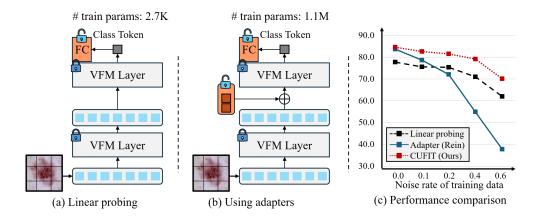


Figure 1: Illustration of linear probing (a) and adapter usage (b). Specifically, the weights of the foundation model are frozen, while the fully connected layer or adapter weights (shown in orange) are updated during the training phase. In (c), a performance comparison using a simulated noisy dataset (HAM10000) is presented. It demonstrates that linear probing is more robust to noisy labels compared to the adapter, whereas the adapter outperforms linear probing when there are no noisy labels.

principle behind these methods is that small-loss samples are likely to be clean, as they are easier to classify and the model memorizes them faster. Additionally, using two different but homogeneous networks to select small-loss samples for each other is more stable than relying on a single model for sample selection. These methods have shown outstanding performance using traditional neural network architectures based on convolutional layers. However, there are practical issues with these methods in two aspects: (i) it cannot be guaranteed that these methods will perform equally well with transformer-based architectures, which have recently gained significant attention, and (ii) their assumption that training starts from scratch is impractical, as it prevents the use of rich features from pre-trained models, which could be beneficial for filtering noisy labels.

Recently, large-scale vision foundation models (VFMs) with transformer-based architectures [15], such as CLIP [16], MAE [17], SAM [18], and DINOv2 [19], have gained attention for their performance and applicability across various tasks. The self-supervised training of VFMs on large-scale datasets enhances their robustness against various image corruptions and improves their generalization capabilities [20, 21, 22, 23]. The inherent robustness and rich features of VFMs can be beneficial for detecting noisy labels. For instance, linear probing of VFMs is relatively unaffected by noisy samples since it does not modify the VFM's feature extractor, preventing the memorization of noisy data, as shown in Figure 1. However, linear probing does not fully leverage the VFM's capabilities when there is a domain gap between the pretraining task of the VFM and the target task (e.g., pretraining on natural images versus medical image classification) [21]. To address this issue, some researchers have proposed using trainable fine-tuning adapters for VFMs [24, 25, 21, 26]. Yet, these adapters might degrade performance by memorizing noisy labels due to their trainable parameters involved in feature extraction. Therefore, we state our research question as follows: *How can we use the power of pre-trained vision foundation models for medical image classification in the presence of noisy labels?*

In this paper, we introduce a Curriculum Fine-Tuning paradigm for vision foundation models in medical image classification under noisy labels, called CUFIT. CUFIT is a curriculum-learning framework designed to fine-tune VFMs with noisy medical datasets. The framework consists of three training modules: the Linear Probing Module (LPM), the Intermediate Adapter Module (IAM), and the Last Adapter Module (LAM). During the training stage, clean samples are selected based on an agreement criterion, where a sample is selected if its annotation matches the module's prediction. Specifically, the LPM is trained using all available samples, as linear probing is robust against noisy labels. Subsequently, the IAM is trained with the samples selected by the LPM, and the LAM is trained with the samples selected by the IAM. This inter-module curriculum training (i.e., LPM—IAM—LAM) is beneficial for increasing the number of clean samples available to train the LAM, considering that the LPM only selects a limited number of samples due to performance degradation caused by the domain gap. Consequently, CUFIT leverages the LAM for final predictions,

offering strong fine-tuning performance for medical image classification in the presence of noisy labels by utilizing the strengths of both linear probing and adapters, as illustrated in Figure 1-c. In summary, the main contributions of this paper are as follows:

- We introduce CUFIT, a simple yet effective fine-tuning paradigm for medical image classification
 using VFMs in the presence of noisy labels. This method leverages the robustness of linear
 probing and the generalization capability of fine-tuning adapters to handle noisy datasets during
 training stage.
- We conduct various experiments demonstrating that CUFIT significantly improves the robustness
 of VFMs against noisy labels in medical datasets. We show that CUFIT outperforms previous
 methods across several medical image benchmarks.
- We provide extensive analyses to enhance the understanding of our fine-tuning paradigm. Additionally, we validate our framework with various VFMs and adapter configurations.

2 Related Work

Vision foundation models. Vision transformers (ViTs) embed 2D images into 1D tokens and model their global correlations using the self-attention mechanism [15, 27, 28]. ViTs are known to be effective when large datasets are used, and the concept of vision foundation models is introduced. Several studies have developed pre-trained vision transformers based on self-supervised learning. For instance, contrastive language-image pre-training (CLIP) provides high-quality visual representations through contrastive learning with a large amount of image-text pairs [16]. Additionally, masked autoencoder (MAE) offers high-capacity models that generalize well through self-supervised learning with masked autoencoding, where the task is to reconstruct token patches from the given masked tokens [17]. Moreover, knowledge distillation with no labels (DINOv1) [29] proposed a teacher-student framework for self-training without annotations, resulting in a well-generalized ViT. More recently, DINOv2 introduced a self-training framework that combines masked autoencoding and teacher-student training based on carefully curated datasets [19].

Since large models and self-training in VFMs provide strong generalization capabilities for various tasks, parameter-efficient fine-tuning has gained attention. Parameter-efficient fine-tuning (PEFT) aims to adapt foundation models to new tasks by training only a few adapter parameters while keeping the model itself frozen. Notably, there is research that proposes low-rank adaptation (LoRA), which introduces trainable rank decomposition matrices into each layer of the transformer architecture in large language models [24]. For the VFMs, visual prompt tuning [25] proposed appending prompts to the input sequence of each transformer block, achieving excellent fine-tuning performance with minimal parameters. Similarly, Adaptformer [26] introduces a novel MLP block to replace the original one in transformer blocks, allowing for the use of both original and few trainable parameters. More recently, Wei et al. proposed Rein, which aims to adapt VFMs for semantic segmentation with domain generalization capabilities [21]. Also, Dutt et al. investigate PEFT algorithms across both convolutional and large transformer-based networks for medical image classification, demonstrating the effectiveness of PEFT, particularly in the low-data regimes common in medical imaging [30]. In this paper, we focus on fine-tuning VFMs for image classification in the presence of noisy labels using adapters. Rather than introducing a new adapter, we utilize an existing adapter within our training paradigm.

Learning with noisy label. Deep neural networks have demonstrated remarkable performance on large-scale datasets. However, it is well-known that neural networks can easily memorize noisy labeled samples, leading to degraded performance. Several studies have been conducted to explore robust supervised learning in the presence of noisy labels. These studies can be categorized into five approaches [5]: (i) robust architectures, (ii) robust regularization, (iii) robust loss functions [31, 32, 33, 34], (iv) loss adjustment [35, 36, 37], and (v) sample selection [10, 38, 11, 12, 14]. In this paper, we categorize our method as a sample selection method, which selects samples with clean labels from a noisy training dataset. While previous sample selection methods typically consider training from scratch, we focus on training starting from a pre-trained model, which is known to be more robust to noisy labels [39]. Additionally, research has explored using CLIP to enable robust training by leveraging its text-image matching capability on noisy datasets [40].

Various methods have been proposed for clean sample selection from noisy datasets. For example, MentorNet introduced the use of a teacher network to guide the student network to focus on clean labels [10]. Similarly, Decoupling proposed updating two networks by using only the samples with differing predictions between them [38]. Co-teaching also trains two networks simultaneously, updating them based on sample recommendations from each other [11]. Co-teaching+ [12] improved upon Co-teaching by introducing the "update by disagreement" strategy, where only the samples with differing predictions between the two networks are used. More recently, Xia *et al.* proposed CoDis, an extension of Co-teaching+ that employs an "update by discrepancy" strategy, selecting samples with high-discrepancy prediction probabilities between the two networks to utilize more samples [14]. These methods are based on the assumption that clean samples can be identified using certain criteria, and that network collaboration is more stable than self-selection, which may lead to error accumulation. In this paper, we develop our method based on same assumption, but we assume that we start the learning process from the pre-trained VFM.

3 Problem Setup

We consider a k-class classification task using a neural network. Let $\mathcal{X} \in \mathbb{R}^d$ denote the input space and $\mathcal{Y} \in \mathbb{R}^k$ represent the ground-truth label space. In a typical classification task, the neural network is trained to align the input space with the label space. To this end, a training dataset $D = \{(x_i, \hat{y}_i)\}_{i=1}^n$ is used for supervised learning with cross-entropy loss. In practice, a sample (x_i, \hat{y}_i) is considered as a noisy labeled sample when human-annotated label \hat{y}_i does not match the true label y_i . The objective of this paper is to develop a fine-tuning approach for VFMs that is robust to noise and capable of performing accurately on noisy datasets.

Given a pre-trained VFM with parameters θ_{VFM} , consisting of a sequence of layers (e.g., attention blocks in ViT [15]) $L_1, L_2, ..., L_M$, where M is the depth of θ_{VFM} , the learning objective for a classification problem can be formulated as:

$$\min_{\theta_t} \sum_{i=1}^n \mathcal{L}_{ce}(p(x_i|\theta_{\text{VFM}}, \theta_t), \hat{y}_i), \tag{1}$$

where θ_t and \mathcal{L}_{ce} represent the parameters targeted for updating and the cross-entropy loss, respectively. Here, $p(\cdot|\theta)$ refers to the prediction for a given input using parameters θ . We refer to the training process as linear probing when θ_t is limited to the parameters of the linear layer θ_l . Additionally, we refer to the training process as full-tuning when θ_t includes θ_{VFM} , and as adapter tuning when it includes adapter parameters θ_a , which are not part of θ_{VFM} .

4 Method

In this section, we begin by describing the adapter method for fine-tuning the VFM in Section 4.1. Following this, in Section 4.2, we introduce our method, CUFIT, which utilizes three modules: a linear layer and two adapters, to combat noisy labels. The key idea behind CUFIT is to leverage the well-pre-trained features of the VFM without updating the feature extractor when handling corrupted samples. Subsequently, the adapters are trained using the samples selected in a curriculum-based training manner, as shown in Figure 2 (i.e., linear probing \rightarrow intermediate adapter \rightarrow last adapter). This approach helps increase the number of selected samples by reducing the domain gap between the pretraining task and the medical image task. It is important to note that our framework does not train the modules sequentially (i.e., where one module starts training only after another finishes); instead, it trains the modules simultaneously on the current batch, similar to multi-task training.

4.1 Learning with Adapter

We consider various adapters for fine-tuning VFMs on medical image datasets. In particular, adapters like Visual Prompt Tuning (VPT [25]), AdaptFormer [26], Low Rank Adaptation (LoRA [24]) and Rein [21] can be used. These methods have been shown to be efficient for various image and video tasks, even compared to full model training [26, 21]. Typically, when an adapter is used for fine-tuning, the parameters of the VFM are frozen and not included in the optimization process.

In this section, we briefly introduce how an adapter works. Note that our goal is not to propose a novel adapter but rather to present a training paradigm that can be applied to various adapters. For

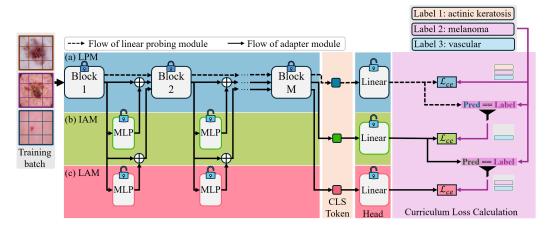


Figure 2: Illustration of our proposed training framework, CUFIT, which consists of a pre-trained VFM and three distinct modules: (a) the linear probing module (LPM), (b) the intermediate adapter module (IAM), and (c) the last adapter module (LAM). During the training stage, the LPM selects clean samples for the IAM based on the *agreement* criterion, and the IAM selects clean samples for the LPM. During the inference stage, only the LAM is used for prediction.

vision transformers (ViTs), the output of the attention block for the given input patches is calculated as follows:

$$x'_{l} = \operatorname{Attention}(Q, K, V) = \operatorname{Softmax}(\frac{QK^{T}}{\sqrt{d}}V) + x_{l-1},$$
 (2)

where x_{l-1} is the output token of the previous block.Here, Q, K, and V refer to the query, key, and value vectors, respectively, which are derived from linear projection and LayerNorm [41] applied to x_{l-1} . The final output of the block, x_l , is then computed using LayerNorm and an MLP. Without using an adapter, this process is formulated as:

$$x_l = \text{MLP}(\text{LN}(x_l')) + x_l', \tag{3}$$

where x_l is the output token of the l-th block. When an adapter is used, the Eq 3 is replaced by the following:

$$x_l = \text{MLP}(\text{LN}(x_l')) + x_l' + \text{Adapt}(x_{l-1}; \theta_{l-1}^a), \tag{4}$$

where $\mathrm{Adapt}(\cdot;\theta_l^a)$ refers to the adapter function for the l-th layer, parameterized by θ_l^a . We consider this process to be an arbitrary function, as various adapters can be used. In the last block, the [CLS] token is passed to the following linear layer for final image classification.

4.2 Curriculum training of three different modules

We consider a pre-trained VFM, θ_{VFM} , with a single linear layer parameterized by $\theta_{\text{LPM}} \in \mathbb{R}^{c \times k}$, an intermediate adapter module parameterized by θ_{LAM} , and a last adapter module parameterized by θ_{LAM} , where c refers to the dimension of the class token (e.g., 384 dimensions for the ViT-small architecture). Then, we propose a curriculum training framework for these three modules, in which the LPM is trained with all samples from the given batch, while the adapter modules are trained with filtered samples selected by their corresponding module using the agreement criterion. The agreement criterion refers to a method where a sample is considered clean if the module's prediction matches the sample's annotation. The idea behind this criterion is that a robust classifier will correctly predict the sample under the assumption that clean labels are in the majority within a noisy class. Therefore, a sample is selected as clean if it meets the agreement criterion (e.g., a "dog" image with a "dog" annotation). Thus, we build the curriculum training framework based on the robustness of the LPM against noisy labels using the agreement criterion.

In particular, the linear probing module (LPM) is trained as follows:

$$\min_{\theta_{\text{LPM}}} \sum_{i=1}^{n} \mathcal{L}_{ce}(p(x_i | \theta_{\text{VFM}}, \theta_{\text{LPM}}), \hat{y}_i), \tag{5}$$

which directly represents supervised learning using the given images and corresponding labels. Here, $p(x_i|\theta_{\text{VFM}},\theta_{\text{LPM}})$ refers to the output of the network using θ_{VFM} and θ_{LPM} for the given image x_i . During the training stage, the intermediate adapter module (IAM) is trained as follows:

$$\min_{\theta_{\text{IAM}}} \sum_{i=1}^{n} \mathcal{L}_{ce}(p(x_i | \theta_{\text{VFM}}, \theta_{\text{IAM}}), \hat{y}_i) \mathbb{1} \{\arg \max p(x_i | \theta_{\text{VFM}}, \theta_{\text{LPM}}) = \hat{y}_i \},$$
 (6)

where $\mathbb{1}\{\cdot\}$ is the indicator function. This simple modification using the indicator function ensures that the adapter module is trained only on selected samples chosen by the linear layer. Finally, the last adapter module (LAM) is trained as follows:

$$\min_{\theta_{\text{LAM}}} \sum_{i=1}^{n} \mathcal{L}_{ce}(p(x_i | \theta_{\text{VFM}}, \theta_{\text{LAM}}), \hat{y}_i) \mathbb{1} \{ \arg \max p(x_i | \theta_{\text{VFM}}, \theta_{\text{IAM}}) = \hat{y}_i \}.$$
 (7)

The Eq 7 is equivalent to Eq 6, but it uses LAM and IAM instead of IAM and LPM, respectively. This simple yet effective sample selection strategy is well-suited for fine-tuning the VFM on noisy image datasets. Notably, it does not require any hyperparameters like the estimated noise rate, which are commonly needed in previous works [11, 13, 14], where they assume the noise rate is known in order to select small-loss samples (e.g., selecting 60% of samples in a batch for a known noise rate of 40%). After training is completed, only the last adapter module is used to predict the given test image.

5 Experiments

5.1 Settings

Datasets. We evaluate our approach on four simulated noisy label medical multi-class image classification benchmarks: HAM10000 [42], APTOS-2019 [43], BloodMnist [44], and OrgancMnist [45]. Additionally, we conduct an evaluation on a real-world noisy label benchmark, Kaggle-EyePACS [46]. In particular, the detail of datasets are as follows:

- HAM10000 [42]: This dataset contains 10,015 dermatoscopic images for skin lesion classification, with each image classified into one of seven possible disease categories. We use all the images for training, and the evaluation is conducted using the 1,512 test images provided by the ISIC 2018 challenge [47].
- APTOS-2019 [43]: This dataset consists of 3,662 retina images taken with fundus photography under various imaging conditions. Each image is rated for the severity of diabetic retinopathy (DR) on a scale from 0 to 4. We use 2,930 images for training and 366 images for evaluation.
- BloodMnist [44]: This dataset contains 17,092 images of individual cells, with each image annotated as one of eight possible cell types. We use 11,959 images for training and 3,421 images for evaluation.
- OrgancMnist [45]: This dataset includes 23,538 images that are center-sliced from the Hounsfield-Unit of 3D images in a coronal view. Each image is labeled as one of eleven body organs. We use 12,975 images for training and 8,216 images for evaluation.
- Kaggle-EyePACS [46]: This Kaggle competition dataset provides 35,126 retina images categorized into five DR severity grades for training, which are known to contain noisy labels [9]. Specifically, some DR category labels (e.g., mild DR labeled as moderate DR) are noisy, and some images considered normal may actually contain retinal diseases such as glaucoma or drusen, which are not included in the classification categories. It is estimated that there is approximately a 30%–40% label error in this dataset [9, 48]. We use the original 35,126 training images and their annotations for training, and all images from APTOS-2019 for evaluation. Additionally, we use the FGADR [49] dataset for further evaluation.

Baselines. We compare the performance of CUFIT with basic training paradigms: full training, linear probing, and fine-tuning with Rein [21]. Additionally, we evaluate our approach against other training-based methods, including Co-teaching [11], JoCor [13], and CoDis [14]. Like ours, these methods do not modify the training loss or architecture. Specifically, Co-teaching trains two networks simultaneously, with each network selecting small-loss samples from its peer's predictions to guide

D-44	Noise rate	Method							
Dataset		Full-training	Linear probing	Rein	Co-teaching	JoCor	CoDis	CUFIT	
	0.1	66.5	75.6	78.6	81.5	81.1	81.9	82.6	
	0.2	62.6	75.3	72.1	79.1	79.4	80.1	81.5	
BloodMnist	0.4	56.1	71.0	54.9	74.3	73.9	74.1	79.1	
	0.6	59.9	61.9	37.8	67.3	67.1	66.1	70.1	
	Mean	61.3	71.0	60.8	75.5	75.4	75.5	78.3	
	0.1	66.8	79.2	82.5	82.8	84.8	83.2	84.2	
APTOS-2019	0.2	65.9	79.4	78.7	81.2	83.1	82.0	84.2	
	0.4	69.9	79.5	77.2	79.5	76.0	79.5	81.6	
	0.6	48.2	66.9	42.0	72.9	74.2	75.7	76.3	
	Mean	62.7	76.3	68.9	79.1	79.5	80.1	81.6	
	0.1	95.4	97.2	95.9	98.6	98.5	98.5	99.0	
	0.2	93.9	96.7	89.0	97.6	97.3	97.2	98.8	
BloodMnist	0.4	91.8	95.8	69.3	93.7	93.0	93.5	98.3	
	0.6	87.9	90.3	45.6	88.7	87.3	88.0	98.2	
	Mean	92.3	95.0	75.0	94.7	94.0	94.3	98.6	
	0.1	85.3	83.3	87.4	92.1	92.1	92.1	93.7	
	0.2	79.9	82.9	82.0	90.9	91.9	90.7	93.6	
OrgancMnist	0.4	72.1	79.9	63.8	85.8	85.3	85.8	91.6	
	0.6	64.5	72.2	43.1	82.8	82.6	81.9	87.4	
	Mean	75.5	79.6	69.1	87.9	88.0	87.6	91.6	

Table 1: Average test accuracy (%) on four simulated noisy datasets with different noise levels. The test accuracy is averaged over the last ten epochs. The best and second-best results in each case are highlighted in **bold** and underline, respectively.

Testset	Method									
	Full-training	Linear probing	Rein	Co-teaching	JoCor	CoDis	CUFIT			
APTOS-2019	34.2	65.4	69.1	70.9	69.3	69.2	69.8			
FGADR	14.3	46.4	48.8	44.9	53.1	53.0	53.7			
Total	27.5	59.0	62.3	62.2	63.9	63.8	64.4			

Table 2: Average test accuracy (%) on real-world noisy datasets (Kaggle-EyePACS for training). After the training is done, we evaluate the model on two datasets: APTOS-2019 and FGADR. The best result and second-best result in each case are highlighted in **bold** and underline, respectively.

learning. JoCor extends this idea by incorporating co-regularization to maximize agreement between the two networks. CoDis further refines this process by selecting samples that not only have small losses but also show high divergence between the two networks. It is important to note that we do not compare our proposed framework with state-of-the-art methods that modify the training loss (e.g., semi-supervised learning) or model architecture [50, 51]. In the experiments, we apply these methods to VFMs with adapters, as they do not require specific model architectures, and VFMs with adapters outperform the linear probing of VFMs (i.e., DINOv2 with the Rein adapter is used as the default setting for training with Co-teaching, JoCor, and CoDis for a fair comparison).

Implementation details. For the experiments, we use DINOv2 [19] with the ViT-small [15] backbone as our basic vision foundation model. Additionally, we use Rein [21] as the fine-tuning adapter, originally proposed for domain-generalized semantic segmentation of VFMs. In our setup, we utilize the class token from the block for classification, rather than the patch tokens from multiple blocks.

We use the PyTorch [52] codebase for our experiments. BloodMnist and OrgancMnist datasets are sourced from MedMnist [53, 54]. We use the ViT-small architecture and the Adam optimizer [55]. All training runs for 100 epochs with a batch size of 32. The initial learning rate is 0.001, which decays by a factor of 10 at epochs 50, 75, and 90. For full-parameter training, however, we start with an initial learning rate of 0.0001. For the simulated noisy label benchmarks, we generate symmetric noise [11] for evaluation, with noise rates set at 10%, 20%, 40%, and 60%.

5.2 Simulated noisy medical image classification benchmark

First, we evaluate our framework on simulated noisy label benchmarks using four medical datasets. The average classification test accuracy for each dataset is provided in Table 1. Our framework consistently outperforms previous baselines, demonstrating its effectiveness under noisy labels by leveraging the pre-trained features of DINOv2 and the Rein adapter. Notably, our framework proves

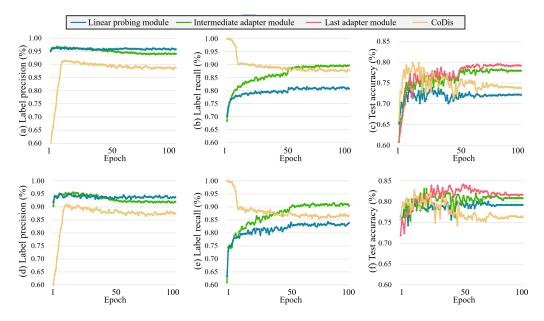


Figure 3: Illustration of label precision (a,d), label recall (b,e), and test accuracy (c,f) vs. epoch. The first row is for HAM10000 with 40% noise rate, and the second row is for APTOS-2019 with 40% noise rate.

to be more effective as the noise rate increases. For example, CUFIT achieves 0.85% relateively higher accuracy than CoDis on HAM10000 with a 10% noise rate, while the improvement rises to 3.7% at a 60% noise rate. This result indicates that the pre-trained features of the VFM are particularly useful for handling noisy labels in the given datasets.

5.3 Real-world noisy medical image classification benchmark

We train DINOv2 with Rein on the real-world benchmark, using the Kaggle-EyePACS dataset for training and the APTOS-2019 and FGADR datasets for testing. Given the highly imbalanced training set (e.g., approximately 73% of the samples are labeled as the normal class), we use weighted cross-entropy loss to train the model. Since previous sample selection methods require a noise rate hyperparameter, we employed the noise estimation method from [56], following Co-teaching [11].

In Table 2, we report the classification accuracy on the APTOS-2019 and FGADR datasets, as well as the overall accuracy across both datasets. Our method outperforms other baselines on the FGADR dataset and the combined dataset, while Co-teaching achieves the highest accuracy on the APTOS-2019 dataset. We believe this discrepancy is due to the distribution of normal class samples—approximately 50% in APTOS-2019 and about 5% in FGADR. Co-teaching performs well in classifying the normal class, whereas our method excels at classifying diseased samples. For example, our method achieves 53.9% macro-average test accuracy, while Co-teaching achieves 48.5% on the combined test set.

6 Discussion

6.1 How does CUFIT works?

So far, we have demonstrated through empirical results that our framework significantly improves the robustness of VFM fine-tuning against noisy labels. However, we have not yet discussed why our framework is effective in learning with noisy labels. In Figure 3, we present label precision, label recall, and test accuracy over the number of epochs to illustrate how our framework functions. In principle, higher label precision indicates fewer noisy samples in the selected data, while higher label recall indicates fewer clean samples in the unselected data. We have following three observations:

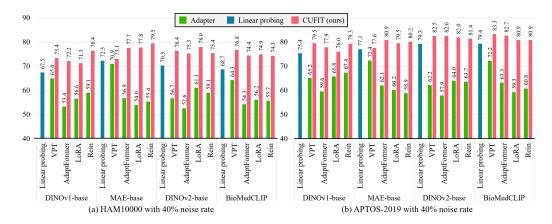


Figure 4: Test accuracy of our method with various VFMs (DINOv1 [29], MAE [17], DINOv2 [19]) and adapters (VPT [25], AdaptFormer [26], Rein [21]). We use HAM10000 and APTOS-2019 with 40% noise rate for training.

Dataset	Noise Rate	Full-training		Linear probing		CoDis		CUFIT		
		ResNet	DINOv2	ResNet	DINOv2	ResNet	DINOv2	ResNet	ResNet+rein	DINOv2
HAM10000	0.2	73.1	66.5	71.1	75.6	74.9	80.1	77.7	79.9	82.6
	0.4	59.6	62.6	67.8	75.3	72.4	74.1	73.8	75.4	81.5
APTOS-2019	0.2	80.4	66.8	80.3	79.2	80.3	82.0	82.4	82.2	84.2
	0.4	64.7	65.9	73.4	79.4	78.1	79.5	80.5	82.2	84.2

Table 3: Average test accuracy on simulated noisy datasets (HAM10000 and APTOS-2019) using the ResNet50 architecture. Test accuracy is averaged over the last ten epochs.

- We find that CoDis exhibits lower label precision during training compared to LPM and IAM, suggesting that previous sample selection methods fail to effectively utilize the pre-trained features of VFMs, leading to lower test accuracy. These methods train the network on all training data without sample selection during the early stages of training (e.g., epochs 1 to 10 in their default setting). However, this approach may harm the feature extraction capability of VFMs and result in degraded performance.
- LPM consistently achieves the highest label precision across epochs but has the lowest label recall, indicating that it effectively prevents the memorization of noisy samples. However, because the feature extractor remains unchanged, its overall accuracy is limited, thus selecting only a small number of clean samples.
- IAM, on the other hand, achieves similar label precision but higher label recall by leveraging the
 adapter module, which contributes to the improved test accuracy of LAM. This suggests that by
 adapting the feature extractor through training the adapter on a few certain clean samples, IAM
 can be a more accurate module. It can then provide more clean samples to LAM, resulting in
 better overall performance.

6.2 Performance comparison across various VFMs and adapters

To validate the performance of CUFIT in various settings, we present experimental results using three VFMs and adapters in Figure 4. We use the same experimental setup (i.e., 100 epochs with the Adam optimizer) to train the network across all backbones and adapters. Specifically, we utilize four backbones, including DINOv1 [29], MAE [17], DINOv2 [19], and BioMedCLIP [57] and four adapters, including VPT [25], AdaptFormer [26], LoRA [24], and Rein [21]. BioMedClip is a CLIP-like model trained with the PMC-15M dataset, which contains 15 million biomedical imagetext pairs collected from 4.4 million scientific articles. Our results demonstrate that our framework consistently helps build a robust classifier across different VFMs and adapters. For example, our framework achieves better performance compared to both adapter-based methods and linear probing. Additionally, we observe that linear probing consistently outperforms the adapter method in all cases, indicating that the performance of adapters can be degraded by noisy labels across various adapters.

Dataset	Noise rate	Method							
		Full-training	Linear probing	Rein	Co-teaching	JoCor	CoDis	CUFIT	
CIFAR10 CIFAR100 ANIMAL10N	0.8 0.08*	25.9 6.3 74.5	79.0 59.6 89.1	24.8 25.6 88.0	78.2 66.7 92.2	75.7 64.2 91.9	76.3 63.7 91.7	83.9 73.8 92.3	

Table 4: Average test accuracy on the natural image dataset with simulated noisy labels (CIFAR, symmetric noise at 80%) and real-world noisy labels (ANIMAL10N [59], which has an estimated noise ratio of 8%). The test accuracy is averaged over the last ten epochs. We use DINOv2 with Rein adapter for the experiment. **Bold** values the best result.

6.3 Performance on CNNs with adapters

We designed CUFIT for VFMs due to their strong pre-trained feature extraction capabilities, enabled by self-supervised training on large datasets. However, CNN-based architectures like ResNet [1] also utilize pre-trained weights instead of starting from scratch. Therefore, we validate CUFIT on ImageNet [58] pre-trained ResNet50, with and without the Rein adapter modified for ResNet. The experimental results are shown in Table 3. We observe that our method outperforms other training paradigms when using the ImageNet pre-trained ResNet architecture. Additionally, the Rein adapter for ResNet improves performance, demonstrating that using fewer trainable parameters with an adapter, compared to full training, is beneficial for combating noisy labels. Finally, we show that the more representative pre-trained features of DINOv2 outperform the ImageNet pre-trained features across all training methods.

6.4 Performance on noisy natural image classification benchmark

Since our framework is easily applicable not only to medical image classification but also to natural image classification, we present experimental results on the CIFAR [60] simulated noisy classification benchmarks and ANIMAL10N [59] real-world noisy classification benchmark in Table 4. We validate our framework under an extremely high noise rate setting (80%) for CIFAR benchmark, as it is intuitive that our framework performs well under low noise rates due to the feature extraction capabilities of VFM. As shown in Table 4, our framework outperforms other sample selection methods in natural image classification benchmarks as well. This demonstrates the effectiveness of our framework, highlighting that using well pre-trained VFMs is beneficial for detecting noisy labels in natural images, as expected.

7 Conclusion

This paper presents a curriculum fine-tuning paradigm called CUFIT, designed to robustly fine-tune vision foundation models (VFMs) for medical image classification. Our framework is based on the insight that linear probing of VFMs is robust to noisy labels, as it does not modify the feature extraction process. Building on this, CUFIT consists of three training modules: the linear probing module (LPM), the intermediate adapter module (IAM), and the last adapter module (LAM). These modules are trained simultaneously, with each selecting clean samples for the next module. Specifically, while the LPM is trained on all samples, the LPM and IAM select clean samples for the IAM and LAM, respectively (i.e., LPM \rightarrow IAM \rightarrow LAM). Experiments demonstrate that CUFIT significantly improves the performance of VFMs in the presence of noisy labels for medical image classification. Additionally, we provide extensive analyses to enhance the understanding of CUFIT. We hope our insights inspire future research to further explore the robustness of vision foundation models when learning with noisy labels for various medical imaging tasks.

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References

- [1] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition*, pages 770–778, 2016.
- [2] Ross Girshick. Fast r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 1440–1448, 2015.
- [3] Kaiming He, Georgia Gkioxari, Piotr Dollár, and Ross Girshick. Mask r-cnn. In *Proceedings of the IEEE international conference on computer vision*, pages 2961–2969, 2017.
- [4] Li Yuan, Yunpeng Chen, Tao Wang, Weihao Yu, Yujun Shi, Zi-Hang Jiang, Francis EH Tay, Jiashi Feng, and Shuicheng Yan. Tokens-to-token vit: Training vision transformers from scratch on imagenet. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 558–567, 2021.
- [5] Hwanjun Song, Minseok Kim, Dongmin Park, Yooju Shin, and Jae-Gil Lee. Learning from noisy labels with deep neural networks: A survey. *IEEE transactions on neural networks and learning systems*, 2022.
- [6] Jonathan Krause, Benjamin Sapp, Andrew Howard, Howard Zhou, Alexander Toshev, Tom Duerig, James Philbin, and Li Fei-Fei. The unreasonable effectiveness of noisy data for fine-grained recognition. In Computer Vision–ECCV 2016: 14th European Conference, Amsterdam, The Netherlands, October 11-14, 2016, Proceedings, Part III 14, pages 301–320. Springer, 2016.
- [7] Devansh Arpit, Stanisław Jastrzębski, Nicolas Ballas, David Krueger, Emmanuel Bengio, Maxinder S Kanwal, Tegan Maharaj, Asja Fischer, Aaron Courville, Yoshua Bengio, et al. A closer look at memorization in deep networks. In *International conference on machine learning*, pages 233–242. PMLR, 2017.
- [8] Cheng Xue, Lequan Yu, Pengfei Chen, Qi Dou, and Pheng-Ann Heng. Robust medical image classification from noisy labeled data with global and local representation guided co-training. *IEEE transactions on medical imaging*, 41(6):1371–1382, 2022.
- [9] Lie Ju, Xin Wang, Lin Wang, Dwarikanath Mahapatra, Xin Zhao, Quan Zhou, Tongliang Liu, and Zongyuan Ge. Improving medical images classification with label noise using dual-uncertainty estimation. *IEEE transactions on medical imaging*, 41(6):1533–1546, 2022.
- [10] Lu Jiang, Zhengyuan Zhou, Thomas Leung, Li-Jia Li, and Li Fei-Fei. Mentornet: Learning data-driven curriculum for very deep neural networks on corrupted labels. In *International conference on machine* learning, pages 2304–2313. PMLR, 2018.
- [11] Bo Han, Quanming Yao, Xingrui Yu, Gang Niu, Miao Xu, Weihua Hu, Ivor Tsang, and Masashi Sugiyama. Co-teaching: Robust training of deep neural networks with extremely noisy labels. Advances in neural information processing systems, 31, 2018.
- [12] Xingrui Yu, Bo Han, Jiangchao Yao, Gang Niu, Ivor Tsang, and Masashi Sugiyama. How does disagreement help generalization against label corruption? In *International conference on machine learning*, pages 7164–7173. PMLR, 2019.
- [13] Hongxin Wei, Lei Feng, Xiangyu Chen, and Bo An. Combating noisy labels by agreement: A joint training method with co-regularization. In Proceedings of the IEEE/CVF conference on computer vision and pattern recognition, pages 13726–13735, 2020.
- [14] Xiaobo Xia, Bo Han, Yibing Zhan, Jun Yu, Mingming Gong, Chen Gong, and Tongliang Liu. Combating noisy labels with sample selection by mining high-discrepancy examples. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 1833–1843, 2023.
- [15] Alexey Dosovitskiy, Lucas Beyer, Alexander Kolesnikov, Dirk Weissenborn, Xiaohua Zhai, Thomas Unterthiner, Mostafa Dehghani, Matthias Minderer, Georg Heigold, Sylvain Gelly, Jakob Uszkoreit, and Neil Houlsby. An image is worth 16x16 words: Transformers for image recognition at scale. In *International Conference on Learning Representations*, 2021.
- [16] Alec Radford, Jong Wook Kim, Chris Hallacy, Aditya Ramesh, Gabriel Goh, Sandhini Agarwal, Girish Sastry, Amanda Askell, Pamela Mishkin, Jack Clark, et al. Learning transferable visual models from natural language supervision. In *International conference on machine learning*, pages 8748–8763. PMLR, 2021.
- [17] Kaiming He, Xinlei Chen, Saining Xie, Yanghao Li, Piotr Dollár, and Ross Girshick. Masked autoencoders are scalable vision learners. In *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pages 16000–16009, 2022.
- [18] Alexander Kirillov, Eric Mintun, Nikhila Ravi, Hanzi Mao, Chloe Rolland, Laura Gustafson, Tete Xiao, Spencer Whitehead, Alexander C Berg, Wan-Yen Lo, et al. Segment anything. In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 4015–4026, 2023.
- [19] Maxime Oquab, Timothée Darcet, Théo Moutakanni, Huy Vo, Marc Szafraniec, Vasil Khalidov, Pierre Fernandez, Daniel Haziza, Francisco Massa, Alaaeldin El-Nouby, et al. Dinov2: Learning robust visual features without supervision. *arXiv* preprint arXiv:2304.07193, 2023.

- [20] Xi Chen, Lianghua Huang, Yu Liu, Yujun Shen, Deli Zhao, and Hengshuang Zhao. Anydoor: Zero-shot object-level image customization. *arXiv preprint arXiv:2307.09481*, 2023.
- [21] Zhixiang Wei, Lin Chen, Yi Jin, Xiaoxiao Ma, Tianle Liu, Pengyang Ling, Ben Wang, Huaian Chen, and Jinjin Zheng. Stronger, fewer, & superior: Harnessing vision foundation models for domain generalized semantic segmentation. arXiv preprint arXiv:2312.04265, 2023.
- [22] Yu Qiao, Chaoning Zhang, Taegoo Kang, Donghun Kim, Shehbaz Tariq, Chenshuang Zhang, and Choong Seon Hong. Robustness of sam: Segment anything under corruptions and beyond. *arXiv* preprint arXiv:2306.07713, 2023.
- [23] Poulami Sinhamahapatra, Franziska Schwaiger, Shirsha Bose, Huiyu Wang, Karsten Roscher, and Stephan Guennemann. Finding dino: A plug-and-play framework for unsupervised detection of out-of-distribution objects using prototypes. arXiv preprint arXiv:2404.07664, 2024.
- [24] Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *International Conference on Learning Representations*, 2022.
- [25] Menglin Jia, Luming Tang, Bor-Chun Chen, Claire Cardie, Serge Belongie, Bharath Hariharan, and Ser-Nam Lim. Visual prompt tuning. In *European Conference on Computer Vision*, pages 709–727. Springer, 2022.
- [26] Shoufa Chen, Chongjian Ge, Zhan Tong, Jiangliu Wang, Yibing Song, Jue Wang, and Ping Luo. Adapt-former: Adapting vision transformers for scalable visual recognition. Advances in Neural Information Processing Systems, 35:16664–16678, 2022.
- [27] Ze Liu, Yutong Lin, Yue Cao, Han Hu, Yixuan Wei, Zheng Zhang, Stephen Lin, and Baining Guo. Swin transformer: Hierarchical vision transformer using shifted windows. In *Proceedings of the IEEE/CVF* international conference on computer vision, pages 10012–10022, 2021.
- [28] Hugo Touvron, Matthieu Cord, Matthijs Douze, Francisco Massa, Alexandre Sablayrolles, and Hervé Jégou. Training data-efficient image transformers & distillation through attention. In *International conference on machine learning*, pages 10347–10357. PMLR, 2021.
- [29] Mathilde Caron, Hugo Touvron, Ishan Misra, Hervé Jégou, Julien Mairal, Piotr Bojanowski, and Armand Joulin. Emerging properties in self-supervised vision transformers. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 9650–9660, 2021.
- [30] Raman Dutt, Linus Ericsson, Pedro Sanchez, Sotirios A Tsaftaris, and Timothy Hospedales. Parameter-efficient fine-tuning for medical image analysis: The missed opportunity. In *Medical Imaging with Deep Learning*, 2023.
- [31] Aritra Ghosh, Himanshu Kumar, and P Shanti Sastry. Robust loss functions under label noise for deep neural networks. In *Proceedings of the AAAI conference on artificial intelligence*, volume 31, 2017.
- [32] Sheng Liu, Jonathan Niles-Weed, Narges Razavian, and Carlos Fernandez-Granda. Early-learning regularization prevents memorization of noisy labels. Advances in neural information processing systems, 33:20331–20342, 2020.
- [33] Yisen Wang, Xingjun Ma, Zaiyi Chen, Yuan Luo, Jinfeng Yi, and James Bailey. Symmetric cross entropy for robust learning with noisy labels. In *Proceedings of the IEEE/CVF international conference on computer vision*, pages 322–330, 2019.
- [34] Zhilu Zhang and Mert Sabuncu. Generalized cross entropy loss for training deep neural networks with noisy labels. *Advances in neural information processing systems*, 31, 2018.
- [35] Taehyeon Kim, Jongwoo Ko, JinHwan Choi, Se-Young Yun, et al. Fine samples for learning with noisy labels. Advances in Neural Information Processing Systems, 34:24137–24149, 2021.
- [36] Junnan Li, Richard Socher, and Steven CH Hoi. Dividemix: Learning with noisy labels as semi-supervised learning. *arXiv preprint arXiv:2002.07394*, 2020.
- [37] Junnan Li, Caiming Xiong, and Steven CH Hoi. Learning from noisy data with robust representation learning. In Proceedings of the IEEE/CVF International Conference on Computer Vision, pages 9485–9494, 2021.
- [38] Eran Malach and Shai Shalev-Shwartz. Decoupling" when to update" from how to update". *Advances in neural information processing systems*, 30, 2017.
- [39] Dan Hendrycks, Kimin Lee, and Mantas Mazeika. Using pre-training can improve model robustness and uncertainty. In *International conference on machine learning*, pages 2712–2721. PMLR, 2019.
- [40] Cheng-En Wu, Yu Tian, Haichao Yu, Heng Wang, Pedro Morgado, Yu Hen Hu, and Linjie Yang. Why is prompt tuning for vision-language models robust to noisy labels? In *Proceedings of the IEEE/CVF International Conference on Computer Vision*, pages 15488–15497, 2023.

- [41] Jimmy Lei Ba, Jamie Ryan Kiros, and Geoffrey E Hinton. Layer normalization. *arXiv preprint* arXiv:1607.06450, 2016.
- [42] Philipp Tschandl, Cliff Rosendahl, and Harald Kittler. The ham10000 dataset, a large collection of multi-source dermatoscopic images of common pigmented skin lesions. *Scientific data*, 5(1):1–9, 2018.
- [43] Omar Dekhil, Ahmed Naglah, Mohamed Shaban, Mohammed Ghazal, Fatma Taher, and Ayman Elbaz. Deep learning based method for computer aided diagnosis of diabetic retinopathy. In 2019 IEEE International Conference on Imaging Systems and Techniques (IST), pages 1–4. IEEE, 2019.
- [44] Andrea Acevedo, Anna Merino González, Edwin Santiago Alférez Baquero, Ángel Molina Borrás, Laura Boldú Nebot, and José Rodellar Benedé. A dataset of microscopic peripheral blood cell images for development of automatic recognition systems. *Data in brief*, 30(article 105474), 2020.
- [45] Xuanang Xu, Fugen Zhou, Bo Liu, Dongshan Fu, and Xiangzhi Bai. Efficient multiple organ localization in ct image using 3d region proposal network. *IEEE transactions on medical imaging*, 38(8):1885–1898, 2019.
- [46] Kaggle diabetic retinopathy detection competition. https://www.kaggle.com/c/diabetic-retinopathy-detection.
- [47] Isic 2018 challenge. https://challenge.isic-archive.com/landing/2018/.
- [48] Xin Wang, Lie Ju, Xin Zhao, and Zongyuan Ge. Retinal abnormalities recognition using regional multitask learning. In *Medical Image Computing and Computer Assisted Intervention–MICCAI 2019:* 22nd International Conference, Shenzhen, China, October 13–17, 2019, Proceedings, Part I 22, pages 30–38. Springer, 2019.
- [49] Yi Zhou, Boyang Wang, Lei Huang, Shanshan Cui, and Ling Shao. A benchmark for studying diabetic retinopathy: segmentation, grading, and transferability. *IEEE Transactions on Medical Imaging*, 40(3):818– 828, 2020.
- [50] Xiaohan Xing, Zhen Chen, Zhifan Gao, and Yixuan Yuan. Gradient and feature conformity-steered medical image classification with noisy labels. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 75–84. Springer, 2023.
- [51] Bingzhi Chen, Zhanhao Ye, Yishu Liu, Zheng Zhang, Jiahui Pan, Biqing Zeng, and Guangming Lu. Combating medical label noise via robust semi-supervised contrastive learning. In *International Conference on Medical Image Computing and Computer-Assisted Intervention*, pages 562–572. Springer, 2023.
- [52] Jason Ansel, Edward Yang, Horace He, Natalia Gimelshein, Animesh Jain, Michael Voznesensky, Bin Bao, Peter Bell, David Berard, Evgeni Burovski, Geeta Chauhan, Anjali Chourdia, Will Constable, Alban Desmaison, Zachary DeVito, Elias Ellison, Will Feng, Jiong Gong, Michael Gschwind, Brian Hirsh, Sherlock Huang, Kshiteej Kalambarkar, Laurent Kirsch, Michael Lazos, Mario Lezcano, Yanbo Liang, Jason Liang, Yinghai Lu, CK Luk, Bert Maher, Yunjie Pan, Christian Puhrsch, Matthias Reso, Mark Saroufim, Marcos Yukio Siraichi, Helen Suk, Michael Suo, Phil Tillet, Eikan Wang, Xiaodong Wang, William Wen, Shunting Zhang, Xu Zhao, Keren Zhou, Richard Zou, Ajit Mathews, Gregory Chanan, Peng Wu, and Soumith Chintala. PyTorch 2: Faster Machine Learning Through Dynamic Python Bytecode Transformation and Graph Compilation. In 29th ACM International Conference on Architectural Support for Programming Languages and Operating Systems, Volume 2 (ASPLOS '24). ACM, April 2024.
- [53] Jiancheng Yang, Rui Shi, and Bingbing Ni. Medmnist classification decathlon: A lightweight automl benchmark for medical image analysis. In *IEEE 18th International Symposium on Biomedical Imaging (ISBI)*, pages 191–195, 2021.
- [54] Jiancheng Yang, Rui Shi, Donglai Wei, Zequan Liu, Lin Zhao, Bilian Ke, Hanspeter Pfister, and Bingbing Ni. Medmnist v2-a large-scale lightweight benchmark for 2d and 3d biomedical image classification. *Scientific Data*, 10(1):41, 2023.
- [55] Diederik P. Kingma and Jimmy Ba. Adam: A method for stochastic optimization. CoRR, abs/1412.6980, 2014
- [56] Tongliang Liu and Dacheng Tao. Classification with noisy labels by importance reweighting. *IEEE Transactions on pattern analysis and machine intelligence*, 38(3):447–461, 2015.
- [57] Sheng Zhang, Yanbo Xu, Naoto Usuyama, Jaspreet Bagga, Robert Tinn, Sam Preston, Rajesh Rao, Mu Wei, Naveen Valluri, Cliff Wong, Matthew Lungren, Tristan Naumann, and Hoifung Poon. Large-scale domain-specific pretraining for biomedical vision-language processing, 2023.
- [58] Jia Deng, Wei Dong, Richard Socher, Li-Jia Li, Kai Li, and Li Fei-Fei. Imagenet: A large-scale hierarchical image database. In 2009 IEEE conference on computer vision and pattern recognition, pages 248–255. Ieee, 2009.
- [59] Hwanjun Song, Minseok Kim, and Jae-Gil Lee. SELFIE: Refurbishing unclean samples for robust deep learning. In Kamalika Chaudhuri and Ruslan Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning*, volume 97 of *Proceedings of Machine Learning Research*, pages 5907–5915. PMLR, 09–15 Jun 2019.

[60] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images.	2009.